The Critique of Crowds: Using Collective Criticism to Crowdsource Subjective Preferences

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ABSTRACT
Crowdsourcing encompasses everything from large collaborative projects to microtasks performed in parallel and at scale. However, understanding subjective preferences can still be difficult: a majority of problems do not have validated questionnaires and pairwise comparisons do not scale, even with access to the crowd. Furthermore, in daily life we are used to expressing opinions as critiques (e.g. it was too cold, too spicy, too big), rather than describing precise preferences or choosing between (perhaps equally bad) discrete options. Unfortunately, it is difficult to analyze such qualitative feedback, especially when we want to make quantitative decisions.

In this article, we present collective criticism, a crowdsourcing approach where users provide feedback to microtasks in the form of critiques, such as “it was too easy/too challenging”. This qualitative feedback is used to perform quantitative analysis of users’ preferences and opinions. Collective criticism has several advantages over other approaches: “too much/too little”-style critiques are easy for users to provide and it allows us to build predictive models for the optimal parameterization of the variables being critiqued. We present two case studies where we model: (i) aesthetic preferences in neural style transfer and (ii) hedonic experiences in the video game Tetris. These studies demonstrate the flexibility of our approach, and show that it produces robust results that are straightforward for experimenters to interpret and inline with users’ stated preferences.

CCS CONCEPTS
• Computer systems organization → Embedded systems; Redundancy; Robotics; • Networks → Network reliability.

KEYWORDS
datastes; neural networks; gaze detection; text tagging

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1 INTRODUCTION
User experience is an increasingly important consideration in systems, services and products, with many applications emphasizing various aesthetic, affective and hedonic properties [21, 22]. Such qualities are particularly important in applications with no instrumental purpose, such as video games, digital toys and interactive artwork [9, 35, 39]. Unfortunately, these applications can be challenging to optimize as they can contain numerous parameters that impact user experience, but for which there are no objective quantities to be maximized and, therefore, need to be set on the basis of subjective preferences. In video games, for example, player speed has a significant impact on user experience: too slow and navigating the game world can be tedious, but too fast and it becomes difficult to control [39]. The sweet spot that balances these two extremes will be determined by user preferences that are influenced by context (e.g. large powerful characters might feel better if they move slower) and other human factors (e.g. lower skilled players might prefer a slower game) [39].

How should we go about setting such parameters? A single user (e.g. the developer) could simply set a given parameter to whatever feels intuitively correct. Alternatively, multiple users could be recruited to provide feedback via questionnaires or to state their preference for one parameterization over another (i.e. pairwise comparisons). Lastly, we could make assumptions about how user behavior relates to experience, e.g. we could assume that engagement (time spent) correlates with positive user experiences. Unfortunately, all these approaches have downsides to inferring subjective preferences: a single user is unlikely to be representative of the user group as a whole, questionnaires need to be validated [30], and pairwise comparisons require large sample sizes [33]. Finally, behavioral data can be misinterpreted, correlating with negative experiences as well as positive ones [42].

In this article, we present an approach for modeling subjective preferences called collective criticism, that combines crowdsourcing with microtasks where users are asked to critique their experiences.
In our approach, critiques are given in a naturalistic and intuitive manner. Some everyday examples of the kind of critiques we use are “the food was too spicy” (or too bland) after eating a meal or “the weather was too hot” (or too cold) when describing a vacation. Such feedback is qualitative, but we can extract quantitative information by considering the context within which it was given. Using the video game example from before, if a player thinks movement is “too slow” and the speed was set to $x$, then this implies the optimal speed lies in the interval from $x$ to $+\infty$ (strictly speaking, the interval $(x, +\infty)$). Importantly, the user does not need to know anything about how the game was implemented to give their critique: it is based solely on experience. Individual observations, however, are subject to random variation and sampling issues (the critic might be a competitive e-sports player, making their opinions non-representative of video game players in general), suggesting we need to perform many experiments to understand how movement speed affects user experience. Indeed, collective criticism uses crowdsourcing to perform randomized experiments to collect users’ critiques over many different parameterizations of the system under investigation. This approach, combined with statistical modeling, allows us to analyze complex relationships between system parameters and user preferences. The main contributions of this paper are as follows:

- A novel crowdsourcing methodology called collective criticism that combines randomized experiments with summary retrospective feedback to collect user preferences.
- A modeling approach that transforms qualitative critiques into censored intervals to be analyzed using existing statistical packages for interval regression.
- We present three studies: a toy worked example and two case studies demonstrating how collective criticism can be used to analyze (i) aesthetic preferences for images generated using neural style transfer, and (ii) hedonic experiences in the video game Tetris.

