

Revealing Abstract Arts with Feedback Induced Crowdsourcing to LLM Sourcing

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Abstract

Crowdsourcing has received a major attention in solving creative tasks in recent times. Some creative problems are so abstract that they require repetitive interaction between the requester and crowd worker. Moreover, defining a ground truth for such creative tasks is a challenge. This paper aims to address the problem of revealing the content of abstract arts with a feedback-induced mechanism – both via crowdsourcing and LLM sourcing. As abstract arts are interpreted in different ways, it is interesting to elucidate the content through interaction. We propose an approach that employs a corrective feedback mechanism to enable the requester and crowd workers to interact. The effectiveness of this approach is demonstrated by annotating 30 abstract arts on a crowdsourcing platform. The results show that feedback motivates workers to provide detailed responses, interact further with the requester, and reveal more on the abstract content. Further sentiment analysis on the discussion data reflects the importance of corrective feedback in crowdsourcing. We further extend this by outsourcing the tasks to LLMs and observed a better output. However, some interesting challenges like hallucination and ethical participation by the LLMs emerge through this.

Introduction

Crowdsourcing exploits the natural human intelligence at scale for solving various kinds of tasks online (Mridha and Bhattacharyya 2019; Gao, Barbier, and Goolsby 2011). Crowdsourcing has already been established as an effective mechanism for getting creative tasks done by the common people (Kittur 2010; Oppenlaender et al. 2020). Unlike the creative problems of designing (e.g., logo design on 99designs.com), abstract creative tasks often require more explicit interactions between the requester and crowd workers. In this paper, we address the problem of elucidating the content of abstract arts through crowdsourcing. It has been shown that crowd workers can be more engaged when they receive feedback (Gaikwad et al. 2015, 2016). Feedback mechanism has also been shown to be useful for getting tasks done in a better way (Drapeau et al. 2016). The feedback is often necessary because there exists an information gap between the requester and crowd workers. So, providing

appropriate feedback is likely to reduce this gap. This is very much important for getting abstract creative tasks done because there is no ground truth in these problems. The aforementioned issues can be addressed by triggering feedback from the requester side, thereby reducing the said communication gap.

In this paper, we introduce a corrective feedback mechanism motivated from its application in the teaching learning process (Lyster and Ranta 1997). Corrective feedback is used in teaching learning process for the improvement of quality of learning. A couple of decades earlier, the very first application of corrective feedback and learner uptake were experimented in four French immersion classrooms at primary level (Lyster and Ranta 1997). The proposed mechanism allows the requester to trigger feedback for assisting the task of abstract art annotation. The proposed feedback mechanism not only enhances the involvement of crowd workers, but also aim to increase the quality of submitted solutions through corrective feedback.

Our proposed approach is experimented through an in-house crowdsourcing platform, namely CrowdBee. Here, we have made an effort to focus on the information gap between the requester and the crowd worker for analyzing the sentiments of the comments that have been posted on the CrowdBee platform. Due to a variety of task types and difficulty levels, workers' performance varies, thereby producing different results (see Fig. 1). Users are impacted by the difficulty of the assignment and their own experiences in several ways. All of these are major hindrances behind producing high-quality solutions task types and user experiences in numerous ways, which is crucial for producing high-quality solutions. Further discussion is necessary if the expected and actual solutions differ.

According to the idea of corrective feedback, rules are established in our proposed approach. Three different sorts of corrective feedback are utilized in this CrowdBee platform: clarification request, metalinguistic clues, and elicitation. The rule states that a task's response is accepted if it satisfies the requester's requirements. If not, presently there a discrepancy between the submitted answer and the real solution. So, more conversation is needed to resolve the issue. For reinforcing future communication, we have executed corrective feedback. In this, the requester may review responses and offer relevant feedback in light of the worker's

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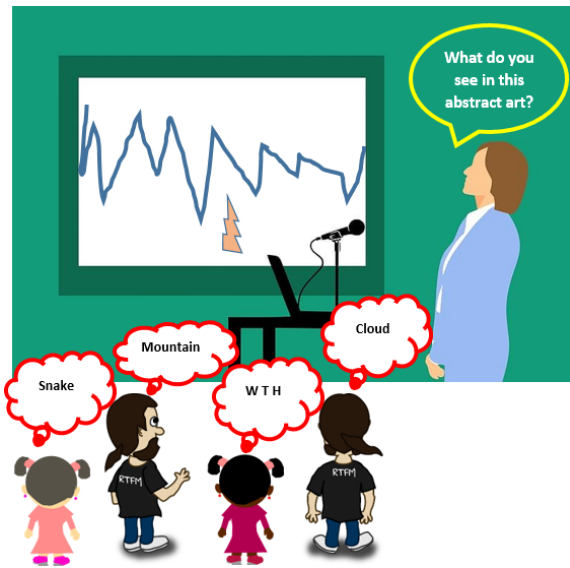


