

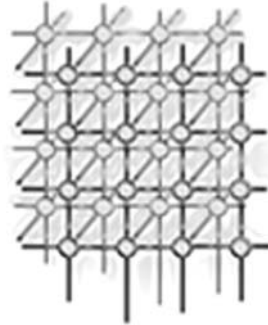
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# The Design of Puzzle Selection Strategies for GWAP Systems

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## SUMMARY

The *Games With A Purpose* (GWAP) genre is a type of *Human Computation* that outsources certain steps of the computational process to humans. By taking advantage of people's desire to be entertained, GWAP attracts people to play voluntarily, and also produce useful metadata as a by-product. The games have shown promise in solving a variety of problems, which computer computation has been unable to resolve completely thus far. In this paper, we propose a metric, called *system gain*, for evaluating the performance of GWAP systems, and also use analysis to study the properties of GWAP systems. We argue that it is important for GWAP systems to implement proper *puzzle selection strategies* in order to collect human intelligence in a more efficient manner. Therefore, based on our analysis, we implement an *Optimal Puzzle Selection Strategy* (OPSA) to improve GWAP systems. Using a comprehensive set of simulations, we demonstrate that the proposed OPSA approach can effectively improve the system gain of GWAP systems, as long as the number of puzzles in the system is sufficiently large.

KEY WORDS: Games With A Purpose; Human Computation; Collaborative Tagging

## 1. Introduction

In the last two decades, the Internet has undergone rapid growth in terms of its usage, population, geographic distribution, and applications. Recent surveys of world-wide Internet usage reported that, in 2008, there were more than 100 million Facebook users [6], 258 million registered YouTube users [6], and more than 16 million active subscriptions to Massively Multiplayer Online Games (MMOGs) [5]. The figures for Facebook and YouTube represent annual growth rates of 305% and 94%, respectively, over the previous year. It is evident that Internet users today want to socialize and be entertained, in addition to exploiting traditional applications, such as the WWW, FTP, and Email.

Among numerous emerging Internet applications, *Games With A Purpose* (GWAP) represents a new paradigm that exploits people's desire to be entertained by outsourcing certain steps of the

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computational process to the players [25, 27]. By taking advantage of people's desire to be entertained and exploiting "human cycles" in computation, the paradigm has shown promise in solving a variety of problems, such as image annotation [26] and commonsense reasoning [17, 30], which computer computation has been unable to resolve completely thus far.

Several GWAP systems have been proposed in recent years [17, 20, 26, 28–31]. Among them, the ESP Game [26] was the first to successfully realize the advantages of GWAP systems, and it was subsequently adopted as the Google Image Labeler [1]. It has been shown that the image labels collected through the ESP game are usually of good quality. Moreover, the game results allow more accurate image retrieval, help users block inappropriate images (e.g., pornographic content), and improve web accessibility (e.g., the labels can help visually impaired people surf web pages [10]).

To be efficient, GWAP systems try to collect human intelligence with the largest possible aggregated outcomes in the shortest possible time for each puzzle. There is a trade-off between these two factors. On the one hand, the system prefers that each puzzle is played only once in order to maximize the number of games that players try to solve. On the other hand, the system prefers to take as many outcomes as possible for each puzzle, which results in the playing of fewer distinct puzzles. Thus, an *optimal puzzle selection strategy* that can accommodate the two goals is highly desirable.

In this work, we define a metric, called *system gain*, to evaluate the performance of GWAP systems. The proposed metric considers two factors: *the average time required for each puzzle*, and *the average outcomes produced by each puzzle*. Both factors are critical for GWAP systems, but unfortunately they do not complement each other. We believe that GWAP systems should be designed and played with strategies. Using analysis, we investigate the inner properties of the *ESP*, *TagATune*, and *Verbosity* games, which correspond to three types of GWAP systems defined in [27] (i.e., the *output-agreement game*, the *input-agreement game*, and the *inversion-problem game* respectively). Based on our analysis, we propose an *Optimal Puzzle Selection Algorithm* (OPSA) that maximizes the system gain by properly accommodating the two opposing factors. Using a set of simulations, we evaluate the proposed OPSA scheme on two widely used schemes, namely the *Random Puzzle Selection Algorithm* (RPSA) and the *Fresh-first Puzzle Selection Algorithm* (FPSA). The results demonstrate that, under the OPSA scheme, the GWAP system yields a much better system gain than under the two compared schemes. In addition, the presented analysis is simple and applicable to other GWAP systems.

The remainder of this paper is organized as follows. Section 2 contains a review of related works on GWAP systems. In Section 3, we describe three GWAP systems, the ESP, TagATune, and Verbosity games, which correspond to the output-agreement game, the input-agreement game, and the inversion-problem game respectively. In Section 4, we present our analysis of the three GWAP systems; and in Section 5, we compare three puzzle selection algorithms for the ESP game, namely the RPSA, FPSA, and OPSA schemes. Section 6 presents a comprehensive set of simulation results, which we analyze and explain in detail. In Section 7, we consider several issues arising from this work. We then summarize our conclusions in Section 8.

## 2. Background

*Games With A Purpose* (GWAP) is a type of *Human Computation*, which provides entertaining games that people play voluntarily and produce useful metadata as a by-product [25, 27]. By taking advantage of people's desire to be entertained, GWAP has shown promise in solving some problems that computer



computation cannot currently resolve completely. In recent years, a substantial and increasing amount of research effort has been invested in the area, and several GWAP systems have been developed for a variety of purposes [1, 3, 4, 7–9, 11, 13, 16, 17, 19, 20, 23, 26, 28–31, 33].