## 2 RELATED WORK

In this section, we briefly review related work on crowdsourcing subjective preferences and how critiquing has been used in different types of information systems.

### 2.1 Crowdsourcing subjective preferences

Crowdsourcing has eased the collection of subjective preferences by reducing cost and turnaround time. Prior studies have shown a high degree of agreement between crowdsourced and lab-based data collection methods [8, 14, 41]. In computing, subjective preferences are used for algorithm development and evaluation, where crowdsourcing has been used to collect relevance judgments [1], data for sentiment analysis [6], assessments of toxicity in online discussions [3] and even examples of irony and sarcasm [19]. In these areas, items are scored independently of one another using either binary (e.g. relevant/not relevant) or ordinal (e.g. negative-positive) labels. While these labels are considered subjective, there is assumed to be a consensus opinion within a given culture or community. As this data tends not to be aggregated but used as training data, each label needs to be correct and, therefore, there is an extensive literature on study design and statistical methods for quality control (for a recent survey, see [25]).

In other domains, crowdsourcing is used to understand the opinions and aesthetic preferences of the general public. It has been used, for example, to study the aesthetics of platforming games [37], 3D models [16] and portrait photography [17]. Crowdsourcing aesthetic preferences has seen extensive use in reconstructive and cosmetic surgery research. In reconstructive surgery, crowdsourcing has been used to compare the aesthetics of cleft lip outcomes [41] and surgical techniques [38]. Whereas, in cosmetic surgery, it has been used to assess buttock augmentation outcomes [45] and to characterize anatomical aesthetic preferences for male and female genitalia [20, 31]. Crowdsourcing is considered important as surgical aesthetic outcomes are usually only assessed by an individual, either the patient or surgeon, which can lead to biased assessments [5]. In this article, we include a case study comparing aesthetic preferences of an individual (in our case, a developer) with our crowdsourcing approach and find similar disparities. Beyond aesthetics, crowdsourcing has recently been used to understand the public perception of topical subjects, such as AI fairness [44] and moral decision-making in the context of autonomous driving [4]. All of the above examples used either questionnaires or pairwise comparisons to infer subjective preferences, both of which have serious disadvantages. Questionnaire response scales need to be validated to ensure they are measuring what they purport to measure [50]. Pairwise comparisons do not suffer from this issue, but can require exceptionally large sample sizes (i.e. multiples of $\binom{2}{2}$ pairwise comparisons), practically limiting assessment to relatively small numbers of items [33]. Our approach does not require validation like a questionnaire: we ask only a single question that is often directly referencing a given parameter (i.e. we do not use multi-item scales and, therefore, do not need to assess construct validity). Furthermore, as users are critiquing individual parameters and not making pairwise comparisons, sample sizes can be much lower.

While not usually considered crowdsourcing, A/B testing uses randomized experiments to compare the effectiveness of two (or more) versions of the same system on the basis of conversion rates, e.g. click-throughs or purchases [27]. This makes the assumption that a given behavior is correlated with positive user experience [28]. However, it can also result in unintended consequences if the measured response corresponds to multiple outcomes, e.g. video watch time is correlated with outrage as well as enjoyment [42]. Our approach is based on stated preferences, avoiding the ambiguity-related issues associated with revealed preferences.

### 2.2 Critiquing

Critiquing has previously been used as an interaction mechanism in both interactive search and conversational recommender systems [13]. In critiquing-based systems, users provide critiques in relation to item features, e.g. “too expensive”, to iteratively navigate a complex information space [13]. The FindMe system was the first critiquing recommender, combining browsing with the critiquing of previously retrieved examples [11]. Later systems utilized the approach to develop interactive retrieval systems for e-commerce [10, 18] decision support [34] and preference-based search [46].
However, the most common application of critiquing is in conversa-
tional recommender systems [23], where they have been applied to
various domains, including movie [47] and music recommendation
[24]. Recently, critiquing-based systems have used language-based
attributes, rather than fixed item features, to automatically identify
attributes of an item that can be critiqued [48].