Figure 1: The same abstract art can be interpreted by different persons in different ways. There is hardly any ground truth for an abstract art until it is explicitly defined by the artist. Still, the viewer can make his own perspective.

performance. The answer to a request may be justified, clarified, or followed by a request for a response. The current paper is themed on this novel approach.

Syntactic characteristics play a significant role in feature-based sentiment analysis. Sentiment analysis allows for the extraction of subjective data from text, including opinions, knowledge, and sentiments in natural language processing (NLP). The field of crowdsourcing uses sentiment analysis as well. It simultaneously extracts and detects the topic's and subjective information's sentiment from text. We have examined crowd content to upgrade the quality of the response. People might be capable to anticipate a better and more effective answer for those particular activities if we can give the right assignments to the right individual. We have used multiple sentiment analysis approaches to examine the communication data obtained by empirically studying the corrective feedback mechanism on the CrowdBee platform. The results demonstrate how the corrective feedback makes the sentiments of the crowd workers stronger over successive rounds of communication.

Related Work

The main motivation of any crowdsourcing model is to get quality work in exchange for proper remuneration. So, the winner is decided if the requester's requirements are fulfilled. Then, the contest is closed with a reward. It might be disappointing to the workers other than the winner. But, if these workers become conscious of the reason for their rejection they can improve themselves for better future performance. So, two-way communication will help them make better their performance. When they communicate among themselves, they desire useful information as much as possible. In this situation, different motivational factors can play a

major role. Among different motivational factors, feedback is an important one that can act as a trigger.

Niu et al. provided an outline of the literature on crowdsourcing technologies, platforms, frameworks, rewarding strategies, crowd qualification for work, crowd organisation structure, workflow, quality control, and the difficulties in combining crowdsourcing with traditional product design and development processes. The resources and methodology needed to build the crowdsourcing process easier (Niu et al. 2019). Vasconcelas et al. introduced the 18-card deck that gives designers domain-specific information to boost user involvement in crowdsourcing projects. They have given participants useful information by utilizing the cards in ten group online design sessions. Consequently, it is noted that this approach advances design research in crowdsourcing initiatives, particularly when it comes to user interaction during the design process (Vasconcelos et al. 2024).

There are different studies connecting sentiment analysis with crowdsourcing. According to need, dictionaries are kept for various types of information. In on field of crowdsourcing, Hong et al. created a sentiment dictionary. A language-independent sentiment dictionary was created in 2013 for the evolution of the crowdsourcing game. There were 135 participants in all. They have emphasised the distinction between their solution and the outcome of the conventional physical annotation method. Therefore, this TOB generated accurate and useful data (Hong et al. 2013).

Alonso et al. created a framework in 2014 for correcting the subjective information of the task and for enhancing the quality label. This framework is utilised for many different jobs, and it evaluates worker dependability while attempting to improve task design in accordance with requirements (Alonso, Marshall, and Najork 2014).

Online users in general occasionally express their opinions, and learning the public's perception of a location in good time is really advantageous. The influences of public opinion are seen in social media. Here, geo-sentiment analysis is carried out, and data from the crowd is gathered for the study. This approach greatly benefits from the design of compound training samples and social sentiment features. In this investigation, accuracy for Social Sentiment characteristics has significantly increased (You and Tunçer 2016).

Opinion of the customer carried a significant role in this domain. In crowdsourcing, the opinion of the customer is highlighted through a model. Here the polarity of reviews in roman Urdu text is displayed. They have examined their data with several machine language algorithms. Among all classification algorithms logistic regression produced the best result (Qureshi et al. 2022).

Analyses are also used to discuss and reveal some current affairs topics. Reddit is a news website and forum where users may share and promote articles by voting. The impact of the COVID-19 epidemic is described in depth here, as well as it describe the specifics of the emotional and behavioural analysis of 2020 Summer Olympics in details. Workers present in Reddiator's pool are serving as an influencer. A method for sentiment analysis of Reddiator's behaviour was proposed using crowdsourcing (Yadav, Misra, and Singh 2022).

