Perceived Social Intelligence: A Tool to Evaluate Socially-Aware Navigation

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***Abstract*— Robot navigation near people can be greatly improved by considering social norms, rather than following the shortest path. This consideration of people in movement behavior is called socially-aware navigation (SAN). Given that socially-conscious navigation behavior often results in longer paths, longer times to get to a goal, or deviation from a planned path, traditional navigation metrics likely don't demonstrate the benefits of socially-aware navigation. However, there is likely a benefit for a bystander's perception of a robot's social intelligence when it considers social factors. Using the newly-validated Perceived Social Intelligence (PSI) scale, we examine the perception of non-humanoid robots in non-verbal social scenarios. The PSI scale measures the perceived social information processing capabilities of robots. We hypothesized that humans would perceive the robot with SAN as more socially intelligent than a robot with traditional navigation. We show that there are significant differences between the perceived social intelligence of robots exhibiting SAN behavior compared to one using a traditional navigation planner in scenarios such as *waiting in a queue* and *group behavior*.**

I. Introduction

Robots can employ navigation behavior that considers social factors (such as personal space) in addition to common performance metrics (e.g., goal distance or path deviation) in order to improve how it is perceived by those around it. This consideration of social information is called Socially-Aware Navigation (SAN). Typically, social navigation behavior is evaluated using performance metrics that don't completely consider how people perceive the behavior of the robot. It can be hard to evaluate the SAN behavior, as many actions that a robot can take to be more socially conscious would make the robot perform worse (more time to get to a goal, a longer path) than traditional navigation planners. Since such social behavior is for the benefit of the people around the robot, it is important to assess how we as humans perceive the robot from a social context.

Socially-aware navigation planners can accommodate for a human's space without invading it [1]. We extended [1] to include not just personal space but also group geometry, social goals to exhibit social behavior when navigating in scenarios such as *hallways*, *art galleries*, *joining a group of people*, and *waiting a queue* [2]. Our prior work utilized examples of human-human interactions to score potential navigation trajectories for social appropriateness. Translating this mutual understanding from human-human interactions into human-robot interactions (HRI) helps robots account for social norms. As social beings, we have a standard and mutual understanding of what behaviors are appropriate for shared human-human interactions. If a robot can abide by these boundaries, it could give the impression that it knows the rules well enough to respect them.

Understanding the perceived social intelligence of robots near people allows us to improve the social behavior of navigational systems. In order to comparatively evaluate SAN behavior, the social intelligence of the robot should be assessed. Social intelligence is defined as the ability to successfully interact or communicate with others to accomplish goals [3] and to navigate social environments [4]. When evaluating a robot, several metrics already exist for examining how a robot's behavior affects its perception. Commonly-used survey instruments examine either positive [5] or negative [6] feelings about a robot. However, some of these scales do not drive at a concept that is demonstrated by socially-aware behavior, social intelligence.

Our perceptions of robots with SAN are measured imprecisely by the current survey instruments used in HRI research. Common constructs, such as *Intelligence* may refer to many aspects of intelligence, not merely social intelligence. We evaluate whether a newly-validated Perceived Social Intelligence (PSI) instrument [4] can be utilized to differentiate bystander responses to SAN behavior when compared to a traditional navigation planner. These scales provide precise measurement for many observable aspects of socially-aware navigation and can be applied to multiple types of robots. This is important because each participant may have different experiences with robots and have an image in mind when rating the "robot".

We extend prior work on socially-aware navigation planning [2] by measuring how people perceive the social intelligence of a robot as it navigates in multiple scenarios. We provide a quantitative understanding of how the social intelligence of robots is perceived with SAN compared to a traditional model of navigation. Assessing the perceived social intelligence of robots with SAN improves their applications in the real-world and how they interact/navigate around humans in a variety of social settings.

II. Background

The adoption of socially assistive robots can suffer if the robots do not follow social norms that people value [7].

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One open question for socially-aware navigation is "*How do we evaluate social mapping/navigation techniques?*" [8]. We posit that SAN approaches related to proxemic rules can be evaluated in the following ways with some advantages and disadvantages associated with them:

In-person experiments: Participants can be asked to fill out questionnaires such as Negative Attitudes towards Robots Scale (NARS) [6] and the Godspeed Questionnaire Series (GQS) [5]. Examples: [9].