In interactive systems, critiques are constraints that are applied
across items. For example, if I want to buy a plane ticket and I
critique that the current recommendation is too expensive, then it
does not make sense to show tickets with higher prices. In this work,
there is no dialogue with the user, just a succession of examples
to be critiqued where immediate personal circumstances are less
relevant. Furthermore, we are collecting user preferences and not
navigating an information space.

3 APPROACH

Our approach to modeling collective criticism requires three el-
ements: (i) critique elicitation (ii) randomized experiments, and
(iii) statistical modeling to analyze users’ preferences and opinions.

3.1 Critique elicitation

During an experiment, each participant performs a microtask where
they, for example, view an image or use a system for a short period
of time. After completing the microtask, participants are asked to
critique the property under study using summary retrospective
feedback. In concrete terms, summary retrospective feedback takes
the form of there being “too much” or “too little” of some property.
For example, suppose we wanted to optimize the volume of a
ringtones, an audible, but discrete, ringtones for an office environment. In an
experiment, we would ask participants to listen to a ringtones and
state whether they thought it was “too quiet” to be audible or “too
loud” to be discrete.

This kind of critique is qualitative: it does not contain informa-
tion related to how much something should change, merely the
direction of that change. This allows participants to respond with
their gut instinct and can be used when an appropriate scale for
quantitative feedback does not exist.

3.2 Randomized experiments

Here, we detail the assumptions of our approach and describe the
steps necessary to design and conduct an experiment.

3.2.1 Assumptions. We assume that investigators have a hypo-
thesis that a given parameter, $p$, affects a specific property of the
system under study. Furthermore, we assume that optimizing $p$
necessitates making a trade-off, i.e. setting $p$ either too high or too
low is detrimental to user experience, but that there exists a “sweet
spot” where users are maximally satisfied.

3.2.2 Effective parameter ranges. Investigators need to determine
the effective range for the parameter, $p$. This could be the entire
range of the parameter, e.g. the decision threshold in a probabilistic
classifier is 0 to 1 inclusive, or be limited to a given interval. In this
article, we determined the effective range of parameters by trial and
error, however, it could also be limited due to physiological reasons,
e.g. human hearing is limited to 20 Hz to 20 kHz, or technological
reasons, e.g. telephony limits audio frequencies to 300 Hz to 3.4
kHz. Therefore, optimizing the frequency of a tone would have
different effective ranges under different circumstances.

3.2.3 Summary retrospective anchors. Study participants give cri-
tiques using summary retrospective feedback guided by the investi-
gator. The study design, therefore, needs to include verbal anchors
to ensure that users critique the correct property. Verbal anchors
are words used to indicate the informal meaning of response scales,
such as “strongly agree” and “strongly disagree”. In our case, anchors
are judgments, such as “too hot” and “too cold”.

Selecting appropriate verbal anchors is important for two rea-
sons: (i) from the participants’ perspective, anchors need to capture
their collective understanding of the extremes of the property be-
ing assessed, and (ii) from the investigator’s perspective, anchors
need to correspond to increasing and decreasing the parameter of
interest.

3.2.4 Experimental procedure. We extract quantitative informa-
tion from summary retrospective feedback by changing the underlying
conditions from which the assessment is made. We achieve this
by randomizing the parameter of interest within the parameter’s
effective range. The experimental procedure is as follows:

(1) We randomly set the parameter, $p$, to a value selected uniformly
at random from the parameter’s effective range.

(2) Participants are instructed to perform a microtask. Microtasks
are study-specific. Participants could be asked to use a system
for a set period of time or simply to look at an image.

(3) After the microtask, participants are asked to critique their
experience with respect to a given property using the experi-
motivation’s summary retrospective anchors (e.g. too high/too low).

(4) For each observation, we record the random value of $p$, the
participant’s critique and any additional metadata or user be-
behavior data that is to be used for analysis (see Section 5 for an
example).

If we want to understand the impact of $p$ on other parameters in
the system, then these additional parameters need to be randomized
and recorded along with $p$ (see Section 4 for an example).