There are recent attempts on visual sentiment analysis of images that might be of high interest in feedback induced crowdsourcing. Instead of using the traditional subjective language that users submit, Ortis et al. extracted an objective text description of images that are spontaneously obtained from the visual content. They presented a technique that establishes a multimodal embedding space by considering the benefits of both textual and visual features. They have carried out sentiment polarity estimates and experiments on a large-scale dataset. Ortis et al. have extended this work by evaluating the combination of the objective features with deep based visual features (Ortis et al. 2021). There are several sentiment analysis models that have been developed in this pathway of research like Vader (?), TextBlob ¹, Transformer (Vaswani et al. 2017), and ensemble methods (?).

Proposed Approach

Corrective feedback is a standard approach that is often used in the teaching learning process (Lyster and Ranta 1997). This mechanism includes different types of feedback and several uptakes. Motivated from this, we adopt some of the feedback actions in our method that works in a crowdsourcing setting. Note that, we impose this idea on a crowdsourcing environment considering the requesters as 'teachers' and the crowd workers as 'students'. Based on this deliberation, we infer the following interpretations of feedback action types (see Table 1) to be triggered by the requester.

Corrective Feedback	Explanation	Adopted as
Explicit Correction	Requester provides the answer in correct form	–
Recast	Requester implicitly reformulates the errors of a crowd worker and provides correction	–
Clarification Request	Requester indicates that the annotation is not understood and asks for repetition or reformulation	Justify
Metalinguistic Clues	Requester poses questions/comments without providing the correct form	Clue
Elicitation	Requester asks question (not Yes/No) and crowd workers give answer	Reply

Table 1: Different types of corrective feedback mechanisms used in the standard teaching learning process. Some of these are suitably modified to be employed by requesters. The purpose is to provide feedback to crowd workers in a crowdsourcing environment for annotating abstract arts. A direct Accept/Reject decision is made without adopting 'Explicit Correction' or 'Recast'.

As can be intuitively understood from Table 1, all the feedback types do not impart the same level of effect on the

¹<https://textblob.readthedocs.io>

crowd worker. Some of the feedback actions are encouraging, whereas a few others are discouraging. Moreover, as we consider the problem domain to be abstract art, we cannot define an explicit error of an annotation because of the lack of ground truth. Therefore, we design a mechanism that considers the involvement of a crowd worker and appropriately adopt the feedback action to be triggered by the requester. To deploy our approach, we create a crowdsourcing platform that incorporates a corrective feedback facility. No remuneration mechanism is incorporated in the platform and the participants volunteer as crowd workers. Note that the users of the platform offer their time as crowd workers without any sort of compensation. We adopted corrective feedback as a sequential process in the crowdsourcing platform and highlighted communications within a task thread. The logins for requesters and crowd workers a password protected and have different action paths.

A requester can post his annotation task by uploading an abstract art and submitting a question. After the tasks become available to the crowd workers, they may choose preferred tasks to access the same. After a crowd worker submits his/her annotation, the requester can take the following types of actions.

1. The requester can either ACCEPT or REJECT the annotation and close it with a reply. The worker has no further role to play.
2. Alternatively, the requester can provide corrective feedback to the workers. The feedback can be any one of the following types: 'Justify', 'Clue', and 'Reply'. The worker can further submit his annotation in the same thread. Feedback of type Justify asks for a justification, Clue provides a clue therein, and 'Reply' further asks new questions.

It is important to note that the users of the platform volunteered as crowd workers without any compensation. We implemented sequential corrective feedback on the crowdsourcing platform and emphasized task thread communications. The crowd workers were able to choose their tasks as soon as they become accessible to them. The requester had a limited amount of time to ask for justification, provide clue or reply once a crowd worker provides his solution. The feedback details automatically gets stored in the database. The collected data appear as reported in Table 2.

The statistical details of the data that we gathered from the annotations of abstract arts employing the proposed mechanism are as follows.

