Gold Digger: a Searching Behaviour Strategy Game

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Masters project proposal

CONTENTS

1. Abstract

This project sets out to evaluate users' searching behaviour through their interactions with a strategy game. The game environment, simulating digging for gold in different mines and at different depths will serve as a "metaphor" for searching, where the issuing of queries will be represented by moving to a particular mine and the examining of the documents returned in the query results will be represented by obtaining gold. This approach will, hopefully, provide us with insight on the topic of search behaviour, in a more context-free evaluation procedure.

2. Introduction

The main objective of the proposed system is to create a controlled environment, where cues that may cause bias towards the selection of a certain piece of information are completely removed. By presenting the experiment as a gold digging strategy game, factors that would normally steer subjects in a particular direction in their quest for relevant information don't have the chance to so. While searching for documents, users might be influenced in their decisions by a number of different factors like the need they have for the information, the topic, the documents' size, format and highlighting and, most importantly, their experience in similar tasks. The approach proposed removes all of these cues in order to evaluate if users' behaviour is the same as it would be if the cues were present. In the case in which users' strategies will not end up matching the ones they would adopt in a cues rich context, then attention will be focused on the reasons why this happens in one setting but not in the other.

In a controlled environment, furthermore, the main variables of query cost and gain can be manually set, making it easier to see if the data collected from the experiment, matches predictions derived from the theory. Secondly, because time will be represented as an integer value and not as standard chronological time, it will be possible to evaluate how this quantity influences decisions made by the user. Theories such as the one of Optimal Foraging (Sinevro2006) consider *chronological time* as one of the most important factors in the decision-making process in searching behaviours. Chronological time (as well as the amount of energy spent in the searching process), in fact, plays an important part in determining the worth of performing an action in relation to the expected gain. For this reason, if time is, instead, represented by an integer variable or "currency" (Sinevro 2006), the user will have the opportunity to spend as much (chronological) time as they want, to decide how to invest their in-game time, in order to perform actions during their search. Comparing the data gathered from this experiment with experiments in which time is not (an cannot be) represented as an abstract value, will offer interesting insights into the role of chronological time in choice making in relation to searching behaviours. Thirdly, the addition of a "random" game type, which sets all of the values of the variables in the system randomly, will allow for the evaluation of users' performance, in conditions that are not easily reproducible in nature, where time and energy consumption as well as gain functions seem to be constant enough for animals to adapt to.

Finally, the nature of the experiment itself might offer the opportunity to gather some interesting data regarding the way users approach the searching task. Because the application devised to study this behaviour is a game, it might be possible to analyse the data gathered taking this factor into account, raising question on users' performance in both game and emulated real life environments, like the ones devised by my colleagues Goodbrand and Hendry.

3. Problem statement

This project proposes to analyse user's searching behaviour in a context deprived of any cues that could allow them to exploit any previous experience in the task in order to achieve an optimal information foraging behaviour.

User's performance will be recorded and evaluated to see if it matches data in experiments in which this context is present. Findings could help provide insight on people's choices when faced with a task that requires the same kind of skills that are required in information foraging with none of the context that they are presented with in experiments based on the same theories.

Finally this project aims at making user's experience as enjoyable as possible for two reasons. Firstly it will avoid users feeling like they are performing work, removing them further from a standard information foraging task. Secondly, in order to enhance the number of users that play the game as well as the amount of games played.

4. Background literature

The background literature for this project can be grouped in two main sections. The first one, includes information regarding the results and findings of experiments on the topic of Searching Behaviour and Information Retrieval. This section will be named "Previous Studies" whereas the second one, named "Background theories" includes the formulation of the theories that the experiment employs in order to evaluate the data gathered.

4.1 Previous studies

In their paper on user adaptation, Smith & Kantor (2008) report their findings on an experiment conducted in order to evaluate user searching behaviour on two systems with different kind performance. The first kind of system was a standard search engine (Google) that returned queries as if it would in non-experimental settings, whereas the second kind of system, would display results according to one of two possible "handicaps". The first kind of handicap was determined by the system only returning results from the 300th ranked item, whereas in the second one the starting point would vary with respect to the kind of query issued. Interestingly, Smith & Kantor report that "Searches conducted using degraded systems were completed just as quickly as were those using better systems, with no difference in search success" where the rate of success was measured by amount of relevant documents found.

This brings Smith & Kantor to deduce that the users might adjust their behaviour "in order to compensate for variability in system performance" Smith & Kantor (2008). In order to build on these findings, the proposed system will offer five different variations of performance (in our case yield functions) and evaluate users' behaviour in each one of them. If users will be able to match their performance with the one of users in Smith & Kantor's study, this will support their conclusions that users "will adjust their behaviour in ways that are dependent on the characteristics of the failure" (the variation on the yield function in our case).

One of the ways in which users managed to adjust their behaviour when presented with sub-standard systems, in Smith & Kantor's study, was by increasing the rate of query entry. This seems to be in line with expectations, if we consider Charnov's Marginal Value Theorem (see section 4.2). According to this theorem, in fact, if the cost of searching is low, it makes sense for a user to enter more queries in order to acquire relevant documents, rather than examine a large number of the low-quality ones available.

Azzopardi et al. (2013) also seem to confirm expectations from the theorem in their paper on "How Query Cost Affects Search Behaviour". Their starting assumption however, is different from (and at the same time complementary to) Smith & Kantor's. They claim that "as the cost of querying increases, users will pose fewer queries and examine more documents per query." Because every action requires a certain cost of some kind, an agent will have to consider carefully several questions of cost vs. benefit (Azzopardi et al. 2013). In their experiment, Azzopardi et al. randomly assigned an interface with different query costs to each user: "Structured (high cost), Standard (medium cost) and Query Suggestion (low cost)". Results showed that "higher query costs correlated with fewer queries" confirming their "*cost-interaction"* hypothesis.

As previously stated, the game that is the subject of this proposal, will present the player with levels subjected to different yield functions but, at the same time, will also provide players with the possibility of altering the rate of gain through the purchase of items. This way, it will not only be possible to see if players prefer to issue a new query (move to a different mine) in relation to the cost in time of doing so, but also evaluate their behaviour if they decide to purchase items that will allow them to better their gain.

To be able to evaluate the data gathered, a series of parameters will need to be considered. In this, the proposed system takes inspiration from Thomas et al.'s paper on "Dilution and User Behaviour". In this paper, Thomas et al. present users with a "diluted" system which returned a selection of results that were either relevant, or related but incorrect. They measured their results in a range of ways. Each of them will be presented here accompanied with its counterpart in the proposed system

- *User click behaviour:* the click frequency at each rank position. This parameter shows which of the listed result of a query the user selects most frequently. In the proposed game, this will be represented by the depth at which a player is willing to dig down a mine to reach the desired spot on the basis of proximal cues.

- *Depth of result page viewing and Query reformulation:* faced with poor results in the "diluted" system users might choose to move down the list of choices returned by the query to look for relevant documents or reformulate the query. In the proposed system this will be represented by the amount of digging operations performed before the user decides to move to a new mine.

- *Time spent on tasks:* because users are using a "diluted" system, this parameter measures whether users are slower in making their decisions as a consequence. In the proposed system this will measure the amount of time elapsed between digging operations depending on the level of accuracy that users can make use of while examining a mine. This ability will be changed depending on the items in their possess.