3.3 Statistical modeling

After all experiments have been performed we model the data set
using interval regression. This requires us to transform particip-
ants’ critiques into censored and/or non-censored intervals. We
use left-censored intervals to represent when participants stated
a parameter was set too high. That is, if the parameter being opti-
imized was assigned the random value $p$, then the resulting censored
interval is $(-\infty, p]$, i.e. while we do not know the optimal value
that would maximize the participant’s experience, we assume that
it is in the interval up to and including $p$. If the effective range of
this parameter, however, is such that $p$ cannot be negative, then
the (non-censored) interval would be $[0, p]$. We use right-censored
intervals, $[p, +\infty)$, when the parameter was set too low, following
the same logic. Figure 1 shows the intervals from the worked ex-
ample in Section 3.4, where left-censored intervals are depicted as
red arrows and right-censored intervals are blue.

In interval regression, we let $y = \beta x + \epsilon$, where $y$ is a continuous
response variable and errors are assumed to be Gaussian, i.e. $\epsilon \sim$
We present a toy cognitive estimation task to provide readers with a simple concrete example of collective criticism.

3.4.1 Objective: We wanted to estimate the number of jelly beans in a jar. Users were asked to critique random counts and, for comparison, to provide an estimate of their own. We determined empirically that the jar could hold \( \sim 1000 \) jelly beans, making the effective range from 0–1000, inclusive. We used “greater than” and “less than” as summary retrospective anchors because users are estimating a count. The ground truth was 568 jelly beans.

3.4.2 Task: For each participant, a number, \( x \), was sampled uniformly at random from 0–1000, inclusive. Participants were shown the jar of jelly beans and asked two questions:

- How many jelly beans are in the jar: greater than \( x \) or less than \( x \)?
- How many jelly beans do you estimate there are in the jar?

The order of questions was intentionally not randomized because we wanted to minimize the effect of respondents’ estimates on their opinions of \( x \). As a follow-up question, we asked participants which of the two questions was more cognitively demanding.

3.4.3 Participants: We recruited 60 participants during the coffee breaks of a conference organized in our department (27 female, 33 male). The participants ranged from PhD students to full professors who had a background in theoretical computer science, optimization or a related field.

3.4.4 Results: The 60 participants gave 60 estimates of the number of jelly beans in total. The difference between participants’ mean estimate of the number of jelly beans (\( M = 465.52, 95\% \) CI [409.98, 521.05]) and the answer derived from collective criticism (\( M = 454.96, 95\% \) CI [382.97, 526.93]) was not statistically significant (\( t \)(62.56) = -0.260, \( p = 0.796 \)), showing that our approach is as accurate as allowing users to directly estimate. Furthermore, a majority of participants (47/60, \( p = 1.22 \times 10^{-5} \), binomial test) reported that they perceived critiquing to be less cognitively demanding than free estimation.

4 CASE STUDY 1: AESTHETIC PREFERENCES

In our first case study, we modeled users’ aesthetic preferences for images generated using neural style transfer. Neural style transfer combines the content from one image (the content image) and the style from another image, usually an artwork (the style image), see Figure 2. We demonstrate how collective criticism can be used to elicit preferences, model different hypotheses and make practical parameterization decisions.

4.1 Objective

Neural style transfer has two hyperparameters: a content weight and a style weight, however, if one parameter is kept fixed, there is only one free parameter. We, therefore, wanted to identify the highest style weight that could be applied to a photo without the subject becoming unrecognizable. Furthermore, we hypothesized that different style weights would be optimal for different kinds of photo, such as head, waist-up and full body shots, i.e. we hypothesized that there is an interaction between style weight and photo type.

4.2 Neural style transfer

4.2.1 Implementation: We used the fast neural style transfer implementation1 included in the PyTorch library [32], which is based on perceptual loss [26] and instance normalization [43].

1https://github.com/pytorch/examples/tree/master/fast_neural_style

Figure 1: Interval data and final result from worked example in Section 3.4. Left-censored intervals are colored red and right-censored intervals are colored blue. The \( y \) coordinate of each interval is the order the tasks were performed in.
We recruited 31 participants from the Faculty of Science by walking up to people in the corridor (10 female, 21 male). All participants were PhD students and postdoctoral researchers from the departments of computer science or mathematics and statistics.