- Total tasks: 30
- Total crowd workers: 16
- Minimum crowd workers for a task: 0
- Maximum crowd workers for a task: 9
- Average workers per task: 2.53
- Workers motivated by feedback: 5
- Total responses: 218
- Total responses (of workers): 142
- Responses (of workers) triggered by feedback: 40

Worker	W
Date Time	7-7-20 11:24
Type	Clarify
Job Id	28
Job Type	Abstract Art
Mechanism	Corrective Feedback
Decision	No
Chat	The traffic signal indicating about the curve left turn not the sharp left turn ..This can be seen on any of the highly busy road generally on high-ways

Table 2: ‘Corrective Feedback’ applied in CrowdBee platform- Example feedback given by requester and worker

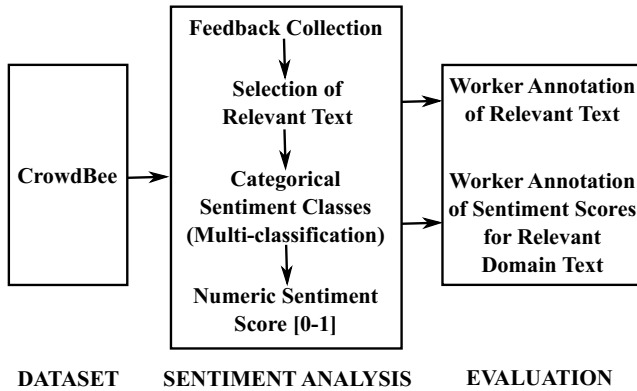


Figure 2: The overall functional framework of the CrowdBee-based platform.

Out of the total 30 tasks posted online using a corrective feedback-induced crowdsourcing platform, we received no annotations for 2 abstract arts. After the removal of punctuations and stop words from the communication between the requester and crowd workers, total 218 statements were obtained that were further analyzed.

Results

We perform statistical analysis as well as sentiment analysis on the communication data. The overall framework of the analyses performed is shown in Fig. 2. The outcome from different analyses are discussed hereunder.

Statistical Analysis

It has been noted that both workers and requesters have participated in various jobs. A certain worker and a requester communicated with one another and given feedback more than once on separate tasks. In this CrowdBee platform, numerous requesters have uploaded a number of abstract art assignments. We have just featured a few of the requesters’ conversations here.

Interestingly, more than 28% of the responses received from the workers were triggered by the corrective feedback mechanism. However, we observed that a limited number of

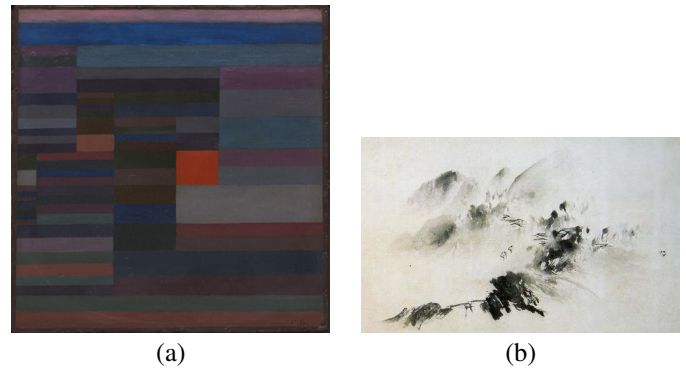


Figure 3: (a) An abstract art by Paul Klee, “Fire in the Evening, 1929”, reflecting the ground truth. (b) The abstract art by Yu Jian, “Mountain market, clearing Mist” is found to be one of the challenging tasks requiring several rounds of corrective feedback.

crowd workers were motivated by corrective feedback.

It became evident from several tasks that a recurring discussion promotes more brainstorming thereby revealing additional information (to describe abstractness of the art). Some of the corrective feedback were so useful that they gave confidence to the workers to further reply and reveal new information (see Fig. 4). In a formal sense, we can hardly define a ground truth for an abstract art. However, sometimes the name given by the artist reflects the theme (see Fig. 3(a) and Fig. 3(b)). To our satisfaction, we observed that hardly any annotation was rejected by the requester. This is possibly because of keeping the option of further discussion open.

We found that using the terms taken from the artist’s title while providing the corrective feedback turned out to be more effective. Hence, it will be effective to further design automated systems that include important keywords in the feedback process. Moreover, exploring the ground truth for abstract arts turns out to be another interesting domain.

Sentiment Analysis

After analyzing the communication data, we made an effort to observe the workers’ sentiment and work-related actions. According to the rule that are established by corrective feedback systems, the requester may seek for an explanation of the response, provide a response, and defend the response since each worker has observed and provided pertinent input, it takes to the declaration of the sentiment of the worker. After that, if the requester is happy with their responses, no more communication is necessary. Otherwise, the requester can get in touch with you directly. The number of communications, though, has not been limited by the system. However, communication only occurs at most thrice for the tasks given.