Among them, the online ESP Game [26] was the first GWAP system (which was subsequently adopted as the *Google Image Labeler* [1]); and it has been shown that the collected labels facilitate more accurate image retrieval, help users block inappropriate images, and improve web accessibility. In addition, the *Peekaboom* system [31] can help determine the location of objects in images; and the *Squigl* system [2] and the *LabelMe* system [20] can provide the complete outlines of the objects in an image. *Phetch* [28, 29] can provide image descriptions that improve web accessibility and image searches, while the *Matchin* system [2] can help image search engines rank images based on which ones look the best. The concept of the ESP Game has been applied to other problems. For instance, the *Herd It* [3, 7], *Major Miner* [4], and *TagATune* [16] systems, which provide annotation for sounds and music, can improve audio searches. The *Verbosity* system [30] and the *Common Consensus* system [17] collect “common-sense” knowledge that is valuable for commonsense reasoning and enhancing the design of interactive user interfaces. In [9], Bennett et al. collect the individual user preferences over image-search results, and extract the consensus rankings from the preferences for the results of a query. The *Context-Aware Recognition Survey (CARS)* system [33] uses ubiquitous sensors to monitor activities in the home, while [8, 11, 13, 19] employ mobile social gaming for geospatial tagging. Moreover, [23] applies human computation to ontology alignment and web content annotation for the Semantic Web using a set of games, such as *OntoPronto*, *SpotTheLinks*, *OntoTube*, and *OntoBay*. Finally, Shenoy and Tan [22] showed that it is possible to design environments in which humans cannot avoid processing some of the tasks (and producing some useful outcomes), even though they are not actively trying to do so.

In addition to designing new GWAP systems, several studies have investigated the performance aspect of human computation recently [12, 14, 15, 27, 32]. For example, Ho et al. [14] proposed to solve the *coalition* problem by integrating both collaboration and competition elements in image labeling games. Gentry et al. [12] proposed a framework of vote-based human computation and gave a probabilistic analysis of the reliability of the voting mechanism and design principles on the payout function. Moreover, in [32], Weber et al. presented a machine learning-based model that can play with the ESP game without looking at the image. Based on the model, they proposed an enhanced scoring system for the ESP game to encourage users to contribute less predictable labels and therefore improve the quality of the collected labels. Jain and Parkes [15] presented game theoretic analysis for the ESP game, and they investigated the equilibrium behavior under different incentive mechanisms and provided guidelines to design incentive mechanisms. Von Ahn and Dabbish [27] proposed a set of evaluation metrics, such as throughput, lifetime play, and expected contribution, to determine whether ESP-like GWAP systems are successful. Moreover, they proposed that the GWAP system has to introduce challenges, competition, variety, and communication in the system in order to provide incentive and strengthen a player’s motivation to stay in the game.



### 3. Game Descriptions

In this section, we describe the ESP game [26], the TagATune game [16], and the Verbosity game [30], which correspond, respectively, to the *output-agreement game*, the *input-agreement game*, and the *inversion-problem game* defined by Von Ahn and Dabbish [27].

#### 3.1. The Output-agreement Game: *ESP*

The ESP Game [26] was the first GWAP system to exploit people's desire to be entertained, and provide useful metadata as a by-product. When a user logs into the system, he/she is automatically matched with a random partner. The two players do not know each other's identity as they cannot communicate.

Initially, a randomly selected image is displayed to both players simultaneously. The players then input possible words to label the image until an "agreement" is reached (i.e., the same word is entered by both players), and a bonus score is awarded to each player based on the 'quality' of the agreed word. In practice, the 'quality' of a word is measured by its popularity; generally, words that are more popular receive lower scores. After the players agree on a word, they are shown another image. In each game, they have two and a half minutes to label 15 images.

The word on which the two players agree becomes the label of the image, and it cannot be used the next time that image is displayed in another game (the word is called a "taboo" word of the image). The rationale for using taboo words is to ensure that each image is labeled with a variety of words.

#### 3.2. The Input-agreement Game: *TagATune*

The TagATune Game [16] is an input-agreement game that provides useful metadata of sounds and music (collectively referred to as *tunes*) by applying the concept of *games with a purpose*. Similar to the ESP game, when a user logs into the system, he/she is automatically matched with a partner, who is selected randomly and anonymously from a pool of available players. Again, the two players do not know each other's identity as they cannot communicate. They are asked to collaborate and determine whether they have been given the same input puzzle (i.e., tune).

In a game round, each player is given an input (tune), but only the system knows whether the inputs are the same or different. The players have to use possible words to properly describe their input. They win a game round (and obtain points) if they both correctly determine whether they have the same input tune; otherwise, they lose the game round (i.e., their score is zeros). During a game round, the players are allowed to stop or replay their respective tunes at any time, and they are allowed to see each other's outputs. Moreover, they can decide to pass over a tune if they both think it is too difficult.

Since the players want to win as many points as possible, it is in their best interest to provide accurate outputs that appropriately describe their respective inputs, so that they can determine if their inputs are the same. As a result, the words collected in a TagATune game are typically good enough to describe the input tunes. Moreover, the outcomes may become official tags of the tunes if enough people agree (the threshold of which depends on the game's statistics).



### 3.3. The Inversion-problem Game: *Verbosity*

The Verbosity Game [30] is a popular inversion-problem game that employs human computation to collect commonsense reasoning related to a word by asking one of the players to guess the input puzzle (i.e., a word) based on the other player's description of the puzzle. Like the ESP and TagATune games, two players are selected at random to create a game; once again, they do not know each other. The players take turns to play the roles of "*Describer*" and "*Guesser*". The *Describer* is asked to provide a number of words to describe the given input, and the *Guesser* has to guess the input based on the *Describer*'s outputs.

To make the game easier, Verbosity provides the *Describer* with a set of sentence templates to describe the input puzzle (e.g., "*it looks like \_\_\_\_*" and "*it is a type of \_\_\_\_*"). The *Describer* can see all of the *Guesser*'s inputs, so he can adjust his playing strategy during the game round. Since both players have to collaborate to win the game, the *Describer* must do his best to help the *Guesser* guess the input. Since the game structure encourages players to enter correct information, the collected descriptions are typically good enough to be used as official tags of the corresponding puzzles.

The inversion-problem game can be regarded as a special case of the input-agreement game, except that (1) the number of outcomes per game round is limited (i.e., there are at most  $m$  outcomes in each game round, and  $m$  is much smaller than the total number of possible outcomes); and (2) a game round cannot be a failure in inversion-problem games (i.e., the two players will pass over a puzzle if they cannot complete it using the first  $m$  descriptions). For instance, in the Verbosity game, there are only 6 sentence templates (i.e.,  $m = 6$ ).

