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# Getting Playful with Explainable AI: Games with a Purpose to Improve Human Understanding of AI

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**Abstract**

Explainable Artificial Intelligence (XAI) is an emerging topic in Machine Learning (ML) that aims to give humans visibility into how AI systems make decisions. XAI is increasingly important in bringing transparency to fields such as medicine and criminal justice where AI informs high consequence decisions. While many XAI techniques have been proposed, few have been evaluated beyond anecdotal evidence. Our research offers a novel approach to assess how humans interpret AI explanations; we explore this by integrating XAI with Games with a Purpose (GWAP). XAI requires human evaluation at scale, and GWAP can be used for XAI tasks which are presented through rounds of play. This paper outlines the benefits of GWAP for XAI, and demonstrates application through our creation of a multi-player GWAP that focuses on explaining deep learning models trained for image recognition. Through our game, we seek to understand how humans select and interpret explanations used in image recognition systems, and bring empirical evidence on the validity of GWAP designs for XAI.

**Author Keywords**

Explainable AI, Games with a Purpose, Interpretable Machine Learning, Visualization

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*CHI '20 Extended Abstracts, April 25–30, 2020, Honolulu, HI, USA.*

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ACM ISBN 978-1-4503-6819-3/20/04.

DOI: <https://doi.org/10.1145/3334480.3382831>

## Introduction

Artificial Intelligence (AI) is becoming ubiquitous in day-to-day human experiences. There are claims that AI has exceeded human performance in certain domains, and its use has proliferated in fields such as healthcare and criminal justice, where AI informs high consequence decisions. While complex AI systems are capable of generating these decisions, they lack the ability to self-explain their thought processes in ways that humans can interpret. Human decision making is driven by forms of observation, experience and logical thinking, and explanation is the core of cognitive processes [10, 15]. The future will rely on human cooperation with AI systems which can be supported through the emerging field of Explainable AI (XAI). We believe making models explainable is a prerequisite for building trust and understanding of AI systems at scale.

Games with a Purpose (GWAP) are games designed to generate usable data as a byproduct of gameplay. These games are designed to make boring tasks, such as labeling data, more interesting [3, 32]. GWAP have been shown to be highly effective at collecting and validating large sets of data generated from online gameplay [3]. GWAP have been used for numerous human computation problems, such as generating descriptive keywords for music [13], labeling speech information for natural language processing [23], making segments in text [16], and folding proteins [5]. We apply GWAP to tackle the problem of XAI, and believe it to be the first GWAP designed with this focus [19, 26].

XAI is an appropriate fit for GWAP, as it requires human evaluation for tasks that can be split into smaller parts. It is typical for GWAP methods to rely on collecting large quantities of data and then excluding low-quality data. Common validation strategies (e.g. agreement design where player contributions are evaluated based on majority play-

ers' opinion) are not appropriate for explainability tasks [8]. For explainability, thoughtful and creative interpretations are needed.

Our motivation to focus on GWAP encompasses the idea that game environments help players operate under uncertainty [28]. Uncertainty in games has been shown to shape experiences, introducing the psychological need for satisfaction which fosters motivation and performance in regard to a given activity [22, 4]. Through GWAP for XAI design, we focus on an intrinsic validation approach, where gameplay choices are aligned to produce data that represents players' creative interpretations. Our contributions provide a verifiable approach to evaluate XAI through GWAP design and experimentation.

In summary, our contributions for this research include 1.) an exploration of the merits that GWAP can bring to the field of XAI, and 2.) a presentation of our approach to design and playtesting of a GWAP for XAI.

## Relevant Work

Explainable AI (XAI) attempts to bring transparency to how AI systems make decisions. The trend toward creating fair and interpretative algorithms [1] arises from decision makers' desire to have AI systems provide reasoning behind the results they generate [6]. In 2018, Abdul et al. presented research which stated that XAI research "tends to neglect the human side of explanations" and questioned "whether they are usable and practical in real-world situations" [1]. This statement is echoed by Zhu et al. who noted that most work in XAI focuses "on new algorithms of XAI rather than on usability, practical interpretability and efficacy on real users" [32].