4.2 Model training: We determined by trial and error that, if the content weight is kept constant at $10^5$, the effective range for style weight is $10^5$-$10^{11}$, where higher values result in an output image more heavily influenced by the style image (see Figure 2). We trained 101 neural style transfer models using the COCO 2014 data set [29] and used an image of a mosaic included with PyTorch as the style image (see Figure 2, far right). Each model had a different style weight parameter where the exponent was incremented by 0.03, i.e. 8.0, 8.03, … 10.97, 11.0 (this increment was chosen empirically so the difference between consecutive models was imperceptible), and was trained for 2 epochs.

4.2.3 Input images: We selected photos from a collection of permissionally licensed stock photographs. We selected three categories of portrait: head shots, waist-up and full body shots. We identified 39 images of similar size, with 13 photos in each of the three categories. All categories included men and women of approximate working age and different ethnicities.

4.3 Task
Participants were told we were creating a new website for our research group and wanted to make our photos look more interesting using neural style transfer. We briefly explained the concept of neural style transfer using example images to illustrate different levels of stylization and stated that the stylized image should be as strongly influenced by the artwork as possible, without the person in the photo becoming unrecognisable. Each participant was shown 10 randomly sampled images, stylized with randomly sampled style weights. After being shown each image, the participant was asked the following question:

Do you think the image should look more realistic or more artistic?

During the study, we logged the photos shown, style weights and user feedback. Each experiment lasted a total of ~3 minutes.

4.4 Participants
We recruited 31 participants from the Faculty of Science by walking up to people in the corridor (10 female, 21 male). All participants

Figure 2: Neural style transfer combines a content image (far left) with a style image (far right). The degree of stylization is controlled by the style weight parameter (middle) which can vary from barely noticeable ($10^5$) to unrecognizable ($10^{11}$).

4.5 Results
The 31 participants examined a total of 310 photos: 95 head shots, 117 waist-up shots and 98 full body shots.

4.5.1 Baseline: There is no validated questionnaire for rating image stylization and pairwise comparisons between all images using all neural style transfer models would require an impractical sample size. Instead, we used a pre-trained network included in the PyTorch distribution that used the same style image as a baseline to understand whether crowdsourcing was necessary or the developer’s intuition was appropriate for this problem. The pre-trained model used a content weight of $10^5$ and a style weight of $10^{10}$.

4.5.2 Preference models: We fitted two preference models using interval regression. In the first model, each study participant was modeled as a random effect due to repeated measures and photo type (head, waist-up and full body) was modeled as a fixed effect:

$$y_j = \beta_0 + \beta_1 p_j + u_j,$$

where $y$ are intervals derived from critiques, $p$ is the photo type and $u$ are random intercepts per user, $j$. The second model was identical to the first, but with photo type excluded:

$$y_j = \beta_0 + u_j$$

The crowdsourced style weights ($log_{10}$) for head ($M = 9.71$, 95% CI [9.46, 9.95]), waist-up, ($M = 9.53$, 95% CI [9.31, 9.75]) and body shots ($M = 9.39$, 95% CI [9.14, 9.63]) were very similar to one another, with overlapping 95% confidence intervals. Indeed, the difference in model fit between explicitly modeling photo type versus not was not statistically significant ($\chi^2$ (1.55, N = 310) = 3.14, p = 0.14). This suggests that the mean style weight for all photos ($M = 9.55$, 95% CI [9.36, 9.73]) is suitable for all three types of photo, assuming all other conditions, such as photo size and the age range of the subject, remain constant. Finally, the style weight parameter used in the pre-trained baseline was $10^{10}$, which was outside of all four confidence intervals and, therefore, the difference was statistically significant.
4.6 Summary

Given these findings, we argue that there is insufficient evidence for using different style weights for each photo type and that the style weight used to train the network should be set to 10.55 in order to balance style and recognizability. However, if we were to collect more data, then it is likely that we could recommend the use of category-specific style weights. This experiment demonstrates how the intuitions of an individual may not match the crowdsourced opinions of the group.

5 CASE STUDY 2: HEDONIC PREFERENCES

In our second case study, we show how collective criticism can be used to model hedonic preferences related to challenge in the video game Tetris. This example demonstrates how to create a model that could be used as the basis for personalization in an adaptive interactive system.