## 4. Game Analysis

For the sake of efficiency, the GWAP system tries to collect human intelligence with the largest possible aggregated outcomes in the shortest possible time, for each puzzle. There is a trade-off between these two factors. On the one hand, to minimize the time required per puzzle, the system prefers that each puzzle is played only once. The rationale is to maximize the number of games that players try to solve. On the other hand, the system prefers to take as many outcomes as possible for each puzzle, which results in the playing of fewer distinct puzzles. Thus, an optimal puzzle selection strategy that can accommodate the two goals is highly desirable. To this end, we propose a metric to evaluate the system gain of the GWAP system, and analyze the puzzle selection problem. We discuss the analysis in the following subsections.

### 4.1. The Output-agreement Game: *ESP*

Let  $N$  be the number of puzzles that have been played at least once in the system,  $T$  be the average time consumed per puzzle, and  $S$  be the total score of all the agreed labels. We define the system gain,  $G$ , of the ESP game as follows:



$$\begin{aligned}
 G &= \ln\left(C_1 \times \frac{N}{NT}\right) \times \ln\left(C_2 \times \frac{S}{N}\right) \\
 &= \ln\left(C_1 \times \frac{1}{T}\right) \times \ln\left(C_2 \times \frac{S}{N}\right),
 \end{aligned} \tag{1}$$

where  $C_1$  and  $C_2$  are two scaling constants that ensure  $\ln\left(C_1 \times \frac{1}{T}\right) > 0$  and  $\ln\left(C_2 \times \frac{S}{N}\right) > 0$  respectively.

Clearly, the system gain increases as the average time required per puzzle (i.e.,  $T$ ) decreases, and/or as the average total score (per puzzle) (i.e.,  $\frac{S}{N}$ ) increases. Suppose that, in the system, each puzzle has the potential to yield  $K$  labels in total; that each tag is associated with one positive score value based on its popularity. For simplicity, we assume there are totally  $X$  distinct scores (i.e.,  $s_1, s_2, s_3, \dots, s_X$ ) in the system; and that  $s_i = e^i$ . Moreover, we assume that  $K_i$  labels have the score  $s_i$ , and that  $K_i = e^{X-i}$ . Therefore, the total number of potential labels per puzzle ( $K$ ) can be derived by Equation 2, and the expected score of each tag ( $E[s]$ ) can be obtained by Equation 3.

$$K = \sum_{i=1}^X K_i = \frac{e^X - 1}{e - 1} \tag{2}$$

$$E[s] = \frac{\sum_{i=1}^X e^i e^{X-i}}{K} = \frac{e^X(e - 1)X}{e^X - 1} \tag{3}$$

For each game round, let  $P_s$  and  $\bar{t}_s$  be the probability and the average time spent when the game round results in an agreement;  $P_p$  and  $\bar{t}_p$  be the probability and the average time spent when the players decide to pass over the assigned puzzle; and  $P_t$  and  $\bar{t}_t$  be the probability and the average time spent when the game round is terminated due to timeout. Since we know that  $P_s + P_p + P_t = 1$ , we can obtain  $\bar{t}$ , i.e., the expected time interval between any two consecutive outcomes in the ESP game, by

$$\bar{t} = \bar{t}_s + \frac{P_p}{P_s} \times \bar{t}_p + \frac{P_t}{P_s} \times \bar{t}_t. \tag{4}$$

Suppose each puzzle has accumulated  $r$  agreements on average (i.e.,  $T = r \times \bar{t}$ , and  $E[s] \times r = \frac{S}{N}$ ). We can then rewrite Equation 1 as follows:

$$\begin{aligned}
 G &= \ln\left(C_1 \times \frac{1}{r \times \bar{t}}\right) \times \ln\left(C_2 \times E[s] \times r\right) \\
 &= \left(\ln(C_1/\bar{t}) - \ln(r)\right) \times \left(\ln(C_2 E[s]) + \ln(r)\right) \\
 &= -(\ln(r))^2 + (\ln(C_1/\bar{t}) - \ln(C_2 E[s]))\ln(r) + \ln(C_1/\bar{t})\ln(C_2 E[s]) \\
 &= -\left(\ln(r) - \frac{\ln(C_1) - \ln(\bar{t}) - \ln(C_2 E[s])}{2}\right)^2 + C,
 \end{aligned} \tag{5}$$

where  $C$  is fixed with a value equal to  $\ln(C_1/\bar{t})\ln(C_2 E[s]) + \left(\frac{\ln(C_1) - \ln(\bar{t}) - \ln(C_2 E[s])}{2}\right)^2$ . Note that  $C$  also represents the largest possible system gain, which occurs when

$$r = e^{\frac{\ln(C_1) - \ln(\bar{t}) - \ln(C_2 E[s])}{2}}. \tag{6}$$



#### 4.2. The Input-agreement Game: *TagATune*

Similar to the analysis in subsection 4.1, let  $N$  be the number of puzzles that have been played at least once in the system,  $T$  be the average time required to solve each puzzle, and  $O$  be the total score of all the game outcomes. We define the system gain,  $G$ , of the TagATune game as follows:

$$\begin{aligned} G &= \ln(C_1 \times \frac{N}{NT}) \times \ln(C_2 \times \frac{O}{N}) \\ &= \ln(C_1 \times \frac{1}{T}) \times \ln(C_2 \times E[O]), \end{aligned} \quad (7)$$

where  $C_1$  and  $C_2$  are two scaling constants that ensure  $\ln(C_1 \times \frac{1}{T}) > 0$  and  $\ln(C_2 \times E[O]) > 0$  respectively, and  $E[O]$  is the expected total score of the game outcomes for each puzzle.

