Web Analytics: The New Purpose towards Predictive Mobile Games

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Abstract. Web Analytics have been confined to an iterative process of collecting online traffic data for the purpose of drawing conclusions. This research presents a concept where internet usage traffic can be predicted against through the means of a mobile game. Through investigating certain industries use and perceptions of playfulness certain aspects are identified for the design and development of the game. Using a usability based methodology for evaluative testing these features are questioned amongst two distinctive versions. From these, the feasibility of a mobile game and its playfulness for users is gauged. The research leaves the concept considering what other contexts web analytics can be used within.

Keywords: Web Analytics, mobile games, serious games, prediction, usability, prediction markets, spread betting, playfulness.

1 Introduction

Prediction is the simple designation to a possible outcome which can lead to one of two eventualities, right or wrong, win or lose [1]. Many businesses and theories exploit either possibility. In the instance of economics or gambling a prediction is supported on the supposed understanding of risk [2]. Placing a prediction in conjunction with a commodity is nothing new. However this concept has previously not been applied to the usage of internet traffic known as web analytics. Web analytics has remained confined to the repetitive accumulation and conclusion of online activity [3], where its predefined purpose has not yet been explored beyond.

The current wide acceptance and ever growing popularity of mobile technology over many cultural and social boundaries has witnessed a level of unity with a user's life [4]. Mobile technologies ability to allow access to games and applications beyond the geographical limitations of desktop computers presents a unique conduit to assess the effective entertainment of an analytic based prediction game. The domestication of users towards the technology has caused an "industrial revolution of data" [5]. The scale of this data explosion can be observed in a singular instance such as social media. Facebook in a single day alone generates sixty terabytes of data [6]. Potentially harnessing these scales of data in the form of a game presents an intriguing pursuit of research.

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Games can draw a player to be immersed in a number of ways. Gambling offers no difference in terms of its playfulness in order to encourage acceptance and extensive use. This addictive quality allows the prolonged success of placing a prediction [7]. Could the same be applied when making a prediction against web analytics in the form of a game?

2 The Aim and Objectives

The purpose of this paper is to explore how web analytics can be used beyond its previous connotations by employing prediction to develop a playful and entertaining mobile game for users. It specifically refers to the following objectives:

- Determine the feasibility of developing an analytics game.
- Identify how, why and what makes data playful.

3 Web Analytics

Web analytics is the process of collecting quantitative or qualitative data through measurement for the translation into an appropriate conclusion or action [8]. The conversion of factual data can be utilized to create an informed decision [9] which has accounted for the successful actions of businesses to improve upon their online presence [8].

3.1 Analytics Current Development of the Web

Google Analytics has developed the process into a cheap, easy and commonly used tool accounting for a significant 55.9 percent of all websites [10], which was once a grueling and drawn out task [11].

Google Analytics offers a three tier service using an iterative process of measure, analyze and change towards improving the online user experience. The fundamentals of the process are based upon the collection of behavioral metrics recorded when a user visits a web page. The simple measurement of a singular visitor can account for time duration spent and the path taken to and from the page [3]. Whilst a single visitor may appear insignificant, the accumulative collection of datasets can create an image towards the impression of a website. For example, three hundred visitors remain on a website for five seconds, which could indicate an inadequacy of content or design amongst issues. The measurement of metrics such as the total time spent can allow for deductions that can encourage change [11].

The iterative process remains a constant trend of use across the internet in many sectors. In particular with games, analytics have acted as a method to record player behavior. These studies have witnessed analytics repeat use to better measure and therefore understand player behavior for the development of in-game artificial intelligence [12] or assess a correct level of difficulty [13]. Overlooking the contexts for analytics, its use remains firmly within the focus towards measuring, analyzing and change. Analytics have remained exclusively to these main areas of use and therefore confined to this limited framework. This encourages new innovations to build upon what analytics is currently defined as, side step its original use by considering how it might be used in a previously unseen manner.