Naturalness of a trajectory: SAN methods that are model-based or learning-based approaches can compare to human-human interaction (HHI) data. Trajectory difference metric (TDM) [10], is a modified Mean Square Error (MSE), which evaluates every point of SAN trajectory to the closest point in the trajectory of HHI. For model-based methods, the probability that a trajectory confined to a particular interaction from HHI can be a great metric to determine if the robot confined to a particular social norm [11].

Performance metrics: These can include: the number of times the robot was able to generate a collision-free social path; time taken to reach a goal; efficiency of the trajectory; efficiency of the algorithms used, etc. Examples: [12].

Proxemic intrusions: Number of times the robot intruded social zones such as intimate, personal, social, and public space. Examples: [13].

Observer experiments: Measures can be obtained through outside observation of the human-robot dynamic as a navigation action occurs. Measures could be obtained either by presenting unaltered video (from side-view or overhead angles) and having a person rate the robot's behavior. An alternative approach, which can be used to control for a viewer's perception of a robot in these tasks, is to use Heider & Simmel-style videos [14] that preserve the spatial relationships of the agents performing navigation actions, but conceal whether those agents are humans, robots, or neither. Observers can then rate agents' behavior for several subjective factors related to the spatial behavior communicated by their movement [15].

A. SAN and Prior Evaluation

Robot navigation planners are improving their roles in the real world. By investigating more than just performance-based metrics and the primary social challenges of these planners, we can validate the nature of a robot's social intelligence. Robot navigation in crowded spaces was demonstrated in a densely populated museum. The robot successfully gave museum tours to visitors for six days. The researchers evaluated the method using performance metrics such as hours of continuous operation and average speed, and evaluated the interaction with people by metric such as an increase in visitors count, number of web visitors [16].

Inverse reinforcement learning-based SAN uses human demonstrations of socially appropriate navigation [17]. Metrics such as closest distance to human, avoid distance, time to goal on a human-generated path, path generated by DWA planner, and their proposed IRL method were used. Althoff *et al.* [18] presented a probabilistic framework for reasoning about the safety of trajectories generated by robots in a dynamic environment with uncertain data about the moving objects in the environment. Probabilistic collision cost was used as a safety assessment cost metric that considers the motion of the moving objects in the environment. Human-robot proxemic preferences, using an HRI study, related comfort to approach distance and approach angle. A fuzzy-based human-robot proxemic model was built using the data collected from the HRI study, and the model's cross-validation results were reported [19].

B. Considering Social Intelligence

In recent work on SAN, most of the validation methods are tailored to specific applications or methodologies used in the implementation of SAN. While such custom validation methods capture insights into the robot side of the interaction, they do not adequately assess the human's perception of the robot's social performance. Many factors influence our perception of socially aware behavior [20]. Mobile robots need to take into account social conventions as a whole to be successful, socially intelligent agents [20]. The importance of a robot demonstrating human-like social conventions (safe and understandable behaviors) may play a more significant role in affecting a human's perception [20]. Taking these social conventions into account, we can examine our perception of a robot with SAN.

Understanding how humans perceive a robot's social intelligence may be crucial to HRI research. When people interact, they orient themselves in a direction and distance that feels most comfortable for them. Research on human space has helped us understand how a robot invading different "zones" of space influences a human's perception of the robot [21]. Counting the number of proxemic intrusions might not validate a social planner as the theory of proxemics is complicated and depends on many demographic factors such as gender, cultural differences, etc.

Validation methods like comparing robot trajectories to that of human-generated trajectories are not always unique as there are uncontrolled factors like skills of humans operating the robot, etc. Well-validated HRI surveys such as the Negative Attitudes towards Robots Scale (NARS) [6] and the Godspeed Questionnaire Series (GQS) [5] are missing the unique evaluation of a robots social intelligence. The GQS measures general intelligence. While there are other standardized questions they get further away from our interest in measuring the perceived social intelligence of robots. The NARS measures the negative attitudes one might already have towards robots, which gets further away from our interest in a robots perceived social intelligence.