Clearly, the system gain increases as the average time required per puzzle (i.e.,  $T$ ) decreases, and/or as the average total score per puzzle (i.e.,  $E[O]$ ) increases. Suppose that each puzzle in the system has the potential to yield a total of  $K$  outcomes, each of which is associated with one positive score based on the outcome's popularity. In addition, suppose the score of the  $k$ -th outcome is  $v_k$ , and the probability that the  $k$ -th outcome will be output is  $p_k$ . For simplicity, we assume there are totally  $X$  distinct scores (i.e.,  $s_1, s_2, s_3, \dots, s_X$ ) in the system, and that  $s_i = e^i$ . We also assume that  $K_i$  outcomes have the score  $s_i$ , and that  $K_i = e^{X-i}$  (i.e., the total number of potential outcomes per puzzle ( $K$ ) derived by Equation 2. Then, we can obtain the expected total score of the new outcomes (per puzzle) in the  $r$ -th game round,  $E[O_r]$ , by Equation 8, and the expected total score of all the outcomes after the first  $r$  game rounds,  $E[O]$ , by Equation 9.

$$\begin{aligned} E[O_r] &= (1 - p_1)^{r-1} \times p_1 \times v_1 + (1 - p_2)^{r-1} \times p_2 \times v_2 + \dots + (1 - p_K)^{r-1} \times p_K \times v_K \\ &= \sum_{k=1}^K (1 - p_k)^{r-1} \times p_k \times v_k. \end{aligned} \quad (8)$$

$$\begin{aligned} E[O] &= \sum_{i=1}^r E[O_i] \\ &= \sum_{i=1}^r \sum_{k=1}^K (1 - p_k)^{i-1} \times p_k \times v_k \\ &= \sum_{k=1}^K p_k \times v_k \times \sum_{i=1}^r (1 - p_k)^{i-1} \\ &= \sum_{k=1}^K p_k \times v_k \times \frac{1 - (1 - p_k)^r}{1 - (1 - p_k)} \\ &= \sum_{k=1}^K v_k (1 - (1 - p_k)^r). \end{aligned} \quad (9)$$



For each game round, let  $P_s$  and  $\bar{t}_s$  be, respectively, the probability and the average time spent when the game round results in an agreement;  $P_p$  and  $\bar{t}_p$  be, respectively, the probability and the average time spent when the players decide to pass over the assigned puzzle;  $P_t$  and  $\bar{t}_t$  be, respectively, the probability and the average time spent when the game round is terminated due to timeout; and  $P_f$  and  $\bar{t}_f$  be the probability and the average time spent when the game round fails. Since we know that  $P_s + P_p + P_t + P_f = 1$ , we can obtain  $\bar{t}$ , i.e., the expected time interval between any two consecutive outcomes in the TagATune game, by

$$\bar{t} = \bar{t}_s + \frac{P_p}{P_s} \times \bar{t}_p + \frac{P_t}{P_s} \times \bar{t}_t + \frac{P_f}{P_s} \times \bar{t}_f. \quad (10)$$

In total, there are  $X$  distinct scores (i.e.,  $e, e^2, e^3, \dots, e^X$ ),  $e^{X-i}$  outcomes with scores equal to  $e^i$ , and the occurrence probabilities are equal to  $1/e^i$ ; hence, we know that

$$\begin{aligned} \sum_{k=1}^K v_k(1 - (1 - p_k)^r) &\approx \sum_{k=1}^K v_k(1 - (1 - rp_k)) \\ &= r \sum_{k=1}^K v_k p_k = rK. \end{aligned} \quad (11)$$

Moreover, since  $T = r \times \bar{t}$ , we can rewrite Equation 7 as follows:

$$\begin{aligned} G &= \ln(C_1 \times \frac{1}{r \times \bar{t}}) \times \ln(C_2 \times \sum_{k=1}^K v_k(1 - (1 - p_k)^r)) \\ &\approx \left( \ln\left(\frac{C_1}{\bar{t}}\right) - \ln(r) \right) \times (\ln(C_2) + \ln(rK)) \\ &= \left( \ln\left(\frac{C_1}{\bar{t}}\right) - \ln(r) \right) \times (\ln(C_2 K) + \ln(r)) \\ &= - \left( \ln(r) - \frac{\ln\left(\frac{C_1}{\bar{t}}\right) - \ln(C_2 K)}{2} \right)^2 + C, \end{aligned} \quad (12)$$

where  $C$  is fixed with a value equal to  $\ln\left(\frac{C_1}{\bar{t}}\right)\ln(C_2 K) + \left(\frac{\ln\left(\frac{C_1}{\bar{t}}\right) - \ln(C_2 K)}{2}\right)^2$ . Note that  $C$  also represents the largest possible system gain, which occurs when

$$r = e^{\frac{\ln\left(\frac{C_1}{\bar{t}}\right) - \ln(C_2 K)}{2}}. \quad (13)$$

### 4.3. The Inversion-problem Game: *Verbosity*

We consider that the inversion-problem game is a special case of input-agreement games, except for the following factors.



1. There are no game round failures in an inversion-problem game (i.e.,  $P_f = 0$ ). Thus, we can rewrite Equation 10 as

$$\bar{t} = \bar{t}_s + \frac{P_p}{P_s} \times \bar{t}_p + \frac{P_t}{P_s} \times \bar{t}_t. \quad (14)$$

2. The number of possible outcomes per game round is limited (i.e.,  $m$  is limited); however, Equations 8 and 9 still hold.

Therefore, similar to input-agreement games, we can obtain the system gain by

$$\begin{aligned} G &= \ln(C_1 \times \frac{N}{NT}) \times \ln(C_2 \times \frac{O}{N}) \\ &\approx - \left( \ln(r) - \frac{\ln(\frac{C_1}{\bar{t}}) - \ln(C_2 K)}{2} \right)^2 + C, \end{aligned} \quad (15)$$

where  $C$  is fixed with a value equal to  $\ln(\frac{C_1}{\bar{t}})\ln(C_2 K) + \left( \frac{\ln(\frac{C_1}{\bar{t}}) - \ln(C_2 K)}{2} \right)^2$ . Note that  $C$  also represents the largest possible system gain, which occurs when

$$r = e^{\frac{\ln(\frac{C_1}{\bar{t}}) - \ln(C_2 K)}{2}}. \quad (16)$$

## 5. Game Strategies

In this section, we present three puzzle selection algorithms for the GWAP system, namely the *Random Puzzle Selection Algorithm* (RPSA), the *Fresh-first Puzzle Selection Algorithm* (FPSA), and the proposed *Optimal Puzzle Selection Algorithm* (OPSA)<sup>†</sup>. We take the RPSA scheme's performance as the baseline (in terms of system gain). The heuristics-based FPSA scheme tries to maximize the first component of Equations 1, 7, and 15 (i.e., minimize the value of  $T$ ); and the OPSA scheme tries to achieve the largest possible system gain based on our analysis (as discussed in Sec. 4).