The last paper that this proposal builds upon is Turpin & Hersh's (2001) study on "Why Batch and User Evaluations Do Not Give the Same Results". In this study, Turpin & Hersh compare Batch and user evaluations of information retrieval addressing concerns regarding the former ones (Bach) maintaining that "real world searching is more complex and that system efficacy cannot be accurately assessed with such studies.". To address this, the proposed system will consider a third kind of evaluation where the user will not be evaluated in a realistic setting but, at the same time, any context relating to a standard searching behaviour will be removed. This way, the hope is to be able to evaluate the user's *innate* searching abilities away from any potentially misleading influence.

4.2 Background theories

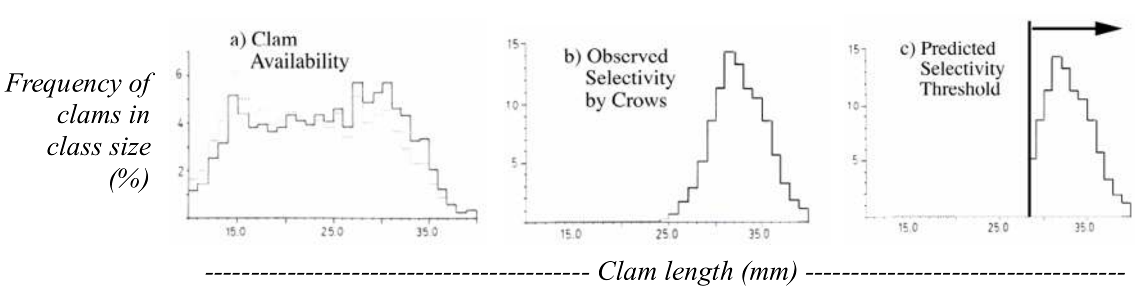
4.3.1 Optimal Foraging Theory

In his chapter on the "Optimal Foraging Theory" Barry Sinevro (2006) provides us with a wealthy amount of field studies on animals in the wild, whose foraging efforts seem to be aimed towards maximising their energy gain per unit of time. This striving towards the implementation of optimal foraging techniques, in fact, represents a large part of the lives of many species and, in turn, a fundamental component in determining their adaptive success. For instance, Sinevro tells us, the common shrew seems to always keep itself a mere few hours from death at all times. Because its small body size, the shrew cannot afford "the luxury of a thick layer of fat." (Sinevro 2006) and has to constantly forage to keep itself alive.

One of the most interesting studies proposed by Sinevro which can help us bring out some interesting points on searching behaviours, is the one on crows foraging on clams. In this study, Sinevro tells us about the foraging behaviour of the common crow (*Corvus caurinus)* in the intertidal. This kind of crow, has developed a technique to open clams which requires it to take a short flight and drop clams on some rocks below it to crack them open. The cost (in energy) of searching for clams, and the one of handling them is almost the same, however, the cost (in time) of performing the same activities is 4 times more expensive with regards to searching. It is then difficult to understand why crows would reject a large amounts of the clams they find, especially given the fact that searching seems to take up so much time. The reason for this behaviour is to be found in the "average net profitability of the clams as a function of size" (Sinevro 2006), which can be represented by the equation:

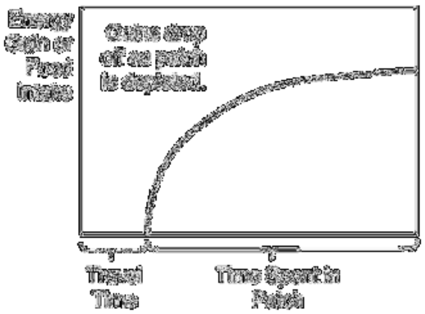
$$\frac{Energy}{Time} = \frac{Energy\ per\ clam\ as\ a\ function\ of\ size - (Search\ Cost + Handling\ Cost)}{(Search\ Time + Handling\ Time)}$$

It is very interesting to notice that predictions on the crow's behaviour in order to maximise energy gain per unit of time according to this formula, closely match its observed behaviour.

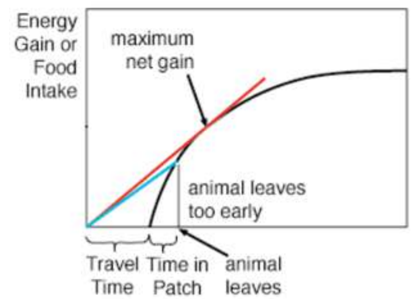


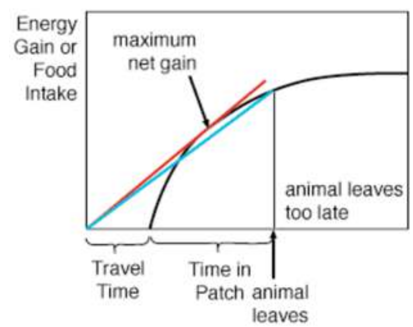
As we can see from (b) and (c), predicted behaviour seems to closely match observed behaviour. This kind of model, however, considers the disposition of prey in the environment to be random but, sometimes, prey items seem to have a patchy distribution (Sinevro 2006). In this case, an animal will have to travel between patches before it can start exploiting a new one. This creates two variables according to which an animal has to "make its decision" in order to maximise its rate of gain. The first one is the time spent *within a patch* to feed, and the second one is the time spent travelling *between patches* in which, crucially, the animal doesn't gain any energy and instead consumes it. A formula that effectively models this choice is:

$$Rate\ of\ energy\ gain = \frac{Energy}{Time} = \frac{Energy\ Gain\ or\ Load\ Size}{(Travel\ time\ to\ patch + Foraging\ Time\ in\ patch)}$$



Also known as "Charnov's Marginal Value Theorem" which generates an energy gain function like the one on the left. Here, we can see how there are two main areas delimiting the Cartesian space, the first one (on the left side of the curve) is the potential time the animal has to spend in between patches, whereas the second one is the potential time spent feeding in a single patch. An optimal allocation of time in foraging for this rate of gain will be represented by the tangent to the curve as shown in the graphs on the right. The red line is the tangent and the point of intersection with the curve determines the time in patch that it would be optimal for an animal to spend feeding.





The aim of this proposal is evaluate subjects' *innate* ability to reproduce similar behaviours while foraging for information rather than for food. To do this, the context of a gold digging strategy game has been chosen, in order to remove all proximal cues that might depend on the user's previous experience. In this environment, the user will have to perform the same *kind* of cost vs. benefit choices, however, he would not be able to adopt the strategies he consciously would. Following I discuss a paper by Pirolli & Card on Information Foraging which seems to support this intuition proposing experimental evidence and mathematical models.

4.3.2 Information Foraging Theory

Pirolli and Card seem to start from the assumption that there are many similarities between the techniques adopted by animals foraging in the wild and the ones adopted by people in "Information Foraging". Because of the structure of today's society, in fact, it is not for food that we forage for. Food is usually readily available almost anywhere human settlements can be found, however, to purchase it, we need to engage in a "complex tributary of cultural tasks that engage our physical and social environments" (Pirolli & Card 1995) which demand us to develop numerous "information-based" strategies, in order to earn a living. Pirolli & Card begin by explaining that our adaptive success seems to be increasingly dependent on our mastery of techniques of information-gathering, sense-making, decision-making and problem-solving strategies. In turn, they claim, this leads us to implement strategies which are similar to the ones seen in foraging behaviours of animals in the wild. Here, we can observe patterns in food foraging behaviours which aim at maximising the energy intake while minimising the amount of energy spent while foraging.