The perception of social intelligence (PSI) scale allows us to measure one's perception of robots' social intelligence with SAN more precisely than the measure of general intelligence. This is important because most robots are still incapable of processing social interactions, but a robot with SAN may be giving us the impression that they do. Navigation systems are becoming more natural (human-like) and less robot-like, which gives us the impression that a robot may be “thinking about” or “acknowledging” human presence when these robots have no cognition similar to what humans have. Because of this, the measures for evaluating a human’s social intelligence are too advanced for current robot abilities [4]. For example, when a robot orients itself much like a human would, it gives us the impression that there is some higher-level cognition going on within the robot due to its actions. By evaluating different HRI scenarios with the PSI measure of social intelligence, we are expanding upon the idea that humans are influenced in basic areas of comfort, naturalness, and sociability when exposed to human-robot interactions [22]. The PSI also allows us to evaluate the perception of a robot by surveying a wide range of social intelligence capabilities [4].

Until now, not much has been done to research our perception of robots’ social intelligence when interacting with SAN compared to traditional navigation. As socially-aware navigation techniques are continuously improving, we must understand how people react and perceive these robots that are integrating into more advanced roles.

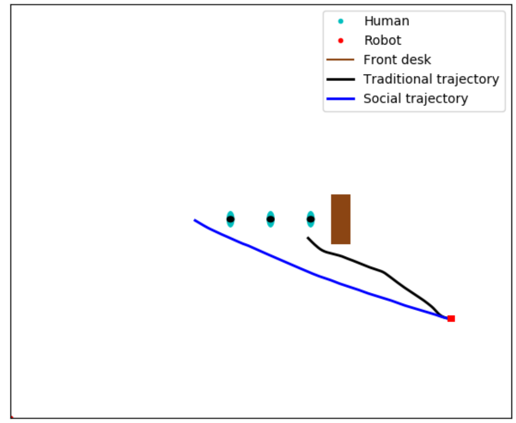

Fig. 1. This diagram shows the robots’ trajectory for socially aware and traditional models of navigation in the “waiting in a queue” scenario, showing a line forming in front of a desk.

III. Methods

We want to experimentally validate that socially-aware navigation behavior will be observable to a bystander. We designed an experiment that will examine how bystanders’ perception of social intelligence changes given different navigation behavior.

Our goal in this work was to create experimental scenarios where participants were able to observe interactions of humans and robots and quantitatively compare their behavior. This is complicated for a number of reasons. It can be difficult to create a controlled experiment for interpersonal interaction. A person interacting with a robot can behave in ways the robot does not expect. It is difficult to create a natural environment that also controls for the necessary experimental variables. Finally, it can be difficult for someone participating in an interaction to note their contemporaneous feelings about an interaction as it is happening.

We developed an experiment where a bystander observes overhead views of robots and humans interacting and rate the resultant robot behavior. Here, we outline the scenarios we chose where the participant was able to be a bystander to the human robot interaction which allowed participants to perceive the robots social intelligence based on the interaction provided (Socially aware vs traditional navigation). These scenarios allow the participant to decide for themselves whether or not the robot is behaving in a socially intelligent way.

To measure social intelligence we use the PSI short form. This short form consists of 20 statements having to do with measuring the robots social intelligence. A high rating on the PSI indicates a strong level of social intelligence while low rating indicates little to no social intelligence. Consequently, it would make sense that if observers will relate social-awareness in navigation to social intelligence, the following hypothesis will be supported:

Hypothesis: Participants who observe a socially-aware navigation planner will perceive the robot as more socially intelligent than one that is utilizing a traditional navigation planner.

A. Experiment Design

To test the above hypothesis, we asked participants to view videos of simulated robot movements near humans and environmental features relevant to the navigation task. These videos were renderings of the robot and person’s positions on a white background (see Figure 1). The figures are rendered as outlines of people or robots, thus simplifying the scene for the viewer. This overhead view also removed considerations of interaction features, like facial expressions or gestures, thus controlling only for movement effects. We asked participants to rate the robot’s movement for each video for perception of social intelligence (PSI). The study was conducted using the Qualtrics platform [23].

There were three simulation scenarios for each navigation category: Socially-Aware navigation and Traditional navigation. Participants were randomly assigned to one of these two categories through the online Qualtrics survey platform and given the PSI short form [4] immediately after watching each video. At the beginning of the survey we asked participants for their age, gender, and career/field of study.