3.2 Analytics to Predict the Future

Tools for analytics reside heavily on the past for visitor behavior [14]. While the past measurement and analysis of data can influence an improved future user experience, analytics does not provide much of a future consideration. For instance, a result or value based upon a future outcome. Generally analytics is not concerned with the future behavior until collected in the present. Whilst analytics has remained rigid in this regard, businesses have made use of the future towards a prediction.

It is not uncommon for businesses to attempt to predict outcomes for its benefit. Google, Best Buy and P&G are known to analyze employee data in order to isolate those that are most likely to gain advantages for the business such as sales. The same can be gained for market segments with promotions and pricing strategies [15].

Both examples of analytic tools and businesses only focus on either the past or the future. Neither makes use of both past and future predictions. The proposed mobile game looks to meet this.

4 Gambling on Prediction

A prediction made by a single individual can provide a standing or belief on a topic. When predictions are applied collectively in a group on a large scale, the culmination of opinion can become a speculative market towards a likely probability [1]. Prediction markets are inherent of this, making use of a collective opinion of a question to become aggregative information. Its predictive ability has been repeatedly tested during the forecast of some of the most profound and controversial topics in recent time such as economic issues and the conclusion of foreign occupations [16]. As such, prediction markets have been seen as a success, which has lead to their wider use across businesses [17]. Specifically, examples of these can be witnessed with Google's Prediction Market (GPM). A question is put forth i.e. Product X will be a success, to employees where the prediction is represented in the form of any number of commodities such as shares [16]. GPM makes use of Goobles placed to determine the certainty that is held over a question. The placing of one hundred Goobles may demonstrate a level of certainty whilst only ten may represent reluctance to the question [1]. The ability to place a commodity for a prediction essentially represents a focal point of opinion, where the believed likelihood of an outcome is concluded with a simple value being placed.

Spread betting makes use of many of the same foundations as prediction markets. The significant difference is contained within the addition of a currency instead of artificial or a fabricated reward [1]. With the opportunity to win, there comes the risk to lose. This is an aspect that has reverberated through economic markets when a prediction is made [2]. Risk has been seen to have a profound effect on behavioral patterns. In particular, a recent win can provide a strong influence to take further risk [18]. The same can be true of losing causing a need to play [19]. It describes the imagery of an individual being drawn to place coins into a gambling machine but ultimately it shows the potential that risk has towards playfulness with a prediction game.

Clearly, the commodity placed against the prediction and the risk involved holds a certain level of playfulness to invoke continued use for industries such as gambling. The similarity that placing a prediction against online traffic has to gambling emphasizes the need to consider these points within the design of a mobile game. It points towards the consideration of how such a design might affect the user and specifically the question, when does playfulness end and addiction begin?

4.1 Addictions Takeover of Playfulness

Playfulness within a game can be associated to a joyful and fulfilling pursuit within a user's leisure time. This describes a positive association compared to addiction which generally indicates a certain need to carry out an action. With such opposing definitions, how could they intertwine where one takes over from the other?

In regards to technological addiction with game play, the repeated description of a level of compulsion and dependability exists [20]. While certain levels exist amongst the physical and digital, addiction appears to be higher online. Users of online gambling games such as roulette and poker are more likely to bet more online in terms of amount and risk compared to those offline [21]. It indicates an increased disregard for the value and risk simply because the game resides in a digital domain.

A further possible amplification of this can be caused by certain underlining psychological traits or predeterminations within users. Specifically, a concept known as the Favorite Long-Shot Bias (FLB) where a player demonstrates a reluctance to make a safer bet in favor of taking a larger risk. This type of behavior has been witnessed when identifying stocks within spread betting where an unpopular underdog is often preferred compared to those more dependable with a history of success [19]. The same has been observed within games when considering sports. For example, an online bookmaker provides a quote of +100 for a popular Team A compared to -120 for the unpopular Team B. When a player places £100 on the unpopular team and they win, the player is rewarded with £120. For a player to be rewarded with Team A they would require placing £100 which would only provide them with £100 assuming they win. The reward for winning on the unpopular Team B demonstrates a significant difference to Team A. The same applies to the risk with the likelihood of winning through the underdog however players continue to do so [22]. While it provides a concerning image of players being drawn to take risks when they are presumably aware of the odds [19], it demonstrates one possible explanation for addiction, psychology. Specific demographics of players such as male, single, young and educated have been found to be more prone to taking these steps towards addiction [21].