We use  $P$  to denote the set of all puzzles in the system, and we define the following three functions used by the puzzle selection algorithms: 1) *Select\_Random*( $P$ ), which randomly selects a puzzle from the input puzzle set  $P$ ; 2) *Select\_Played*( $P$ ), which selects the puzzle from the input puzzle set  $P$  that has been played most frequently; and 3) *Select\_Fresh*( $P$ ), which selects the puzzle from the input puzzle set  $P$  that has been played least frequently. We discuss the three algorithms in the following.

<sup>†</sup>Note that, in this paper, the presented OPSA strategy is designed to maximize the proposed system gain in GWAP systems (cf. Equations 6, 13, and 16), and it may not always yield the optimal performance of the GWAP system if we consider additional factors in the system gain metric, such as positive, negative, and zero outcomes.




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**Algorithm 1** The Random Puzzle Selection Algorithm (RPSA).

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- 1: **Function RPSA**
  - 2:  $p \leftarrow \text{Select\_Random}(P)$
  - 3: Return  $p$
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**Algorithm 2** The Fresh-first Puzzle Selection Algorithm (FPSA).

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- 1: **Function FPSA**
  - 2:  $p \leftarrow \text{Select\_Fresh}(P)$
  - 3: Return  $p$
- 

### 5.1. RPSA and FPSA

Algorithms 1 and 2 detail the steps of the *Random Puzzle Selection Algorithm* (RPSA) and the *Fresh-first Puzzle Selection Algorithm* (FPSA) respectively. In each round, RPSA selects a puzzle at random from the puzzle pool  $P$ . FPSA, on the other hand, selects the puzzle that has been played least frequently in the system. It is a greedy, heuristics-based approach that tries to maximize the first component of Equation 1.

### 5.2. The Proposed Scheme: OPSA

In the proposed Optimal Puzzle Selection Algorithm (OPSA),  $N$  denotes the number of puzzles that have been played, and  $E$  denotes the expected score of each label. In addition,  $r$  denotes the optimal number of rounds (discussed in Sec. 4); and for each entry  $p$  of  $P$ ,  $p.r$  represents the round number in which the puzzle  $p$  was played. Suppose that the puzzle set  $P_0$  contains all the puzzles that have not been played;  $P_1$  contains all the puzzles that have been played at least once, but less than  $r$  rounds; and the set  $P_2 = P - P_0 - P_1$  contains the other puzzles. We detail the OPSA algorithm in Algorithm 3.

## 6. Evaluation

### 6.1. Output-agreement Games

In this section, we describe the simulations performed to investigate the intrinsic properties of the ESP game based on our analysis. We also evaluate the system gain of the three puzzle selection strategies. For simplicity, we set the values of the two scaling constants  $C_1$  and  $C_2$  to 200 and 1 respectively<sup>‡</sup>. Moreover, we set the values of the parameters  $(\bar{t}_s, \bar{t}_p, \bar{t}_t)$  to  $(0.2, 0.4, 0.15)$ <sup>§</sup>; and the

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<sup>‡</sup>The selection of the values of the two scaling constants depends on how we weight the two factors in the performance metric. The values of  $C_1$  and  $C_2$  must satisfy the criteria that  $\ln(C_1 \times \frac{1}{T}) > 0$  and  $\ln(C_2 \times \frac{S}{N}) > 0$ , as described in Equation 1.

<sup>§</sup>Intuitively,  $\bar{t}_p > \bar{t}_s$ , since the players tend to pass over a puzzle when they realize it will be difficult to reach an agreement. Moreover, the players may be forced to terminate a game round simply because they do not have enough time to finish the



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**Algorithm 3** The Optimal Puzzle Selection Algorithm (OPSA).