The sentiment of each communication was assessed and score was calculated. We were able to determine each comment’s polarity and mood-Positive, negative, or neutral. We were able to collect sentiment type and score for all 218

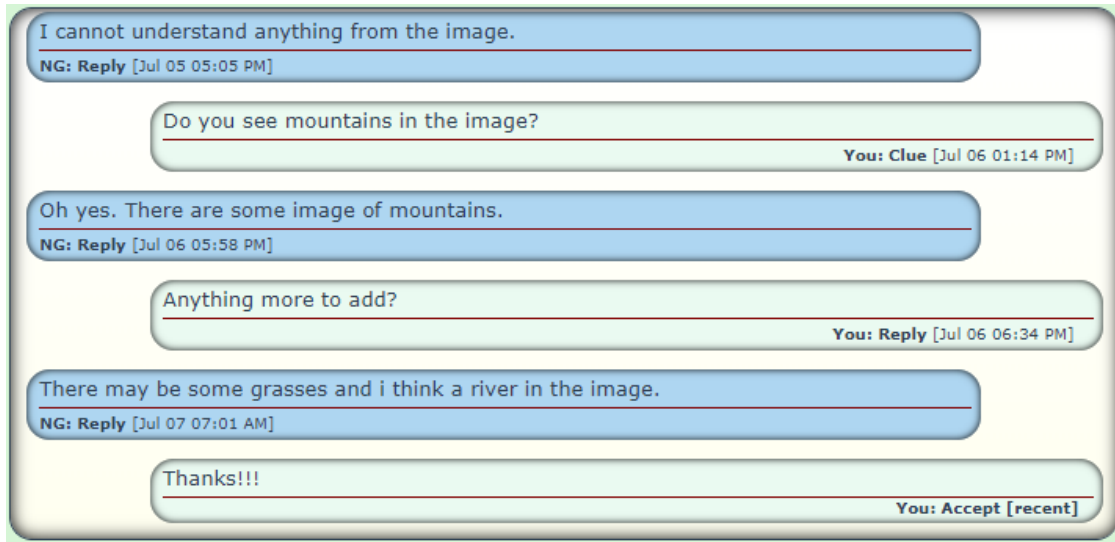


Figure 4: We allow requesters to provide the respective corrective feedback to the crowd workers in different forms. The requester can either ACCEPT or REJECT the submitted annotation for an abstract art and close it with a reply. Alternatively, the requester can provide corrective feedback to the crowd workers in the following forms: Justify, Clue and Reply. The corrective feedback triggers further communication between the requester and crowd workers. This is an example communication for the abstract art shown in Fig. 3(b)

Algorithm	Task ID	Worker ID	Worker Feed 0	Worker Feed 1	Worker Feed 2	Requester ID	Requester Feed 0	Requester Feed 1	Requester Feed 2
VADER (Hutto and Gilbert 2014)	8	3	0.361	0.401	0.361	12	0	0	NA
	9	3	0	-0.241	0	12	0	0	NA
	11	3	0.401	0	-0.276	12	0	0	NA
	7	3	0.599	0.440	NA	12	0.273	-0.077	NA
	7	5	0	-0.34	NA	12	0	NA	NA
	10	3	0	0.401	0	12	0	0	0.440
TextBlob	8	3	0	0	0	12	0	0	NA
	9	3	0	-0.25	0	12	0	-0.066	NA
	11	3	0	0	-0.5	12	0	-0.325	NA
	7	3	-0.15	0.5	NA	12	0	-0.3	NA
	7	5	0	0	NA	12	0	NA	NA
	10	3	0	0	0	12	0	0.5	0.2
Transformer (Vaswani et al. 2017)	8	3	0	0	-0.5	12	-1	-1	NA
	9	3	-1	-0.5	0	12	-1	-1	NA
	11	3	1	0	-0.5	12	0	0	NA
	7	3	0	0	NA	12	-1	-1	NA
	7	5	1	1	NA	12	0	NA	NA
	10	3	-1	0	0	12	0	0	1
Ensemble (Datta and Chakrabarti 2023)	8	3	0.120	0.133	-0.046	12	-0.333	-0.333	NA
	9	3	-0.333	-0.330	0	12	-0.333	-0.355	NA
	11	3	0.467	0	-0.425	12	0	-0.108	NA
	7	3	0.149	0.313	NA	12	-0.242	-0.459	NA
	7	5	0.333	0.22	NA	12	0	NA	NA
	10	3	-0.333	0.133	0	12	0	0.166	0.546