In other words, our lives are increasingly dependent on the ways in which we organise and retrieve information in order to use it effectively to navigate and survive today's social (and sometimes physical) landscape. Pirolli & Card go on to claim that, the Information Foraging theory's main tenant is that: "when feasible, natural information systems evolve towards stable states that maximise gains of valuable information per unit cost. Cognitive systems engaged in information foraging will exhibit such adaptive tendencies" (Pirolli & Card 1995).

As a consequence, it is to be expected that people will modify their information foraging strategies as well as the structure of the environment itself, whenever possible, to "maximise the rate of gaining valuable information" (Pirolli & Card 1995). Better strategies will be the ones that will allow someone who adopts them to yield more information per unit cost. Furthermore, it is also expected that these strategies will evolve through time, in order to reach a seemingly stable state that maximises the potential gains.

The process of analysing the development of this kind of behaviour, is called "adaptation analysis". This kind of analysis is conducted here, as well as in biology, through the use of "optimisation models" to study the design features of organisms and artefacts. Optimisation models include three major components:

- *Decision assumptions*, determine how much time is to be spend analysing a certain collection of information as well as which kind of content is worthwhile pursuing.

- *Currency assumptions*, determine how the choices made through decision assumptions are to be evaluated. In the context of Information Foraging, the relevant currency will be amount of relevant documents found, as opposed to the amount of energy gained in food foraging strategies.

- *Constraint assumptions,* determine what kind of limits will apply to the relationship between decision and currency assumptions. In Information Foraging, these include (but are not limited to) previous knowledge, available technology and task structure.

These models allow us to construct a framework for the evaluation in Information Foraging, however, it is not to be expected that any single individual will fully be conscious and even evolve towards, an optimal awareness and implementation of these models. These models simply outline the possibility of "an advantageous adaptation if not blocked by other forces".

The main decision an organism has to make in its foraging endeavours (being it for food or for information) is determined by a problem of "Enrichment vs. Exploitation" of a certain "patch" of relevant documents (or food). The careful weighing of one against the other, will, in turn, determine its searching behaviour, comprehensive of "in-patch" and "between-patch behaviours". When we decide to "enrich" a certain patch of information, we engage in certain "enrichment strategies" which are meant to maximise the amount of relevant information per unit of cost that we are able to get from a patch. However, the adoption of these strategies themselves has a cost which should be considered when making the decision to move to a different patch and select a new set of documents. There are two main "in-patch" enrichment strategies.

The first one is based on producing information packages that *yield better results*. This involves strategies like developing or acquiring better search tools, as well as spending time mastering them. The second one is based on *filtering* the incoming information into relevant topics or according to other decisional criteria devised by the foragers and that they came to realise as useful to their foraging needs.

Another way foragers can increase their gain in yielded by their foraging behaviours is by using “between-patch” enrichment strategies. These are also of two kinds. The first one is constituted by what Pirolli & Card call “scent-detection strategies”. These strategies are based on the identification of proximal cues in the environment in order to make a choice on whether it would be fruitful to explore a certain “patch” or move to another one based on detection of proximal cues. In the context studied by Pirolli & Card, this translates into identifying the relevance of a certain document, or group of documents by, for instance, its title and payoff, perceived clarity of writing or length.

A second kind of in-patch enrichment strategy is based on reducing the cost of getting from one information patch to another. While this is usually impossible for animals in the wild, because it involves modifying the environment, it is instead a very efficient way for information foragers to improve the rate of gain per unit cost. In the example proposed by Pirolli & Card this is shown in the re-organisation of the workspace of an employee whose job is to write a Business Intelligence Newsletter. The subject of their experiment, in fact, organised the different areas of his office, in order to minimise the time spent searching for relevant document by disposing the material he knew he would need more frequently, the nearest to his working station.

For the purpose of this proposal it is also important to consider the conventional models of foraging on which Information Foraging Theory is based. As it can be expected, to provide an efficient model of foraging, we will have to take into account equations which model both *in-patch* and *within-patch* behaviours. Given what previously stated, Pirolli & Card start by characterising the rate of gain of valuable information per unit cost R as the ratio of the total net amount of valuable information gained G divided by the total amount of time spent between patches T_B and exploiting within patches T_w:

$$R = \frac{G}{T_B + T_w}$$

Notably, this equation assumes that (1) “the total amount of information gained can be represented as a linear function of between-patch foraging time:

$$G = \lambda T_B g$$

And that (2) “the total amount of within-patch time can be represented as:

$$T_W = \lambda T_B t_W$$

This, in turn, gives Holling’s Disc Equation:

$$R = \frac{\lambda T_B g}{T_B + \lambda T_B t_W}$$

$$= \frac{\lambda g}{1 + \lambda t_W}$$

This formulation, however, “addresses the problem of allocation of time between in-patch vs. between patch under certain strong assumptions”. Because of this, Pirolli & Card have to devise their own interpretation which takes in to account that “(a) there might be different kinds of patches and (b) the total gains from a patch depend on the within-patch foraging time which is under the control of the forager. For this reason they have to include a value *i* representing the type of patches encountered at a rate of λ_i and a value t_{wi} representing the *policy* adopted by a forager on how much time to spend within each patch. The total gain can then be represented as the sum of all the values of *i* between 1 and P.

$$\begin{aligned} G &= \sum_{i=1}^{P} \lambda_i T_B g_i(t_{wi}) \\ &= T_B \sum_{i=1}^{P} \lambda_i g_i(t_{wi}) \end{aligned}$$

In the same way, the total amount of time spent within patches could be represented as:

$$\begin{aligned} T_W &= \sum_{i=1}^{P} \lambda_i T_B t_{wi} \\ &= T_B \sum_{i=1}^{P} \lambda_i (t_{wi}) \end{aligned}$$

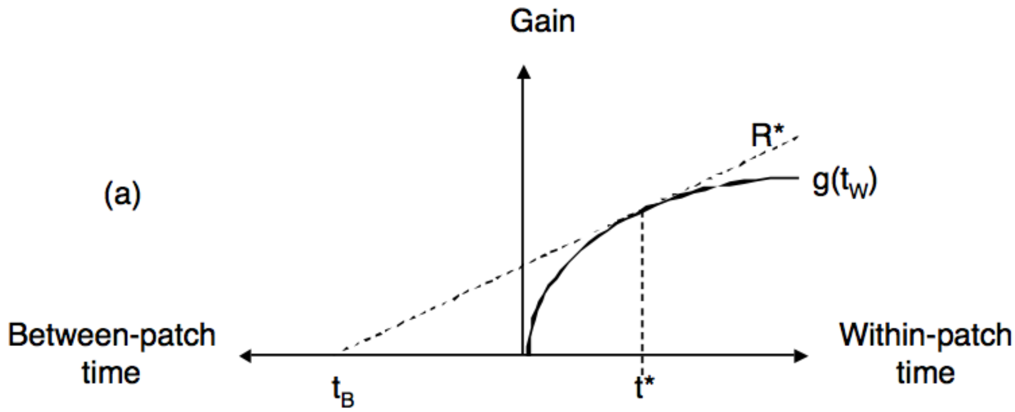
Combining these two equations according to:

$$R = \frac{G}{T_B + T_w}$$

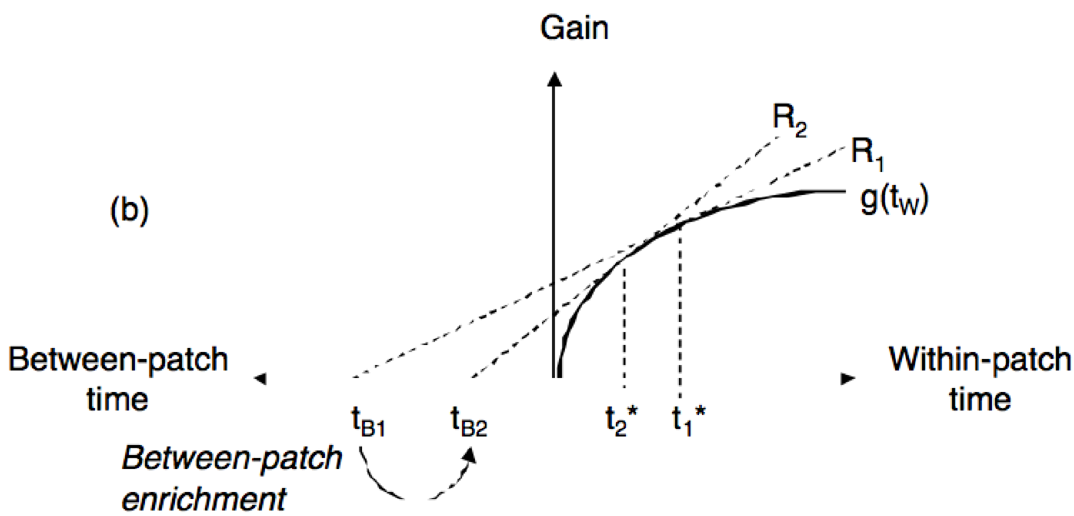
Gives us:

$$\begin{aligned} R &= \frac{T_B \sum_{i=1}^{P} \lambda_i g_i(t_{wi})}{T_B + T_B \sum_{i=1}^{P} \lambda_i t_{wi}} \\ &= \frac{\sum_{i=1}^{P} \lambda_i g_i(t_{wi})}{1 + \sum_{i=1}^{P} \lambda_i t_{wi}} \end{aligned}$$

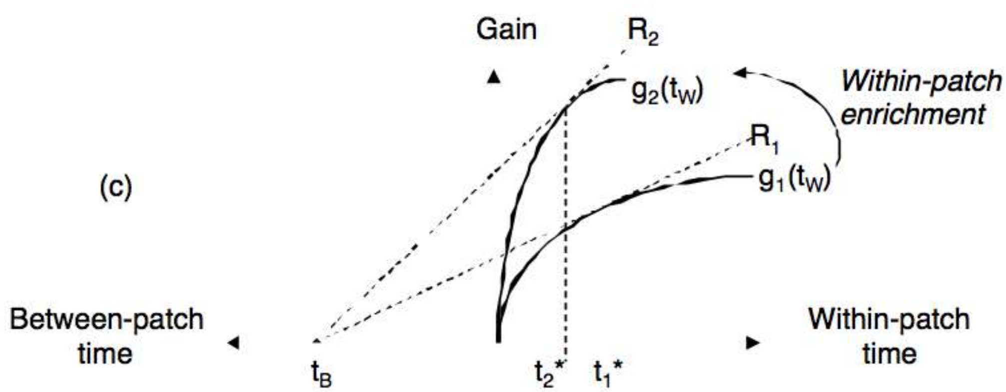
This last equation is what Pirolli & Card call the "*patch model for information foraging*" which takes into account patches that yield different kinds of gain functions as well as different strategies to exploit them.



(a) **- The Graph illustrates Charnov's Marginal Value Theorem where t^* denotes the optimal amount of time spent within-patch given the intersection between the gain function $g(t_w)$and the tangent passing from t_B (the time spent between patches)**



(b) **– Shows the changes generated by the adoption of between-patch enrichment strategies. The tangent to the gain function $g(t_w)$ passing from t_{B2} determines that the optimal amount of time to spend in a given patch is now t_2^* . The forager is now able to afford to spend less time in each patch.**



(c) **- Shows the changes generated by the adoption of within-patch enrichment strategies. The new gain function $g_2(t_w)$ has a higher rate gain which allows foragers that spend the same amount of time between patches t_B will be able to reap more results in a shorter time.**

Figures (a), (b) and (c) are the graphical representation of the functions presented in the previous section according to Charnov's Marginal Value Theorem, they model the problem of allocation of time between in-patch vs. between-patch strategies. Here, between-patch search times t_B , t_{B1} and t_{B2} generate different tangents to the $g(t_w)$ gain function which, in turn, determines the optimal rate of gain R. The outside of the curve on the x axis represents between-patch time while, the inside of it, represent within-patch time. To determine the optimal rate of gain R^* one draws the tangent line to the gain function $g(t_w)$ and passing through t_B . The point of tangency will determine the "optimal allocation of within-patch foraging time t^*".

This means that, the more time is spent between-patch, the less a forager will find it beneficial to spend time exploiting a given patch, always depending on the gain function $g(t_w)$. In Figure 2, in fact, we see the effects of a between-patch enrichment like the one described previously (office re-disposition) which sets the optimal rate of gain in such a way that it will be more beneficial for the forager to spend more time within-patch to exploit it. Finally, in Figure 3 we can see the effect of within-patch enrichment (for instance, making information packages that yield better results). As we can see, within-patch enrichment, changes the gain function $g(t_w)$ determining higher gains per unit of time spent within-patch.

The objective of the experiment outlined in this proposal, is to be able to evaluate the strategies adopted by subjects in order to reach an optimal rate of gain and to analyse how they are able to choose between within/between-patch enrichment strategies to better their rate of gain per unit cost.

5. Approach

The approach that will be adopted, in order to further research in searching behaviour strategies, will be based on a strategy game: Gold Digger. In this game, a mine will represent the possibilities held by the result of a query while digging deeper and deeper in the mine will represent examining those results. In turn an examination yielding useful documents will be symbolised by finding gold nuggets. In this comparison, the more useful is the document, the higher the amount of gold. Thus, for instance, a very useful document that is found very quickly, will be represented by a large amount of gold found after only one or two digging operations. If examining the results (digging) of the present query (a mine), didn't yield enough useful results (gold), the user would then be able to perform a new query (moving digging in a different site).