A recent perspective from social scientists suggests that "most work in explainable artificial intelligence uses only

the researchers' intuition of what constitutes a 'good' explanation" [17]. Current evaluation approaches for XAI have been referred to as "you'll know it when you see it," rather than being evidence-based [6]. Cognitive psychology research on explanation has also demonstrated that when people can generate or are provided with explanations, they make more informed judgements which are "less likely to be based on covariation (in the case of causal attribution) or on similarly-based metrics (in the case of category-based induction)" [14]. Evaluative approaches of AI which are focused on collective explanations will allow humans to better judge the validity of AI predictions.

Initial evaluations in Human Computer Interaction suggest that explanations have value to users who rely on machine learning [27]. Interactive visual analytic systems offer promise in making complex AI more transparent by providing interaction techniques to reveal insights about decisions [9]. A variety of visual systems have been proposed to help AI algorithms be clearer for users [11, 30, 31, 12]. However, these evaluations typically focus on task-specific tools for a small number of users.

### **Applying GWAP Design for XAI**

Traditionally, GWAP rely on eliciting high-quality player contributions through intrinsic design methods [8], while weeding out bad data [19]. Expanding research on eliciting high-quality data expands the fields of both GWAP and XAI. Additionally, designing GWAP for XAI is challenging because there is no ground truth to this topic other than player understanding.

#### *Divergent and Transactive Approaches*

With GWAP design for XAI, we are interested in exploring the trade-offs of divergent and transactive approaches to elicit player contributions. The divergent approach is drawn

from creative theory and values uniqueness in player responses: it is better to get many different contributions and have diverse ideas [21]. The transactive approach builds on learning theory: participants build on each others' ideas and deliver fewer contributions with stronger confidence [29]. In our prototype, we produce opportunities for divergence and transactivity by controlling whether players see others' guesses.

#### *Useful Mechanics*

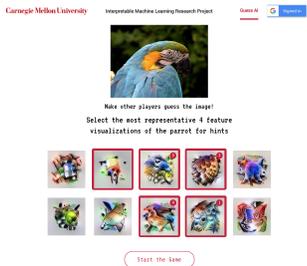
From a design perspective, GWAP mechanics which involve action, verification and feedback will allow players to focus on engaging in problem solving which lends itself to XAI. Action mechanics allow the player to solve the human-computation problem at hand; verification mechanics collect player data which is structured into task-relevant outcomes (e.g. quality of player provided data); and feedback mechanics provide responses to players on both in-game behavior and their performance [26].

#### *Success Metrics*

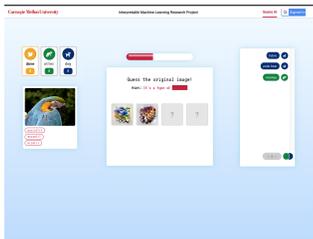
GWAP are varied in their design, and innovation for educational games is ongoing [19, 26, 20]. Metrics for evaluating the success of a GWAP include 1.) task metrics - how many tasks were completed in a given time frame, and 2.) player engagement metrics - how often players return or improve in subsequent games [26]. Success on both task and engagement metrics are critical to GWAP, as games should provide a good player experience while collecting data.

#### *Visualization Techniques*

We designed our first GWAP as an XAI assessment game that focuses on deep learning models for image recognition. Feature visualizations [18] and saliency maps [24] are popular visualization techniques used by researchers and practitioners to explain image recognition-tasks. These techniques can yield intuitive and occasionally beautiful vi-



**Figure 1:** The explainer is given a source image (e.g. the parrot), and selects the top 4 explanations that they believe will lead other players to guess the correct answer (parrot) as quickly as possible.



**Figure 2:** Other players (guessers) compete against each other to guess what selected visualizations represent.

sual representations that provide clues that neural networks may be behaving properly, making "the hidden layers comprehensible" [30]. These examples, sometimes selected by model builders to demonstrate efficacy of neural networks, may not be useful in providing evidence that the neural networks perform as expected, as it is difficult to assess the scope and quality of explanations [2]. Therefore, we identified image recognition as a relevant area for designing scalable validation techniques.