5.1 Objective

Tetris is a tile-matching video game that gets progressively more challenging as the speed of the game increases (see Section 5.2 for a description of gameplay). A game of Tetris starts out slow; not presenting the player with any challenge. During the endgame, however, Tetris can become frustratingly fast, making the player anxious (see Figure 3). We wanted to create a model for an adaptive version of Tetris where the level of challenge is personalized for each player. Namely, we wanted to identify how game speed and other contextual factors could be used to keep players feeling challenged, but not overwhelmed. This could be viewed as modeling a kind of flow state [15]: one of many considerations that go into game design [7] and is actively studied in the development of, for example, slot machines [36].

5.2 Tetris

5.2.1 Gameplay: In Tetris, players control falling shapes called tetrominoes to achieve a high score. Players can move tetrominoes left and right, increase their speed of descent (called a "soft drop") or force them to immediately drop to the bottom of the play field (a "hard drop"). When the player completes a line (i.e. a row of blocks without any gaps), it disappears and the player’s score increases. After clearing a fixed number of lines, the difficulty level is increased and, along with it, the speed of the game. The game ends when a tetromino overlaps the top of the play field.

5.2.2 Implementation: Figure 3 shows our web-based implementation of Tetris. The play field is 12×20 tiles and the surrounding interface shows the score, the number of lines cleared and a timer indicating how much time is remaining in the experiment. In most versions of Tetris, the scoring function is proportional to the level and, therefore, the current game speed, i.e. clearing a line is worth more points at level 2 than level 1. In our implementation, however, we used the same scoring function irrespective of the current game speed: 5 points for each placed tetromino and 20 points for each line cleared.

The game speed is determined by the delay in milliseconds for a tetromino to move down the play field by one block. We determined by trial and error that the effective range of this delay was 100-600 ms, where 100 gave the fastest speed and 600 resulted in the slowest speed.

5.3 Task

Prior to the task, participants were asked to fill out a background questionnaire to capture (i) demographic information, (ii) how often they played video games, (iii) their familiarity with Tetris and (iv) their opinion of Tetris. After completing the questionnaire, participants were allowed to play as many warm-up games of Tetris as they wanted.

During the study, each participant played 3 games of Tetris. In the first game, the fall delay was sampled uniformly at random from the full effective range, 100-600 inclusive. In the second and third games, we altered the upper or lower bounds of the delay range to reflect user feedback. For example, if in the first round a delay of 300 was too slow, then in the second round the delay would be sampled from the range 100-300 (lower delays mean higher speed). Each game of Tetris lasted a maximum of 2 minutes. After 2 minutes had expired, or the game was lost, participants were asked the following question:

We are collecting data to create a game of Tetris that helps players improve their skill level. It should be just fast enough to feel like a challenge. For a player of your skill level, do you think the game you played should have been faster or slower?

During the study, we logged game data (fall delay, time spent playing, score, number of lines cleared) and interaction data (keyboard events and their associated timestamps). Each experiment lasted a total of ~10 minutes.

5.4 Participants

We recruited 50 participants who were studying at the university library (24 female, 26 male). Participants were aged between 20-49 with a median age of 28. According to the background questionnaire, over 2/3 of participants played video games at least occasionally (never (14), occasionally (23), every week (9), every day (4)), and a majority of participants, 45/50, had at least some prior exposure to Tetris (never (5), a few times (31), many times (12), experienced (2)).
Overall, participants were neutral in their opinion of Tetris (mean = 2.98 on a 5 point scale where 1 = hate and 5 = love).

5.5 Results

The 50 participants played a total of 150 games of Tetris. We compared a model created using collective criticism with a baseline based on behavioral data.

5.5.1 Baseline: We assumed that the fall delay that maximised the average score would also maximise players’ hedonic experience. We fitted a linear mixed model with delay as linear and quadratic fixed effects and participant as a random effect:

\[ y_j = \beta_0 + \beta_1 d_j + \beta_2 d_j^2 + u_j, \]

where \( y \) is the score, \( d \) is delay and \( u \) are random intercepts per user, \( j \). The baseline found that the average score was maximized when the delay was 308.68 ms (see Figure 4, dashed blue curve). The baseline does not provide any uncertainty estimates for the optimal delay, only standard errors for the coefficients of the delay terms in the model. Furthermore, this analysis is based on assumptions and we do not know whether this delay is truly inline with user preferences.