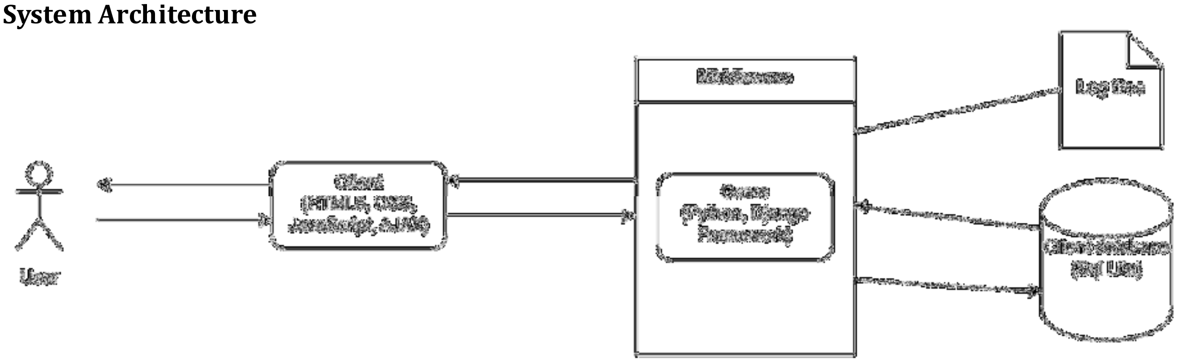
Players will only have partial information with regards to the expected amount of useful documents they might expect to find in their search. Depending on their level of expertise (the level), players will be able to estimate, thanks to visual cues (specs of gold in the ground on different levels of depth), how much gold a determinate mine might hold and thus choose if it beneficial to continue digging or to move to another mine instead. Both of these actions, in turn, will cost time, giving the players a "currency" to evaluate their actions against. However, and unlike in "real life" situations, units of time will have no relation to the actual chronological time elapsed from the beginning of the game. Time, in this instance, will be a pre-determined, tokenised value which players are is free to administrate as they please.

This game scenario, gives the players the possibility to weight and evaluate their searching behaviour in a more "controlled" and structural way than in the case of a real life simulation. Firstly, players will be able to more or less accurately (depending on their level) have a very quick, visual understanding of the results it might be reasonable to expect from the examination of the documents returned by a query. There is very little interpretation on the side of the players, if a mine contains many levels of gold-speckled ground, it will probably contain much gold, if not, the player is free to move to the next mine. Secondly, and most importantly, players have all the time they want to weigh their choices, which will allow us to test the results gathered from their behaviour in the game, where time is a static “currency”, against the ones gathered in setups in which chronological time itself seems to be the deciding factor over which decisions are taken. With an infinite amount of (chronological) time, in fact, nothing would stop us from examining every single result returned by a query, freeing us from weighing our choices in order to strike the right balance between, time spent examining result, and their meaningfulness. In the context of Gold Digger, instead, players will not have to make this choice in the same way. Time will be a value, a “currency”, that they will be able to spend as they wish, without it incessantly decreasing, influencing their decision making and possibly their focus, through the anxiety generated by its approaching expiration. A player will evaluate the status of a mine and then consider how many units of time it would cost to move to another site, and how many it would cost to dig and finally make her choice.

This approach will allow us to study the player/user search behaviour in a new way, opening the data gathered to comparison with search behaviour data obtained through different experimental procedures.

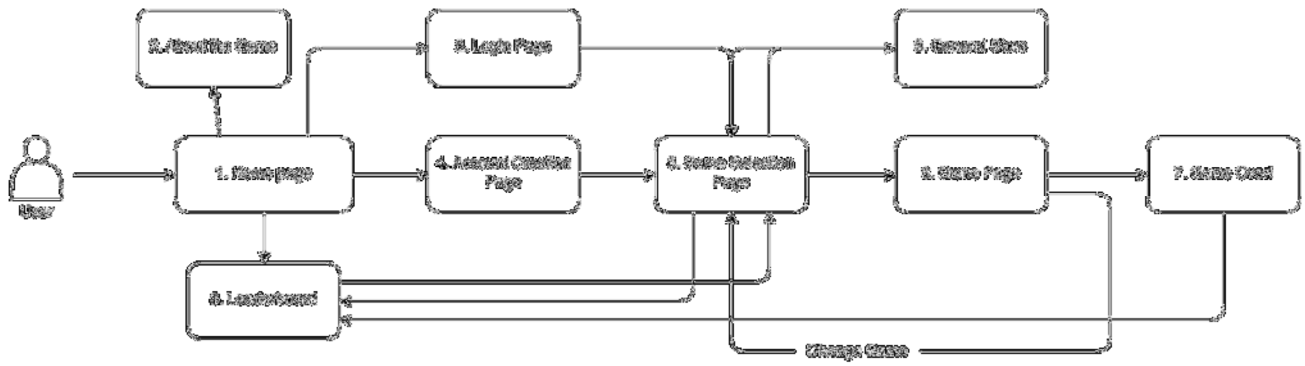
6. System Overview

61 System Architecture



The application will be based on a 3-tier architecture in which each user will be able to create an account (client) containing all of the user details together with a set of variables pertaining to the games played, set to their respective initial values. The client side will include HTML5 and CSS elements in order to provide a user friendly environment as well as JavaScript and AJAX components to provide responsive and real time updates. With their account users will be able to access the game logic which in turn relies on a Django Framework (based on Python) for implementation. All of the game graphics will be stored in a Sql Lite database in order to be retrieved according to the tile-set and configurations of the current game. In addition to this, data concerning user performance in each played game will be stored in a log file, so that it will be possible to analyse their behaviour at a later stage.

6.2 Site Map



The above diagram shows the Site Map of the system. On the home page, users will be presented with a short description of the game together with some screenshots, in order for them to quickly identify the purpose of the website. From the Home Page (1), the user will be able to navigate further to different pages:

(2) About the Game (About Page)

This page will contain information about the aims of the game, as well as the details of the author and client. The page will also contain an explanation regarding the importance of the data collected through the system together with links to appropriate papers and websites detailing the background on which the game is based in its capacities as an experiment. Finally, this page will also contain the privacy statement for the treatment of the data collected by the system from the users.

(3) Leaderboards

This page will present the user with the game's leaderboards. These will contain all of the scores for each of the five game types, for each player. The scores will include:

- Player name
- Number of games
- Max. Score
- Level

The leaderboards will be visible to anyone who enters the site, whether they are logged in or not.

(7) Login Page

Users who already own an account for the site will be able to login from this page. This will be a standard login page, requiring their username and password to proceed. Once authenticated, the user will be brought to the Game Selection page. In the event of incorrect details being entered, the user will be alerted through a message on the same page (the user will not be redirected to another page before being able to re-enter their details).

(4) Account Creation Page

From here users will be able to create a new Player Account for Gold Digger. Users will be asked to enter username, password, email, age, location and occupation. While these details are not necessary for the game itself, they will be important if and when the data gathered from their play throughs is analysed. For this reason a link to the About Page will be provided, in order for the users to understand the reasons behind the request of these details.

Once the user has logged in or created a new account, they will be presented with the Game Selection Page (5). From this page, they will be able to select one out of five game types, which will differ in appearance as well as in setup. The game types will be:

- High yield, High cost (HH) – Klondike River
- High yield, Low cost (HL) – Sutter's Mill
- Low yield, High cost (LH) – River Helmsdale
- Low yield, Low cost(LL) – Dusty Skull
- Random yield, Random cost (R) – Fool's Creek

Fig. 1 – Possible wireframe of the game selection page

The variable "yield" will be the factor determining how much gold the player will be able to expect by digging in a particular mine, while the variable "cost" will determine both the cost in time of doing so, and the cost of moving to a different mine. Finally, in an (R) type game, these variables will be unknown to the user and will be determined randomly instead.