Table 3: Requesters’ and Workers’ sentiment scores for their comments on various abstract art tasks calculated using different sentiment analysis algorithms. The term ‘Feed n ’ denotes the feedback provided in the n^{th} turn.

statements, involved in the communication according to the experiments. As can be seen from Table 3, the sentiment score of the workers has enhanced over time through the corrective feedback. Moreover, the sentiment scores has also changed to positive from negative for some task. This highlights the importance of introducing corrective feedback in

crowdsourcing environments.

Here, we have emphasized the one that demonstrates the frequency of conversation between the requester and the worker. We have underlined the fact that among numerous workers, worker (id 3) participated in six jobs involving abstract art and spoke to another worker a maximum of three

times. One particular Worker (id 5) has interacted twice with the requester and completed one abstract art task. Sentiment analysis of their comments from various communications has been done, and the sentiment score is provided below. The sentiment score of the worker is displayed for Feedback 0, 1, and 2.

Here, we used four methods to analyze the communication between the worker and the requester using Vader (Hutto and Gilbert 2014), TextBlob², Transformer (Vaswani et al. 2017) and an ensemble algorithm (Datta and Chakrabarti 2023). Sentiment scores for workers and requesters, are shown in Table 3.

Many workers may have participated multiple times as a result of the large number of requesters who have uploaded their job. However, they have only spoken to one another a very small number of times. We have just highlighted the most important exchanges between the requester and the worker. Requester (id 12) has taken part in six different abstract art challenges. Additionally, we counted the number of times this worker participated—at most three and at least two. The single communication between one requester and workers, in addition to an analysis of their sentiment score, can be shown in this work’s limitation.

The Vader algorithm increases the worker’s (id 3) sentiment score for task 10 from 0 to 0.401 in Feedback 0 and 1, respectively. On the other hand, the requester’s (id 12) sentiment score remains to be 0 both in Feedback 0 and 1. However, as the requester finally sent a “Thanks” message (Fig. 4), which is why the sentiment score improved to 0.440. However, from Feedback 1 and 2, the requester’s score declines, while the worker’s score in all the feedback is zero in the TextBlob method for the same task. The worker’s sentiment score increases from Feedback 0 to Feedback 1 in Transformer’s algorithm for task 10, whereas the requester’s sentiment score increases from Feedback 1 to Feedback 2.

A similar kind of results is also observed for the case of ensemble algorithm. Sentiment scores of crowd workers are affected by the corrective feedback mechanism.

As can be observed from Table 3, sentiment scores of crowd workers significantly change via corrective feedback, often reaching to a higher value on the same side (positive) or completely flipping to the opposite side (from positive to negative). This reflects higher confidence levels of the crowd workers. In most of the cases, the sentiments of the requester remain as neutral or diminishes, thereby indicating a stabilization of effort. Though Transformer based approach appears to be more robust in exploring the sentiments, the other two also reveal same kind of sentiment patterns. This highlights, as a whole, that the requesters become more confident though corrective feedback and the requesters become satisfied.

Analysis through LLM Sourcing

Very recently, AI sourcing has emerged as an important tool for replacing crowdsourcing methods (Christoforou, Demartini, and Otterbacher 2025). In this section, we further analyze how the tasks like abstract art annotation can be im-

proved with LLMs assisted by corrective feedback. We fed the annotation tasks to ChatGPT version 3.5 as images followed by questions. As can be seen from Fig. 5, the first response from the LLMs are quite detailed and appropriate. However, on applying corrective feedback, interesting additional details are obtained from the LLMs.

Though the use of LLMs appears promising, however, when applying corrective feedback repeatedly, sometimes the LLMs start hallucinating. As observed from Fig. 5, the second round of corrective feedback enforces the LLMs to return additional details on the images. It starts pointing out the coexistence of human and nature within the image. This is nothing but unacceptable as an annotated detail. Moreover, the ethical issues related to making claims by LLMs on abstract arts that are drawn by humans are somewhat threatening.