The next sections describe the simulated scenarios the participants viewed:

1) Waiting in a Queue: In the waiting in a queue scenario, the robot demonstrates socially-aware navigation by joining the queue behind the last human in that queue (see Figure 1). In the traditional navigation scenario, the robot cuts to the front of the queue. Cutting off those already in the line.

2) Joining a Group: In this scenario, the robot with socially-aware navigation joins in the group by completing the “O” formation [24] (see Figure 2). Interacting groups

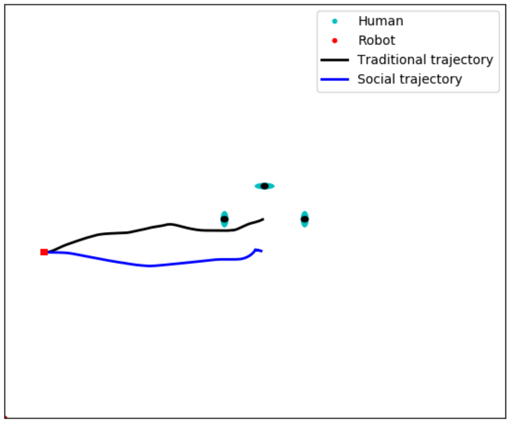

Fig. 2. This diagram shows a robot with traditional navigation joining a group as indicated by the black line, and shows the robot with socially aware navigation joining the group as represented by the blue line.

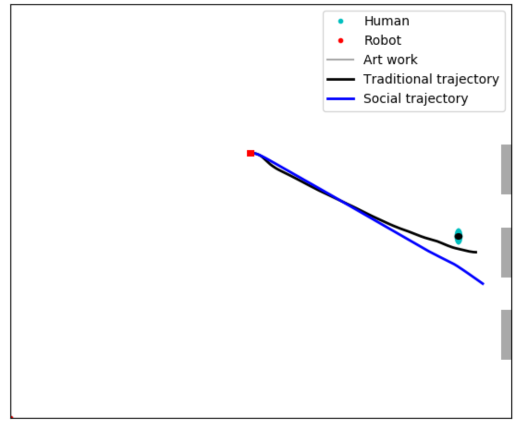

Fig. 3. This diagram shows the robot with traditional and socially aware navigation joining a human observing art as indicated by the black and blue lines.

typically form O-formations, participants of the group tend to conform to it, and others tend to respect it. The robot approaches the human closest to the outside before joining the group. The traditional navigation robot joins in the group by cutting into the center of the group getting close to the other humans and not accounting for the social norms of a group setting. The traditional trajectory would alarm humans that the robot does not know they are present as it invades ones personal space. However, the social trajectory would indicate that the robot knows they are there and joins the group as a peer.

3) Art Gallery: In this scenario, the robot with socially-aware navigation approaches the human and oriented itself to the side of the "art" or item on the wall so as to "present" to the human (see Figure 3). However, the robot with the traditional navigational planner crossed the humans personal space orienting itself in front of the human and in front of the "art" or item on the wall.

B. Participants

We recruited a total of 70 participants, 25 Female, 43 Male, 1 Agender Flem Flux and 1 Non-Binary. The age range was from 18-65 with a mean of 28. One participant was omitted from the data set due to the failure of answering all questions in the Group scenario PSI rating. Each participant was randomly assigned to one of the two interactions conditions, socially-aware navigation or traditional navigation. A Shapiro-Wilk test was used in R [25] to determine if the data was normally distributed. Two out of the three conditions were normally distributed therefor an ANOVA was run for the normally distributed conditions (Queue and Group). A Kruskal-Wallice test was used for the non-normally distributed data for the Art scenario.

IV. Results

After conducting an ANOVA on the waiting in a queue scenario, there was a statistical significance between PSI ratings of robots with socially-aware navigation compared to traditional navigation ($F(1,67)= 10.32$, $p<0.01$). Figure 4 shows the significant difference between the socially aware (SAN) and traditional (TRA) navigation groups for PSI ratings. Robots with SAN were rated significantly higher on the PSI compared to the traditional navigation.

In addition, there was a statistical significance after conducting an ANOVA on the joining a group scenario. Robots with socially-aware navigation were rated as significantly more intelligent on the PSI than robots who demonstrated the traditional navigation ($F(1,67)= 12.46$, $p<0.001$). Figure 5 shows the significant difference in PSI ratings for the SAN and TRA groups.