At the end of a play-through, the user will automatically reach the Game Over Page (7) followed by the Leaderboard (3) where they will be able to compare their performance with the ones of other players. From there, the user will be able to, either return to the Home Page (1), select another game type from the Game Selection Page (5) or get to

(9) The General Store

In the General Store users will be able to purchase different items to help the in their mining endeavours. They will be able to purchase three kinds of items.

- Digging equipment: this kind of equipment will help players extract more gold from a mine, it will include items such as the sledgehammer, and the dynamite. Acquiring these items will constitute a metaphor for the application of "within-patch enrichment" strategies.
- Scanning equipment: this kind of equipment will help players to be more accurate in the detection of proximal cues that match the actual amount of gold in the "patch". These items will include a dowsing rod, a metal detector and other kind of devices. Acquiring these items will constitute a metaphor for the application of "scent-detection techniques"
- Moving equipment: by purchasing this kind of equipment, users will be able to reduce the cost of moving to a different site (mine). Moving equipment might include: a wheelbarrow, a mule and a wagon. Acquiring these items will constitute a metaphor for the application of "between-patch enrichment" strategies.

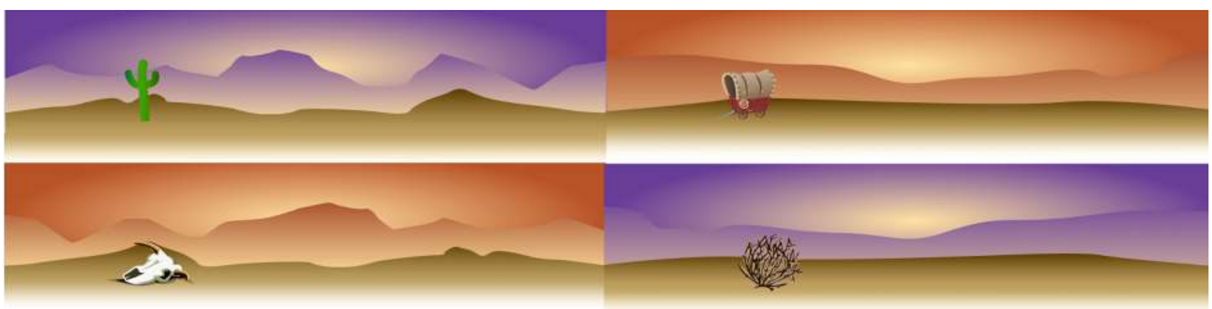


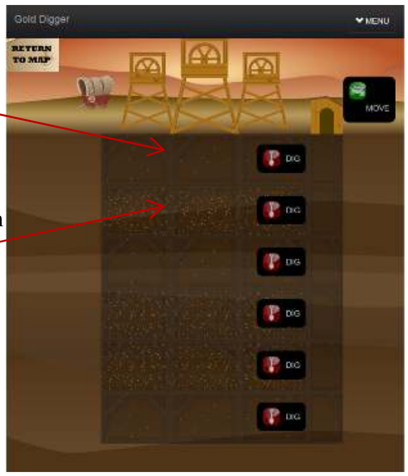
Fig. 2 – Possible scenarios for the different kinds of game

6.3 Walkthrough

1. From the Game Selection Page (Map) the player selects the "Sutton's Mill" level. This level is characterised by a HH pattern (High yield, High cost). This means that if the player decides to dig, the price in days he will have to spend is 3 days per digging operation and 5 days if he decides to move to a different site (mine) however, potential payoff will be higher than in any other level.

Low concentration of gold specks

High concentration of gold specks



2. At the beginning of the level the player is presented with a digging site with a number of possible mining levels. Different kinds of concentrations of gold specks can be seen at different depths, these will be the player's proximal cues (or "scent") that he will be able to base his decision to digging vs. moving on.

Level: Sutton's Mill
Time: 100
Mine: 1
Gold: 0
Depth: 0
Equipment: miner's pick
Accuracy: naked eye

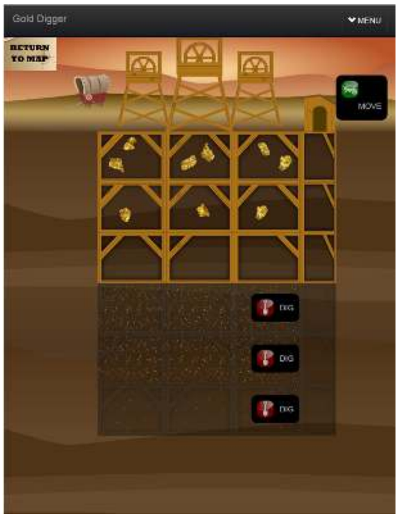
3. The first level of the mine only showed a few specks of gold, but the player has decided to start digging anyway and has been rewarded!

Level: Sutton's Mill
Time: 97
Mine 1
Gold: 10
Depth: 1
Equipment: miner's pick
Accuracy: naked eye

At the beginning of the game the player is equipped with basic items which allow him to only dig one level at the time. The accuracy of the correspondence between the concentration of gold specks and gold nuggets actually present at a certain level of the mine is also at its first stage here (naked eye). However, in this instance, this turned out to be in favour of the player whom found more gold than the concentration of gold specks suggested there being.

4. The player has decided to continue digging and has found a modest amount of gold nuggets (5gn).

Level: Sutton's Mill
Time: 94
Mine 1
Gold: 15
Depth: 2
Equipment: miner's pick
Accuracy: naked eye



1. The player has decided to continue digging once more but this time he was unlucky and this level of the mine didn't even hold a single nugget, again even though some specks of gold indicated a low possibility of finding nuggets, the low level of accuracy of the player determined a wrong prediction.

Level: Sutton's Mill
Days: 91
Mine 1
Gold: 15
Depth: 3
Equipment: miner's pick
Accuracy: naked eye

Afraid he might not get any more gold from this mine, the player decides to click on the top right button (MOVE) and move to a different site for the price of 5 units of time.

2. After moving, the user is presented with a whole new site, with a different set of mining levels showing different proximal cues (gold specks).

Level: Sutton's Mill
Days: 86
Mine 2
Gold: 15
Depth: 3
Equipment: miner's pick
Accuracy: naked eye

3. When the units of time at the user's disposal are depleted, the user is brought back to the Map Page, where he would be able to choose to try his luck in another one of the five available scenarios as well as check out what he could purchase from the general store.

4. In the store, the player can see a lot of equipment that will improve his digging (within-patch enrichment), as well as infrastructures that will help him better his gold nugget detection (scent detection techniques), or even move to a new mine at a lower cost (between-patch enrichment). He decides to buy a sledgehammer for the price of three gold nuggets. The sledge hammer will allow him to dig two mine levels at the same time!

6.4 System Requirements

The following are high level specification for the system. For clarity the specifications will be assigned to the page to which they pertain. Furthermore, a MoSCoW method will be adopted in order to show whether each requirement Mill (), Should( ), Could ( ), or Won't () be implemented in the system.