Conclusion

Understanding human behavior has greatly benefited from sentiment analysis. This outcome demonstrates how to monitor workers’ activity and work-related actions in accordance with positive, negative, and neutral comments in addition to the requester’s values. It is also interesting to devise an information-theoretic measure to quantify the information gap between a requester and a crowd worker. As a result, it is seen that for multiple tasks, both the worker’s and the requester’s sentiment scores improve. Therefore, it is possible to say that providing corrective comments can help to improve quality. Quality enhancement is a challenging issue in crowdsourcing (Ai et al. 2020). Our approach of elucidating abstract art also requires an attention in quality control. However for creative tasks, quality control is still not well-defined in the literature. This is certainly a promising area of future exploration. We finally show that the use of LLMs are quite appealing for such problems although they bring new challenges to deal with.

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Authors’ Contributions

BSB, BM and MB formulated the problem together and designed the experiments. BM collected the data. BSB and BM and RK carried out the data processing, run the experiments, and analyzed the data. AB and MB prepared the interpretation of results. Rest of the authors have critically reviewed the results and provided important feedback. BSB and MB drafted the first version of the manuscript. All the authors read and approved the final version of the manuscript.

Conflicts of Interest

The authors declare no conflict of interest.

Availability

Data and source codes will be made available on reasonable request.

²<https://textblob.readthedocs.io>



Prompt: What can you see in this image?

This image appears to be a traditional East Asian ink wash painting (possibly Chinese or Japanese), known for its minimalist and expressive style using brush and ink on paper or silk.

Here's what can be observed:

- **Mountains or hills:** Soft, misty forms in the background suggest a mountainous or hilly landscape, rendered with delicate shading and washes.
- **Trees and vegetation:** The darker, more defined brush strokes likely represent clusters of trees or dense vegetation, especially in the middle and foreground.
- **Buildings or huts:** Several angular strokes in the central area resemble traditional rooftops, suggesting small homes or village structures nestled in the natural setting.
- **Path or bridge:** In the lower left, there seems to be a horizontal form resembling a small footpath or a wooden bridge.

The overall impression is one of serenity, solitude, and a harmonious relationship between humans and nature—hallmarks of classical East Asian landscape painting. The use of empty space (negative space) evokes mist, distance, and atmosphere.

Prompt: Do you see mountains in the image?

Yes, I see what appear to be **mountains or large hills** in the image. They are represented using **soft, faded ink washes** in the upper and middle parts of the painting, giving the impression of mist-covered peaks in the distance. This is a common technique in traditional East Asian ink wash painting, where forms are intentionally left indistinct to suggest depth, atmosphere, and the natural blending of landscape elements into fog or clouds.

Prompt: Anything more to add?

Yes—here are some additional observations and interpretations that add depth to the image:

1. Atmospheric Perspective:

- The **misty and fading effect** creates a strong sense of depth. Distant forms (likely mountains or hills) are rendered with very light ink, almost blending into the paper, suggesting they are far off and partially obscured by fog or clouds.
- This use of "void" or empty space is deliberate—it doesn't mean "nothing," but rather symbolizes **air, water, distance, or spiritual openness**.

2. Human Presence:

- The **small angular lines** that resemble rooftops or houses nestled among the trees suggest human habitation. This subtle inclusion implies harmony between people and nature—an important theme in traditional Chinese and Japanese aesthetics.

3. Brushwork:

- Notice the **variety of brush techniques**: dry brush for the trees and foreground, wet wash for the mountains, and dots and strokes for texture.
- This technique showcases the painter's **control and spontaneity**, hallmarks of literati painting (especially in Chinese ink art, where the act of painting is as important as the final result).

4. Philosophical Undertone:

- The image may carry a **Daoist or Zen Buddhist influence**, emphasizing simplicity, impermanence, and the beauty of the natural world. The lack of detail invites the viewer to reflect rather than just observe.

5. Compositional Balance:

- The image is asymmetrical but balanced: the darker, denser strokes in the lower right balance the lighter, mistier shapes in the top and left, guiding the eye naturally through the composition.

This is more than just a landscape—it's a **visual poem** reflecting the artist's inner world and their relationship with nature.

Figure 5: We can provide corrective feedback to the LLMs in various forms, including accepting or rejecting an abstract art annotation, justifying, clue, and reply, triggering further communication. This is an example communication for the abstract art shown in Fig. 3(b). This shows how corrective feedback brings more information to the annotation task done by LLMs.

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