There was no statistical significance after conducting a Kruskal-Wallis on the art scenario. The PSI of a robot with SAN was rated similarly to the ratings of a robot with the traditional model of navigation (Chi-squared= 0.35, $p>0.05$). Figure 6 shows the similarities between PSI ratings for the SAN and TRA navigational groups.

V. Discussion

The findings largely support the hypothesis that participants will rate a simulated agent higher if it is exhibiting socially-aware navigation behavior than behavior typical of a traditional planner. The distinct differences between social and traditional trajectories for these scenarios closely relate to the acceptable and unacceptable behaviors of a human-human interaction. These results support the use of the PSI to note bystander judgements of the effectiveness of a SAN planner.

These effects were observed in both the *queue* and *group* scenarios. These are scenarios where the robot utilizing a

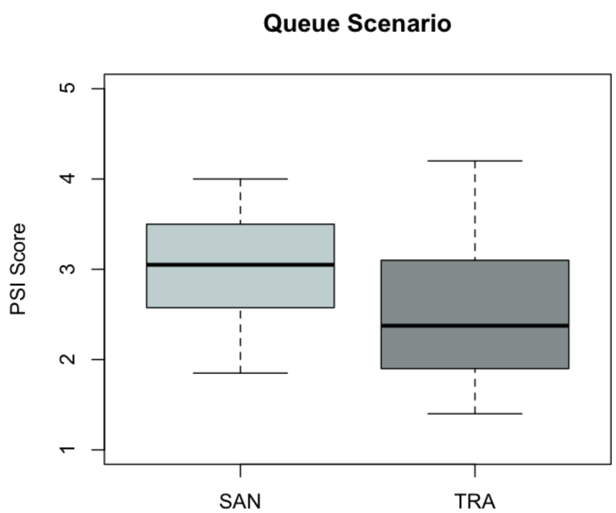

Fig. 4. PSI ratings for the waiting in a queue scenario (F(1,67)= 10.32, p<0.01). SAN indicates participants viewing the SAN planner, while TRA indicates participants viewing the traditional navigation planner. The black line through each box indicates the median.

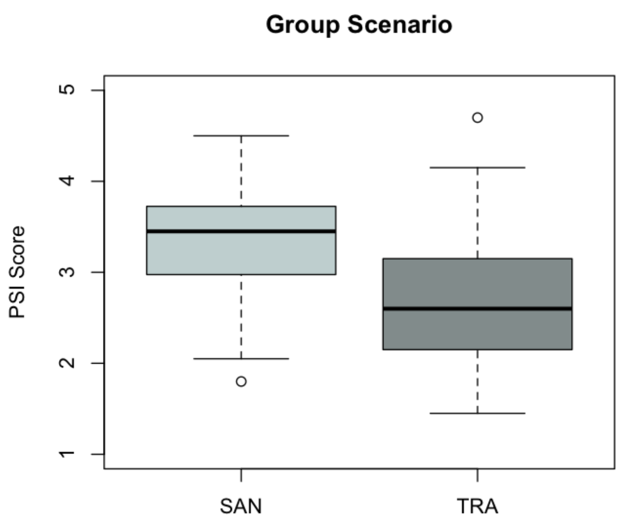

Fig. 5. Graph of the group scenario showing the significant difference between PSI ratings for the socially aware navigation (SAN) and traditional model of navigation (TRA) conditions (F(1,67)= 12.46, p<0.001).

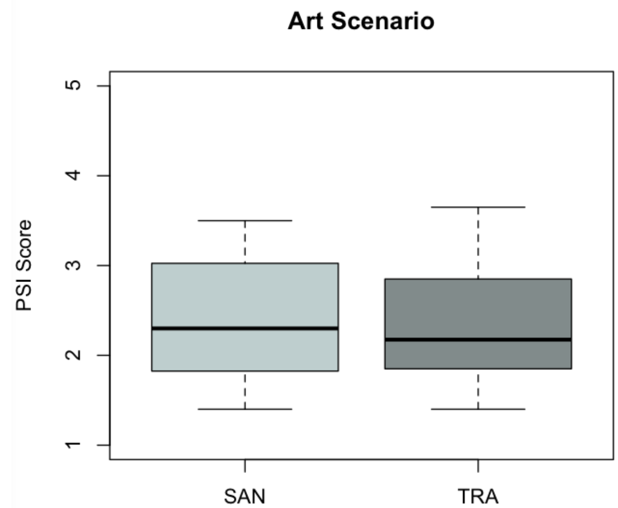

Fig. 6. Graph of the art scenario showing no significance between the socially aware navigation group (SAN) and the traditional model of navigation group (TRA) (Chi-squared= 0.35, p>0.05).