Home Page

- M Must clearly outline the name and the nature of the game.
  - S Should give a very brief (one or two sentences) description of the game in order for the user to quickly understand the nature of the site.
- M Must allow users to access the About, Register and Leaderboard pages.
  - S Should provide clearly visible and understandable links leading to each of these pages.
- M Must provide a link for the user to logout.
- C Could contain some screenshots of the games in order to give the user a quick idea of the kind of game they can expect to play.

Account Creation Page

- M Must allow users to register by entering their email and password
  - M The Username must be entered in a standard text entry field
  - M The Password must be entered in a standard password entry field (text will be replaced by blocks)
- M Must check for the username entered by the user to be unique.
  - M Must display an information message in case someone else has already chosen the username
- M Must require the users to enter the password twice and check if they are the same
  - Must be implemented in a second password field
- M Must encode the user's password before saving it
  - This functionality must be provided by the Django Framework
- M Must ask the user for their gender, sex and occupation
- M Must provide a link to the About page in order to explain the reasons for the request of such details.
  - M The link must be clearly visible, the user must be able to find it easily.
- M Must allow the user to return to the Home Page
- M Must display a message upon successful registration
  - M The user must then be automatically brought to the Game Selection Page
- M Must send the user's details to the database in order for them to be stored

Login Page

- M Must allow the user to enter their email and password details in two different fields.
  - M The field provided must be a standard text entry and a standard password entry field (input masked).
- M Must Bring the user to the Game Selection page upon successful authentication.
- M Must display a message to the user in the event of incorrect details being entered.
- M Must include a link to the homepage.
- C Could allow the user only a certain number of attempts after which their contact is

deactivated.

About Page

- M • Must provide details regarding the purpose of the game, its design and its specifications.
- M • Must inform the users of the reasons for them to provide their details.
- M • Must contain a link to the University of Glasgow website.
- M • Must contain contact information about the author(s) of the game.
- M • Must be accessible by registered and unregistered users alike.
- M • Must include a link to the Home Page
- C • Could provide links to information about the background theories that the game was devised in order to test.

Leaderboard Page

- M • Must include rankings for each of the five game types.
    - Each player will be represented as a line in a table including the following columns:
        - Ranking.
        - Player username.
        - Thumbnail.
        - Highest score.
        - Games played.
        - Level.
- S • Should allow all users to be listed in the rankings.
    - S Users with equal scores should have the same ranking.
- M • Must Include a link to the main page

Game Selection Page

- M • Must allow the user to choose between 5 different game types.
    - High yield, High cost (HH)
    - High yield, Low cost (HL)
    - Low yield, High cost (LH)
    - Low yield, Low cost(LL)
    - Random yield, Random cost (R)
        - S Game types should have different names
- M • Must display a different image and name for each game
- M • Must include a link to the main page
- S • Should provide a short help text to outline the difference between the games

Game Page

- M • Must display the appropriate tile-set for the game type
- M • Must display the following parameters on screen
    - Username
    - Game type [string]
    - Game number [int]
    - Time left [int]
    - Gold found [int]

- Mine number [int]
- Digging cost [int]
- Moving cost [int]
- Level [int]
    - All of these should be appropriately updated in real time

M • Must provide the player with visual cues on the amount of gold he can expect to find on each level of a mine.

S
- Each mine should be more than 10 levels deep.

M • Must allow the player to dig through the mine one level at the time.

M • Must allow the player to dig at any time until the end of the mine (if they can still pay the cost in time).

S
- A distinctive sound should be played each time the user decides to dig.

S
- Digging must be performed by clicking a button on the screen.

M • Must allow the player to move to a different mine at any time (if they can still pay the cost in time).

S
- A distinctive sound should be played each time the user decides to move to a different mine.

M
- Moving to a different mine must be performed by clicking a button on the screen.

M • Must notify the user of how much gold was found in each digging operation.

S
- A distinctive sound should be played in this event.

S
- The notification shouldn't stop the user from playing.

S
- The notification should not slow down gameplay.

S
    - The user should just be moderately aware of these notifications.

M • Must notify the user when they reach a new level.

M • Must record the user's actions and store them in a log file.

- The parameters stored will be:
    - Gold obtained per game
    - Number of digging operations performed per mine
    - Number of mines visited per game
    - Amount of chronological time elapsed
    - Game selection preference

M
    - Must include a way for the user to abandon the current game.

S
- The user should be notified that their progress will not be saved in this instance.

General Store

M • Must contain a variety of items that the user can purchase that will be divided into three categories

- Digging equipment
- Scanning Equipment
- Moving equipment

M • Must allow users to purchase each of the items if they own enough gold

M • Must display the current amount of gold in the user's possess and the cost of each item

S • Should ask user to confirm their purchase before carrying it out

S • Should display a message in the event of the user not having enough gold to purchase an item

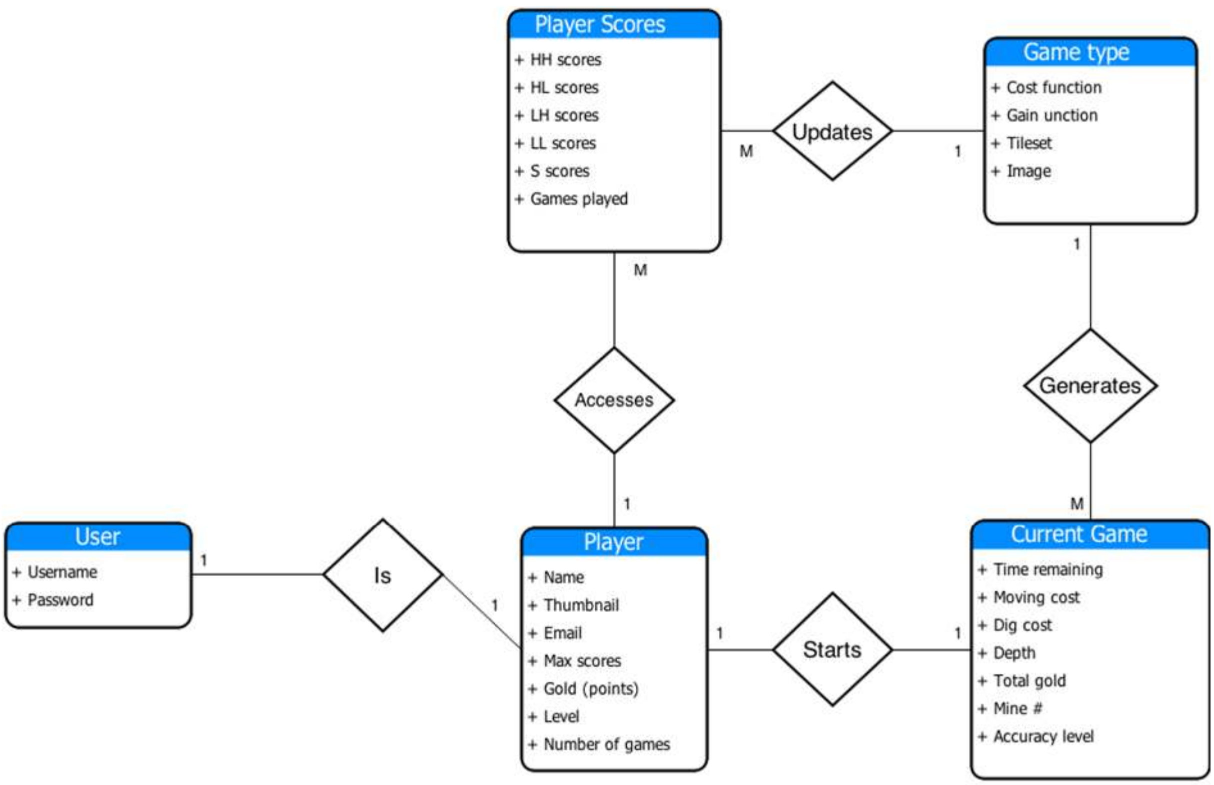
- After he clicked on it

C • Could have a background music characteristic of the shop environment.