## Designing the Game: XAI for Image Recognition

To demonstrate the value of GWAP for XAI, we designed a multi-player GWAP for image recognition. The game was implemented in JavaScript using the React library <sup>1</sup>.

### Learned Feature Visualizations

Feature visualizations are produced by making neural network interpretation of images visible. Over the course of multiple layers, abstractions are built from detected edges, textures, patterns and parts of an image. We computed feature visualizations from images of animals and objects using the Lucid library <sup>2</sup>.

### Player Roles

One player, the "explainer," is given a source image (Figure 1). The explainer selects the top explanations that they believe will lead the other players to guess the correct answer (e.g. parrot) as quickly as possible. Two other players are "guessers," who compete against each other to guess what the feature visualizations represent.

### Points as Incentives

Guessers receive one visual explanation to start, with a new explanation revealed every fifteen seconds (e.g. 2 of

the 4 visualizations are revealed to guessers in Figure 2). The quicker a guesser identifies the correct answer, the more points the guesser and explainer gain. If the guessers are unable to guess the image (e.g. parrot) after all four images are revealed, they receive a text hint (Figure 3). We utilize transactive design, where all guesses are visible to the explainer and to the guessers. This allows each guesser to build on their own and other players' guesses. Providing accurate data is the ideal way to play this game, because both explainers and guessers aim to get to a correct guess as quickly as possible. In particular, we hypothesize that guessers are highly motivated not only by being quick to guess, but by being the first to guess, as only one of the two guessers receives points. Early pilot testing suggested that players find reaching agreement quickly to be satisfying and valuable.

### Data Collection

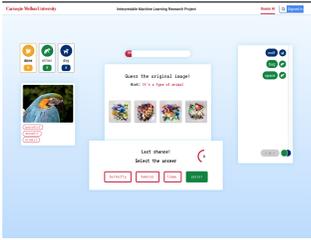
The game generates relevant data for explainable AI in two ways. First, the explainer is given ten visual explanations to select from, of varying explanatory quality as judged by our algorithms, and the explainer is only allowed to select four of the ten. Explainers also dictate the order in which the images are shown to guessers. Of the four visualizations they select, they are instructed to select the most helpful explanation first. Second, the guessers type guesses conveying how they interpret the visualizations and give information about which image(s) help them guess correctly. Guessers provide copious and timely data: they can guess as often as they want within a time limit.

### Adjusting Parameters

Through versions of the game, we can capitalize on opportunities for divergence and transactivity by controlling whether the players can see each others' guesses. If the explainer can see all guesses, but players can only see

<sup>1</sup><https://reactjs.org/>

<sup>2</sup><https://github.com/tensorflow/lucid>



**Figure 3:** If the guessers are unable to guess the image after the 4 explanations are revealed, they receive a text hint.

their own, we are testing a divergence-supporting system; if players can see each others' guesses and are incentivized to build on each other's contributions, we are testing a transactive-supporting system.

## Evaluating the Game: Playtesting

### *Participants*

There are two primary methods for recruiting GWAP studies. The first relies on crowdsourced labor platforms [7] and the second recruits from groups likely to take an interest in the domain [16]. For our initial tests, we recruited participants who are interested in artificial intelligence.

### *Procedures*

Participants use computers to play the game. Each playtest session is designed to take no more than 30 minutes. Logging in with an email address is required to play the game; this serves as the player identification and provides the ability to track progress during a single game or over multiple games. As participants play the game, the web server running the game logs player responses in a password-protected database. Participants are asked if they are interested in a post-game interview. This interview provides qualitative feedback which can capture information to supplement log data (e.g. player motivation, points of confusion, additional thoughts).

### *Playtesting Tasks*

As part of the research study, players are provided instructions to complete in their role as the 'explainer.' In the first game, the task is to select the animals category, and within the category to choose the parrot. Selection of the parrot will create a high quantity of data for the parrot and create a consistent experience for users in their first playthrough of the game. In the second game, the task is to choose the same category, animals, but pick another image. In the third

game, players can choose a different category, and any image.