5.5.2 Static preference model: We used collective criticism to fit a model for users’ speed preferences with no explanatory variables other than participant as a random effect:

\[ y_j = \beta_0 + u_j, \]

where \( y \) are intervals derived from critiques and \( u \) are random intercepts per user, \( j \). The preference-based model found that the optimal delay is 314.70 ms (95% CI [283.34, 346.05]). This is very similar to the point estimate from the baseline model, despite using different response variables and very different assumptions, however, it also allows us to estimate the uncertainty in the mean delay (see Figure 4, dashed red line). As the baseline result (308.68 ms) falls into the 95% confidence interval for the preference-based model, there is no statistically significant difference between the two results. However, in the preference model we know that the optimal delay is inline with user preferences.

5.5.3 Personalized preference model: Predicting the optimal delay for the average participant masks the variability between players and we assume that unskilled and expert players will have different ideas of what constitutes a challenge. Unfortunately, this is not possible to model with the baseline because the score—a key measure of player ability—is already being used as the response variable. However, the preference model can incorporate the score as an additional explanatory variable.

Figure 5 shows in-sample predictions from the best model we found based on AIC score (AIC = 163.65). This model used Tetris familiarity and Tetris opinion from the background questionnaire, as well as the number of lines cleared during a game as explanatory variables (using the game score had a slightly higher AIC, but the two variables are strongly correlated):

\[ y_j = \beta_0 + \beta_1 s_j + \beta_2 f_j + \beta_3 o_j + u_j, \]

where \( y \) are intervals derived from critiques, \( s \) is the number of lines cleared, \( f \) is a factor for familiarity, \( o \) is a factor for opinion and \( u \) are random intercepts per user, \( j \). Figure 5 shows that as player performance (number of lines cleared) increases, the predicted fall delay decreases to offer a greater challenge. Similarly, higher Tetris opinions and familiarity tended to correlate with lower predicted fall delay. We investigated the use of many additional variables in the model, e.g., average number of hard drops per tetromino and average time between key presses were highly predictive, however, including them in a model together with number of lines cleared resulted in higher AIC.

5.6 Summary

The difference between the baseline and the two models created using collective criticism was the incorporation of preference information, making us confident that we are modeling user experience and not potentially misinterpreting behavioral data.

While the baseline model would only satisfy the average player, the additional flexibility of freeing up the score variable allows us to create a model for personalization based on player performance (as determined by the prior two minutes of playtime). Furthermore, the preference models directly output the value of the delay parameter,
whereas the baseline required us to maximize a quadratic function to calculate the optimal result.

6 CONCLUSIONS AND FUTURE WORK

In this paper, we introduced a crowdsourcing approach for understanding subjective preferences called collective criticism. Collective criticism combines randomized experiments with critiques in the form of summary retrospective feedback, such as "too high/too low". These critiques are transformed into intervals and analyzed using interval regression.

We evaluated collective criticism on three problems: (i) a cognitive estimation problem, (ii) aesthetic preferences in neural style transfer, and (iii) modeling users’ perceptions of challenge in Tetris. In the cognitive estimation problem, we found no statistically significant difference between the results given by collective criticism and the average free estimate, however, a majority of participants felt that critiques were the least cognitively demanding of the two feedback mechanisms (Section 3.4). In neural style transfer, we were forced to use a pre-trained model as a baseline because performing pairwise comparisons on 39 photos and 101 neural networks would have required at least $\binom{39}{2}$ comparisons and a validated questionnaire for our specific problem does not exist. We showed that the optimal parameterization was different from a baseline pre-trained model and found insufficient evidence in the data collected to support there being an interaction between style weight and photo type (Section 4). In Tetris, we demonstrated that modeling subjective preferences using collective criticism allowed us to create more complex models than behavioral data alone. Furthermore, we did not need to make assumptions about how behavior maps to user preferences (Section 5).

In future work, we will investigate how to make collective criticism more sample efficient. We can see in Figure 1, for example, that asking users to critique experiences that are either very high or very low is wasteful after a certain amount of evidence has already been accumulated. Therefore, we plan to investigate combining collective criticism with Thompson sampling [12]. In Thompson sampling, the next data point is sampled from the posterior distribution, so the effective parameter range gets narrower as the experiment progresses and participants are only asked to critique the areas of greatest uncertainty. Thompson sampling has the disadvantage that you need to specify the model a priori, which could lead to sample inefficiency if the model is unnecessarily complex. For well-defined problems, however, this should not be an issue.

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