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```
1: Function OPSA
2: if  $\{P_1\}$  is NOT empty then
3:    $p \leftarrow \text{Select\_Played}(P_1)$ 
4:    $p.r \leftarrow p.r + 1$ 
5:   if  $p.r = r$  then
6:     Move  $p$  from  $P_1$  to  $P_2$ 
7:   end if
8:   Return  $p$ 
9: else
10:  if  $\{P_0\}$  is NOT empty then
11:     $p \leftarrow \text{Select\_Random}(P_0)$ 
12:     $p.r \leftarrow 1$ 
13:    if  $p.r < r$  then
14:      Move  $p$  from  $P_0$  to  $P_1$ 
15:    else
16:      Move  $p$  from  $P_0$  to  $P_2$ 
17:    end if
18:    Return  $p$ 
19:  else
20:     $p \leftarrow \text{Select\_Fresh}(P_2)$ 
21:     $p.r \leftarrow 1$ 
22:    Return  $p$ 
23:  end if
24: end if
```

---

parameters  $(P_s, P_p, P_t)$  to  $(0.6, 0.3, 0.1)$ <sup>¶</sup>. All the results are based on the average performance of 100 simulations.

### 6.1.1. The Optimal $r$

In the first set of simulations, we evaluated our analytical model's accuracy in determining an optimal  $r$  value for the ESP game. We assumed that the number of puzzles in the system was infinite, and that all of them were unsolved at the beginning of the simulation (i.e., no labels were discovered for any puzzles). Figure 1 shows the evaluation results in terms of the system gain for  $r$  values between 2 and 100, when the maximum score value  $X$  was fixed at 6. In the figure, the analysis curve is derived by Equation 5, where  $E[s]$  can be obtained by Equation 3. The optimal  $r$  value is equal to 10.3353 when

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puzzle, i.e.,  $\bar{t}_s > \bar{t}_t$ . We also note that, the selection of the time scale used for  $\bar{t}_s$ ,  $\bar{t}_p$ , and  $\bar{t}_t$  can be any time units (e.g., hours, minutes, and seconds), as long as it satisfies the criteria that  $\ln(C_1 \times \frac{1}{T}) = \ln(C_1 \times \frac{1}{r \times \bar{t}}) > 0$ .

<sup>¶</sup>It is important to ensure that  $P_s > P_p$ ; otherwise, the players may feel frustrated when playing the game. Moreover,  $P_t$  must be very small so that the players have sufficient time to solve the puzzles in order to increase the system efficiency.

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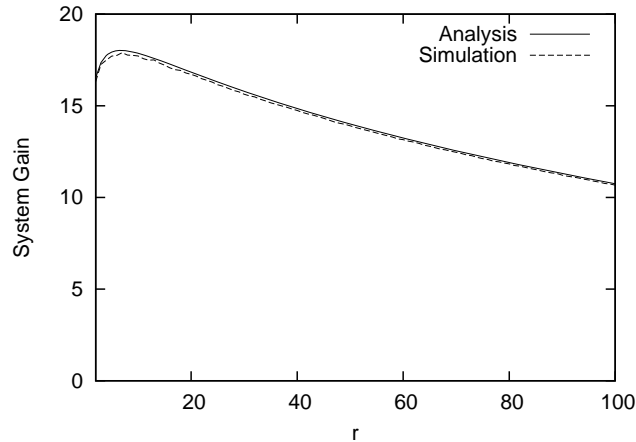


Figure 1. Comparison of the system gain under various  $r$  settings in both the simulations and the analysis. ( $X = 6$ )

$X = 6$ . We observe that the analysis curve matches the simulation curve very well, and the optimal  $r$  values (i.e., those that yielded the largest system gain) of the two curves are also comparable.

Next, we varied the maximum score value  $X$  in the range 2 to 10 and compared the derived optimal  $r$  values using both simulations and analysis, as shown in Figure 2. The results indicate that the analysis curve only matches the simulation results well when  $X \geq 3$ . The reason is that, in the analytical model, the optimal  $r$  value is larger than the total number of potential tags per puzzle ( $K$  in Equation 2) when  $X < 3$ , as shown in Figure 3. Thus, the model can not be used when  $X < 3$  because the optimal number of rounds per puzzle ( $r$ ) is larger than the number of tags ( $K$ ) that a puzzle has in the system.

Figure 2 shows that, when  $X > 3$ , the optimal  $r$  value decreases as the  $X$  value increases. This confirms our intuition that the value of  $E[s]$  increases as  $X$  increases (cf. Equation 3). As a result, based on Equation 6, the optimal  $r$  value will decrease as  $X$  increases. We find that if there are several different scores in the system, more rounds of each puzzle must be played in order to achieve a better overall system gain.

In addition, we evaluate the relationship between the system parameters (i.e.,  $P_s$ ,  $P_p$ , and  $P_t$ ) and the number of game rounds required to maximize the system gain  $r$  in the proposed Optimal Puzzle Selection Algorithm. Figure 4 shows the comparison results of  $r$  and different values of  $P_s$  and  $P_p$  ( $X$  is fixed at 6 and  $P_t = 1 - P_s - P_p$ ). From the results, we find that the values of  $r$  increase with the values of  $P_s$ ; whereas, given the same value of  $P_s$ ,  $r$  is more resilient against the changes in  $P_p$  and  $P_t$  values. In other words, the optimal  $r$  value is highly correlated to the probability of achieving an agreement in a game round. Moreover, the higher the likelihood of reaching an agreement in each game round, the larger value of  $r$  will be.

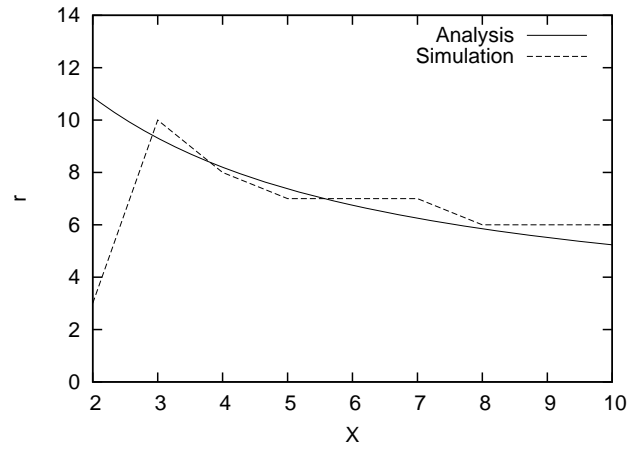


Figure 2. Comparison of the optimal  $r$  values derived by simulations and analysis, where  $X$  varies between 2 and 10.

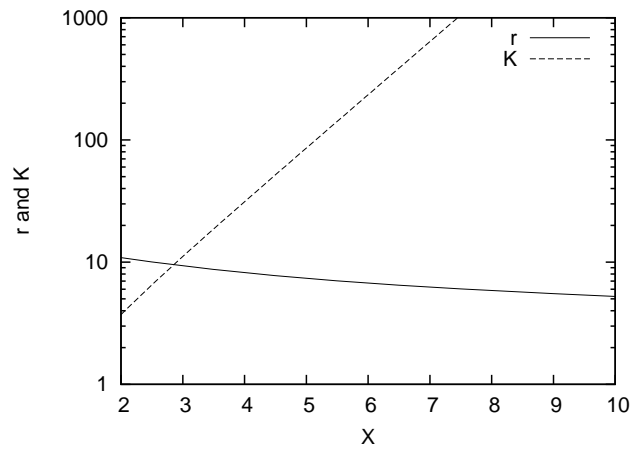


Figure 3. The relationship between the values of  $r$  and  $K$  in the logarithmic scale for various  $X$  values.

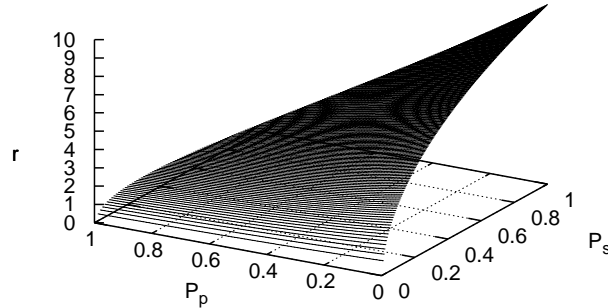


Figure 4. The relationships between the values of  $r$  and the different values of  $P_s$  and  $P_p$ , where  $X = 6$  and  $P_t = 1 - P_s - P_p$ .