### *Measures and Analyses*

Our analysis of our playtesting is currently in-progress. We are leveraging analysis during playtesting to understand the effectiveness of explanations and gauge user reactions to gameplay. This includes determining agreement between the explainers and the guessers to understand if explanations that the explainers select lead to correct interpretations by the guessers.

Patterns of agreement can also provide evidence that explanations make sense to multiple people. Tracking guessers' responses is useful to determine if explanations are ambiguous and lead to a diverse set of guesses, or if they converge on a singular interpretation. Surveying engagement can tell if users are willing to repeat playing the game. To collect data at scale, keeping the players engaged is critical for use of GWAP for XAI. Tracking engagement allows us to analyze why users may improve at interpreting explanations over time, by comparing their performance at different levels of their experience with the game.

## Evaluating the Game: Data Analytics

We are currently performing user playtests while scoping milestones and upcoming features. To generate data through playtesting, quantitative and qualitative methods are used.

### *Quantitative Data through Web Analytics*

Through quantitative data collection, the category of image and subsequent explanations which the explainer chooses to describe the image are tracked along with the order in which the explanations are selected. As explanations are revealed to guessers, guesses are logged and associated information (e.g. how long it takes guessers to identify an

image from explanations) is logged. Quantitative data collected through playtesting helps answer the following questions about GWAP for XAI image visualization:

- What explanations are chosen from those provided?
- How do explainer-selected visualizations align with those the AI selects as top-ranked explanations?
- Will guessers be able to interpret AI top-ranked explanations better than AI lower-ranked explanations?
- How does accuracy of player interpretation of explanations evolve over multiple games (e.g. guessers guessing the correct image after fewer reveals and explainers selecting more 'top-ranked' visualizations)?
- What effect might gamification [25] provide to identifying explanations and improving user satisfaction during gameplay (e.g. tracked through points earned)?

#### *Qualitative Survey Data*

As part of playtests, users are surveyed about their experience. Following the first and second games, clarifying questions are asked to determine areas of uncertainty and gauge user perspective of their performance. Following playtesting, questions are asked to gather additional feedback (e.g. would there be something to motivate you to play more?; would you share your game results with others?; what makes this appealing, why or why not?). Users are also surveyed with questions where they select an answer: Strongly Agree, Agree, Neutral, Disagree, Strongly Disagree. These survey questions try to capture how users might perceive and experience the game (e.g. I consider myself a gamer; I felt engaged when selecting visualizations; selecting visualizations was intuitive; replaying the game made me more successful in guessing).

## **Discussion**

Playtesting our game is providing feedback and metrics to help us assess if GWAP can provide value for XAI. Initial insights from playtests suggest that players perceived explaining and guessing for everyday animals or objects to be easier compared to those which were less familiar. For example, players expressed guessing a cat was more intuitive than a jellyfish. From the game, players also expressed appreciation for AI. A player shared, "I didn't know how much of a hurdle recognition was. So I've gained some appreciation for the difficulties the field [of AI] faces." We will continue to evaluate player responses and collect data to assess potential of GWAP for XAI image visualization. Through deploying our game we are 1.) producing an initial dataset, and 2.) analyzing the dataset to understand the impact of specific image explanations on players' ability to identify original images. Further playtesting and analysis data will demonstrate if our approach of GWAP for XAI can produce usable data and engage players.

## **Conclusion**

This project will contribute significant empirical and technical knowledge of how to create human-powered systems for assessing explainable AI (XAI). This research will contribute to literature on XAI, image recognition, and GWAP. This work will also provide discussion as to the utility of GWAP designs for XAI.

## **Acknowledgements**

This work was a collaboration between the Data Interaction Group and the OH!Lab within the Human-Computer Interaction Institute at Carnegie Mellon University. We thank individuals who participate in our user research, as well as previous contributors Shivang Gupta and Pranav Dheram who contributed to building our GWAP XAI prototype for image recognition.

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