Game Over Page

M ▬ • Must clearly display a "Game Over" notice
M ▬ • Must display the player's final score
S ▬ • Should display a notice if the user beat their previous high score.
M ▬ • Must contain a link to the leaderboard
M ▬ • Must contain a link to the main page

6.5 ER Diagram



The above is the ER diagram for the system. It is comprised of five models (or entities) and five relationships between them. Each User will be able login through their username and password details and access their Player account model which will hold the information on the user, including their stats, on the previously played games. Each game will be generated by a Game Type model setting the cost of digging and moving, the expected gain, and the tile-set. A Game Type model will be able to generate many Current Game objects. The current game model will store the current state of the game, comprising of all the variables that are influenced by the user's behaviour, such as the time remaining and the amount of gold obtained. Finally, the Player's Score model will hold information regarding the scores and ranking of all the players in each of the five games. A Player will be able to access many Player scores.

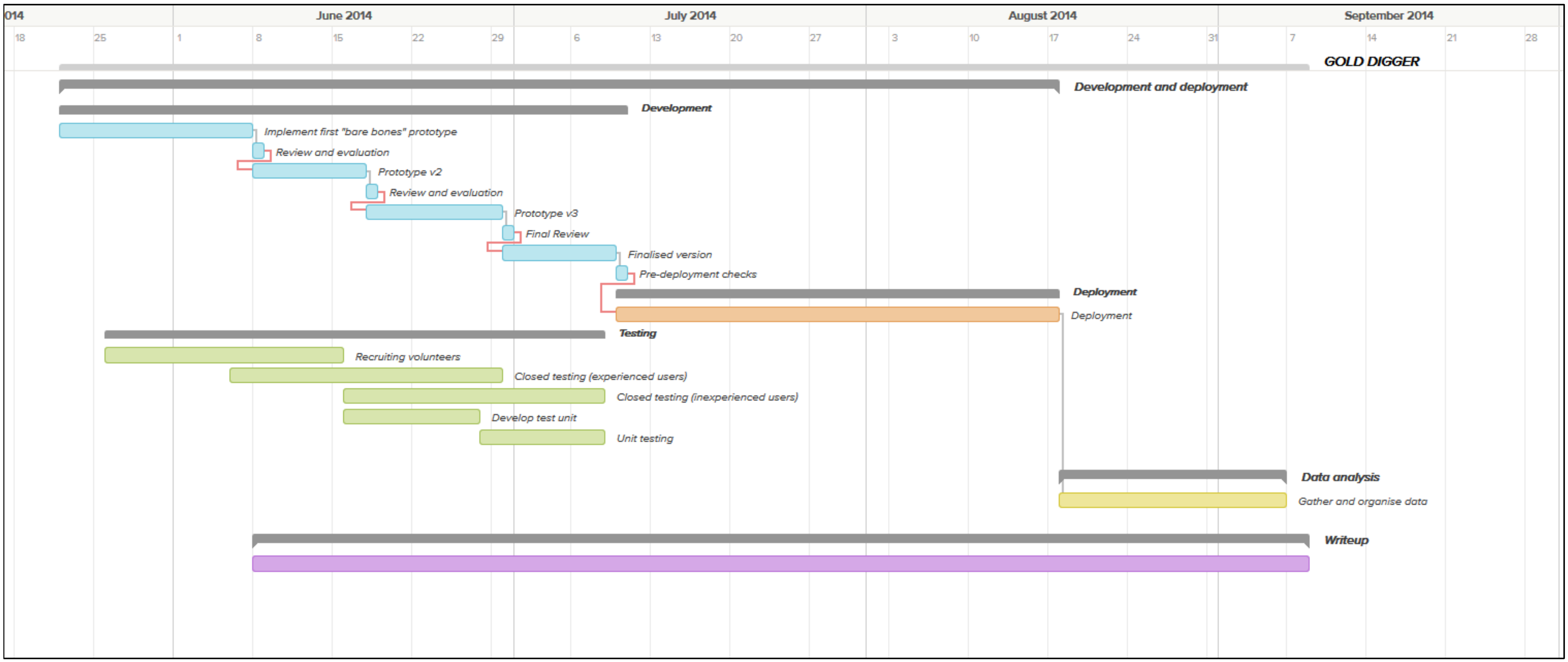
7. Work plan

The work plan has been devised aiming to generate a sufficient number of implementation-review-implementation cycles as possible, followed by a deployment period which will allow for the collection of a large amount of data to be analysed in the final phase. As we can see from the Gannt chart below, three iterations through the implementation-review-implementation cycle have been planned, after the first “bare bones” implementation. This last one will be the first prototype and will contain only the functional parts of the system with no added embellishment or additional graphics. This implementation will serve as a model to build on in the following iterations of the development cycle. De development cycle will start in late June (23rd) and end in July (31st) with the review of the final version of the system. After the development cycle, the deployment period will start. In this period, spanning almost a month, the system will be deployed on the internet and open for anyone to access and use.

During the Development and Deployment cycle, two important processes will also be running parallel to it. The first one is “human” and “machine” testing of the system. The former one will be performed by two different user categories, experienced users (Tutors, PhD students, Supervisor, Colleagues) and inexperienced users (anyone who would is willing to test the system that has no familiarity with it or similar ones). The recruitment of this last kind of users will start shortly after the beginning of development and it will end on the 27th of July, roughly a week after experienced user testing has begun. In parallel with the beginning of experienced user testing, the development of “machine” testing will also begin. This will include the development and the successive employment of unit testing and parameter testing for the system. Both inexperienced user testing and unit testing will end before the final review of the system.

The second process running in parallel with Development and Deployment will be the write-up for the project. This will be incrementally expanded throughout the whole duration of the project development and will include gathering, organising and reformulation of the findings as well as notes on progress and the review of the present proposal.

Finally, once the deployment phase has ended, the final phase of data gathering and analysis will begin. In this phase, all of the user data recoded in the game's log files will be processed to be included in the final writeup.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June 2014
July 2014
August 2014
September 2014
18
25
1
8
15
22
29
6
13
20
27
3
10
17
24
31
7
14
21
28
GOLD DIGGER
Development and deployment
Development
Implement first "bare bones" prototype
Review and evaluation
Prototype v2
Review and evaluation
Prototype v3
Final Review
Finalised version
Pre-deployment checks
Deployment
Deployment
Testing
Recruiting volunteers
Closed testing (experienced users)
Closed testing (inexperienced users)
Develop test unit
Unit testing
Data analysis
Gather and organise data
Writeup

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