### 6.1.2. Comparison of RPSA, FPSA, and OPSA

We now evaluate the performance of the three puzzle selection algorithms on the ESP game in terms of the system gain. In the simulation, we set  $X = 6$  and calculate the system gain after 10,000 agreements are reached in each simulation run. Let  $M$  denote the total number of puzzles in the system. The simulation results are shown in Figure 5.

The results in Figure 5 show that when  $M$  is small (say, smaller than a threshold  $M'$ ), the three algorithms are comparable in terms of the system gain achieved. However, when  $M$  is larger than  $M'$ , the system gain of OPSA remains constant, regardless of the changes in the value of  $M$ . In contrast, the system gain of FPSA and RPSA degrades as the value of  $M$  increases, although RPSA degrades slightly less than FPSA when  $M$  is very large. More precisely, the threshold  $M'$  represents the minimal number of puzzles required to achieve the maximum system gain (i.e.,  $M' = N = 10000/r$ ). Since  $X = 6$ , we know that  $E[s] = 10.3353$  and  $r = 7$  (from Equations 3 and 6 respectively). Therefore, in this case,  $M' = 10000/7 \approx 1429$ . The results indicate that, under the OPSA scheme, the ESP game must maintain at least a certain number of puzzles to achieve the maximum system gain<sup>||</sup>; otherwise, it will favor the RPSA and FPSA schemes because their performance is comparable to that of OPSA and they are relatively easy to implement.

<sup>||</sup>Fortunately, this is not usually a problem, since the number of the puzzles can be easily increased by adding new puzzles from the Internet.

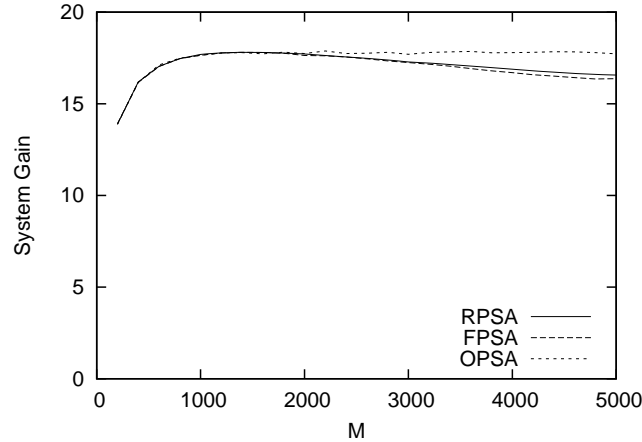


Figure 5. Comparison of the system gain achieved by the OPSA, FPSA, and RPSA schemes with various numbers of puzzles, where  $X$  is set to 6 and the system gain is calculated after 10,000 agreements are reached in each simulation run.

## 6.2. Input-agreement Games and Inversion-problem Games

Next, we discuss the simulations performed to investigate the inner properties of the TagATune game. We also evaluate the system gain of the three puzzle selection strategies. For simplicity, we set the values of the two scaling constants  $C_1$  and  $C_2$  to 200 and 1 respectively\*\*. Moreover, we set the values of the parameters  $(\bar{t}_s, \bar{t}_f, \bar{t}_p, \bar{t}_t)$  to  $(0.2, 0.2, 0.4, 0.15)^{\dagger\dagger}$ , and the parameters  $(P_s, P_f, P_p, P_t)$  to  $(0.5, 0.3, 0.1, 0.1)^{\ddagger\dagger}$ . All the results are based on the average performance of 100 simulations.

### 6.2.1. The Optimal $r$

In the first set of simulations, we evaluated the accuracy of our analytical model in determining an optimal  $r$  value for the TagATune game. We assumed that the number of puzzles in the system was infinite, and all of them were unsolved at the beginning of the simulation (i.e., no labels were discovered

\*\*The selection of the values of the two scaling constants depends on how we weight the two factors in the performance metric. The values of  $C_1$  and  $C_2$  must satisfy the criteria that  $\ln(C_1 \times \frac{1}{T}) > 0$  and  $\ln(C_2 \times E[O]) > 0$ , as described in Equation 7.

$\dagger\dagger$  Intuitively,  $\bar{t}_p > \bar{t}_s$ , since the players tend to pass a puzzle when they realize it will be difficult to reach an agreement; and  $\bar{t}_s = \bar{t}_f$ , since they are both equal to the average time required for the players to reach an agreement. Moreover, the players may be forced to terminate a game round simply because they do not have enough time to finish the puzzle, i.e.,  $\bar{t}_s > \bar{t}_t$ . Note that, the selection of the time scale used for  $\bar{t}_s, \bar{t}_p$ , and  $\bar{t}_t$  can be any time units (e.g., hours, minutes, and seconds), as long as it satisfies the criteria that  $\ln(C_1 \times \frac{1}{T}) = \ln(C_1 \times \frac{1}{r \times \bar{t}}) > 0$ .

$\ddagger\dagger$  It is important to ensure that  $P_s > P_p$ , otherwise the players may feel frustrated when playing the game. Moreover,  $P_t$  must be very small so that the players have sufficient time to solve the puzzles in order to increase the system efficiency.

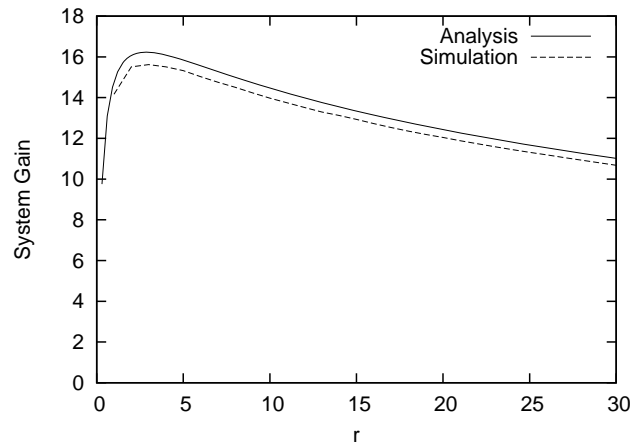


Figure 6. Comparison of the system gain under various  $r$  settings in both the simulations and the analysis. ( $X = 3$ )

for any puzzles). Figure 6 shows the evaluation results in terms of the system gain for  $r$  values between 2 and 30 when the maximum score value  $X$  was fixed at 3. In the figure, the analysis curve, which is derived by Equation 12, matches the simulation curve, and the optimal  $r$  values (i.e., those that yielded the largest system gain) of the two curves are also comparable.

We also evaluated the relationships between the system parameters (i.e.,  $P_s$ ,  $P_p$ ,  $P_t$ , and  $P_f$ ) and the number of game rounds required to maximize the system gain  $r$  under OPSA. Figure 7 shows the comparison results for  $r$  and different values of  $P_s$  and  $P_p$  ( $X$  is fixed at 3,  $P_p = 0$ , and  $P_t = 1 - P_s - P_f$ ). From the results, we observe that the value of  $r$  increases with the values of  $P_s$ ; whereas, given the same value of  $P_s$ ,  $r$  is more resilient against the changes in  $P_p$  and  $P_t$  values. Clearly, the optimal  $r$  value is highly correlated to the probability of achieving an agreement in a game round; that is, the higher the probability, the larger value of  $r$  will be.