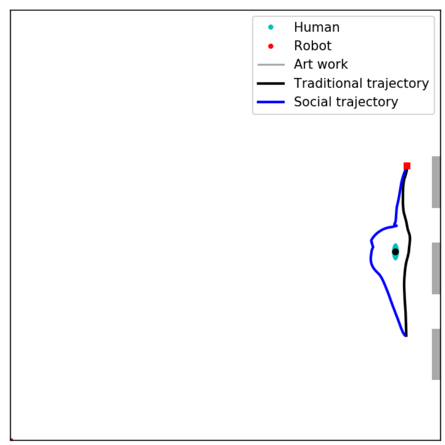

Fig. 7. This diagram shows how a robot with the traditional navigation trajectory approaches the art in front of the human, but the social trajectory approaches the art by navigating behind the human that is already observing.

traditional planner commits gross social violations (cutting in line, breaking into the center of a group of people that are in social proximity). The participants clearly viewed these actions as indicative of lower social intelligence.

In the art gallery scenario, there was no significance between the perceived social intelligence of robots with socially aware navigation compared to the traditional model of navigation. We attribute this to the minor difference between the socially-aware planner and the traditional planner in the simulations participants viewed. As we can see from figure 3, the robot with the traditional model of navigation (indicated in black) approaches the human getting quite close and orients itself in front of the human blocking or obstructing their view). However, in figure 3, the trajectory for the robot with socially-aware navigation gives the human more space than the traditional model when passing by, but proceeds to get closer to the artwork than the present human. This is a potential dilemma because if a robot (regardless of the model of navigation) proceeds to be closer to an object than the present human can be perceived as not socially intelligent.

We have come up with an alternative art scenario (see Figure 7) where the robot is approaching from one side of the person viewing the art/poster. The socially aware navigation trajectory is approaching the human looking at the art and navigates behind them, but the traditional navigation trajectory navigates in front of the human observing the art. We believe that a new approach scenario like this will more distinctly highlight a social violation, it will be similar to the other two scenarios where the robot is in the human's view prior to approaching them. It will be more like the queue and group scenarios where the robot approaches from the side and interacts in a face-to-face manner.

A. Limitations and Future Work

The PSI seems to be able to observe differences in perceived social intelligence when gross social violations occur for bystander interactions, but not minor when social violations occur. This could be because the (metaphorical) distance a bystander has from the social scenario reduces the impact of a minor violation below a threshold captured by the PSI. It could be the case that a participant in an interaction where the robot is interacting with them and commits a minor social violation, that participant may then rate the robot as lower on a social intelligence scale.

Some limitations to this research is the population we surveyed. The majority of the participants were college educated or had some higher education. This is a limitation because robots are likely to be deployed in a variety of work settings that take into account all levels of education.

Additional limitations include not acquiring the participants locations or culture. Geographical/demographic data like this can influence an experiment such as this where the approach behavior is monitored. Western cultures may have different cultural norms and socially accepted behaviors than other countries/cultures. When interpreting cultural differences this may have some effect.

Future work could apply these simulations to a real-life HRI scenario. This would allow participants to interact directly with the robot that either has socially-aware navigation or the traditional model of navigation. It will be interesting to see how ratings of PSI remain the same or differ when the participant is a real-life bystander.

VI. Conclusion

We present an experiment meant to isolate social navigation behavior for observation by a bystander. This experiment is meant to validate the use of the perception of social intelligence (PSI) scale for comparing socially-aware navigation behavior. In our experiment, participants rated a robot with SAN as more socially intelligent in scenarios such as waiting in a queue and joining a group. This partially supports the hypothesis that robots with socially-aware navigation would be perceived as more socially intelligent than robots demonstrating the traditional model of navigation and that the PSI can be used to observe this difference.

Acknowledgements

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