### 6.2.2. Comparison of RPSA, FPSA, and OPSA

Here, we evaluate the three puzzle selection algorithms on input-agreement and inversion-problem games. In the simulation, we set  $X = 3$  and calculate the system gain after 5,000 agreements are reached in each simulation run. Let  $M$  denote the total number of puzzles in the system. The simulation results are shown in Figure 8.

The results in Figure 8 show that when  $M$  is small (say, smaller than a threshold  $M'$ ), the three algorithms are comparable in terms of the system gain achieved. However, when  $M$  is larger than  $M'$ , the system gain of OPSA remains constant regardless of the changes in the values of  $M$ . In contrast, the system gain of FPSA and RPSA degrades as the value of  $M$  increases, although RPSA degrades slightly less than FPSA when  $M$  is very large. More precisely, the threshold  $M'$  represents the minimal number of puzzles required to achieve the maximum system gain (i.e.,  $M' = N = 5000/r$ ). Since

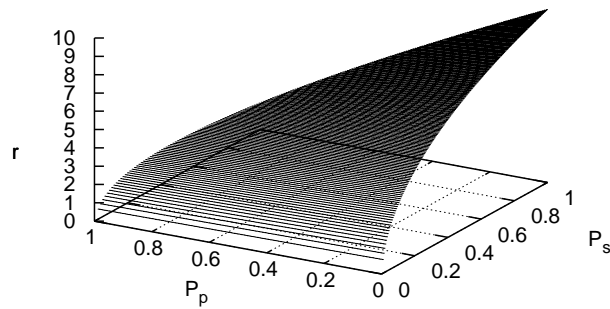


Figure 7. The relationships between the values of  $r$  and different values of  $P_s$  and  $P_p$ , where  $X = 3$ ,  $P_p = 0$ , and  $P_t = 1 - P_s - P_f$ .

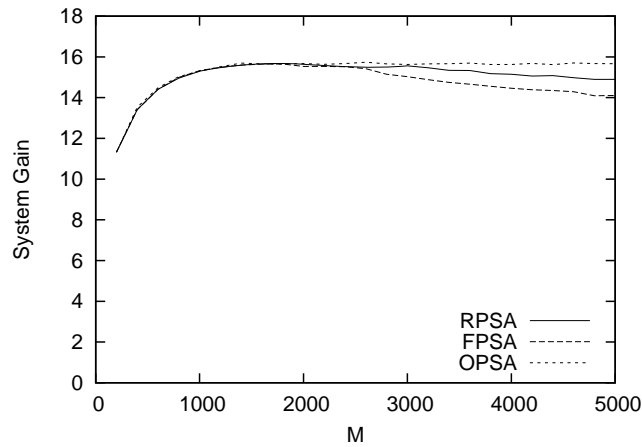


Figure 8. Comparison of the system gain achieved by the OPSA, FPSA, and RPSA schemes with various numbers of puzzles, where  $X$  is set to 3 and the system gain is calculated after 5,000 agreements are reached in each simulation run.



$X = 3$ , we know that  $r = 3$  (by Equation 13). Therefore, in this case,  $M' = 5000/3 \approx 1667$ . The results indicate that, under the OPSA scheme, the TagATune game must maintain at least a certain number of puzzles to achieve the maximum system gain; otherwise, it will favor the RPSA and FPSA schemes because their performance is comparable to that of OPSA and they are easy to implement.

## 7. Discussion

We have presented an analytical model for evaluating the system gain of three types of GWAP systems. In addition, we have proposed the *Optimal Puzzle Selection Algorithm* (OPSA), which strategically selects the puzzles that should be played next in order to achieve the largest possible system gain. However, there are some issues that have yet to be addressed. Below, we briefly discuss those issues and suggest possible solutions.

First, the proposed analytical model is only valid for two-player GWAP systems. However, recent studies have reported that multi-player games should improve the performance (i.e., the efficiency and quality) of future GWAP systems [18]. Therefore, extending the proposed model to support multi-player GWAP systems as well as other emerging types of GWAP games (e.g., mobile GWAP systems) would be beneficial.

Second, in this study, we assume that each game round produces an outcome with a positive score. However, it is possible for a round to have a negative outcome (e.g., if incorrect labels are assigned either intentionally or accidentally). Thus, we need a validation mechanism to examine the outcomes of games [24]. Moreover, it is necessary to extend the proposed analytical model to consider scenarios of zero and negative outcomes for more general cases. We defer a detailed evaluation of this issue to a future work.

Finally, our current analytical model does not consider the factor of *player diversity*, such as the player's age, gender, interests, language proficiency, education, and occupation, in the design of GWAP systems. Since it is widely accepted that diversity is a key factor in improving efficiency, productivity, and overall success [21], GWAP systems would benefit substantially by embracing the diversity of players. To this end, it is necessary to combine research on human computation and social networks, and design a set of *player selection strategies* to better utilize player diversity in GWAP systems. Again, we leave a detailed discussion of this issue to future work.

## 8. Conclusion

In this paper, we have studied GWAP systems, which represent an emerging human computation paradigm, and proposed a metric called system gain for evaluating a game's performance. Moreover, we argue that it is important for GWAP systems to implement proper puzzle selection strategies in order to collect human intelligence in a more efficient manner. Based on our analysis, we propose and implement the *Optimal Puzzle Selection Algorithm* (OPSA) to provide guidelines for improving GWAP systems. Using a comprehensive set of simulations, we investigated the properties of GWAP systems, and demonstrated that the proposed OPSA scheme substantially outperforms other schemes in all test cases. Furthermore, the proposed analysis is simple and applicable to other GWAP systems,



and the proposed puzzle selection strategy shows promise for use in the design and implementation of future GWAP systems.

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