Many online games such as those mentioned make use of targeting these demographics with tactics that are likely to encourage players by isolating its appeal within their psychology. This appears to be the point at which playfulness within game play vanishes and addiction issues takeover. Clearly, addiction has a negative connotation associated with it, which is not in the interests of the user therefore it is noteworthy to emphasize the reluctance to employ such concepts within a game design.

5 Data-Driven Games

5.1 Discovery of Knowledge

Data is a powerful medium for all aspects within the digital and physical world. As such, the same applies to games. The usage of data to drive a game is not a new concept. With new and innovative forms of data, there has always been a purpose to capture it and utilize it for a previously unexplored purpose. Data was once used purely for the purpose of knowledge. Internet search engines have enabled this data to be accessed through a coherent and structured means [23]. Recent projects such as A Google A Day have investigated how data might be used further by making use of search data as a key aspect of a game. Specifically, A Google A Day provides a trivia question for the user to find through carrying out searches [24]. Each day a new question will require the user to engage their understanding of retrieving the correct topic to highlight an answer against a time limit [25].

Fig. 1. A Google A Day (Source: The New a Google a Day)

It makes use of a normal skill of searching for an answer into a playful activity. The pursuit of an answer encourages knowledge to be gained through discovery [27]. The development and change towards this new type of game has been as a result of recent findings. A significant effect in a user's ability to search effectively has been highlighted when appropriately engaged on an educational level [28]. Learning in an exploratory fashion can ensure that the search skills are retained far beyond the stage it was taught. This discoverable concept of enforcing a skill has begun to be seen amongst other business's products such as Bing, which demonstrates the popularity to engage with users in a playful manner [29]. While it has only recently begun to be integrated into games, other applications have made use of the same concept but through a different context.

Another project by Google known as the wonder wheel allowed users to visually identify possible words or phrases that may relate to those entered.

Fig. 2. The Wonder Wheel (Source: CSQI)

From the word entered, a visual link to possibly related phrases could be displayed. Users could follow a single word through a long list of corresponding meanings that may appear within a search. It enabled marketers to identify the most relevant keyword in order to gain the highest number of visitors. Essentially the user gained knowledge through a process of discovery [27]. The application has since been redesigned and launched as the Contextual Targeting Tool [30] after inspiring academic papers and success amongst users [27]. The new application has removed the visual representation used to find a word [25], which appears to have removed the core of discovering knowledge.

The commonality that the A Google A Day game and the Wonder Wheel applications shared was the obvious ability to allow the user to discover knowledge through their own means. Certain contradictions could be observed between the two, where a visual representation was a crucial feature whilst it was not relevant to the other as a result of its context. Ultimately, each instance demonstrated the power of using data and transforming it into an innovative product towards a certain context.

6 Design

In order to determine the feasibility of developing an analytics based prediction game and the success that it might have towards a user, two distinctive versions were created. Firstly, a web application consisting of the core functionality and features discussed. Secondly, a mobile game that would take into account the lessons learned from the first version.

Understandably, the technologies employed to make the versions possible were significantly different. The web application utilized ASP.NET C# with jQuery making it viewable to mobile devices. The mobile game made use of a JavaScript based native app as the front end to the user where results and data could be passed back and forth between an online web service via Ajax calls. Commonly, both versions made use of the Google Analytics Core Reporting API to channel data from a live analytics account to their users. The analytics account was linked to an online blog being supplied data by regular visitors.

The clear dependence on design and development required the repetitive approval of core aspects. A Rapid Application Development methodology was applied allowing for referral and demonstration to various users. As a result, the initial development became an evolutionary process moving from a web application to a game which was more enjoyable, usable and playful.

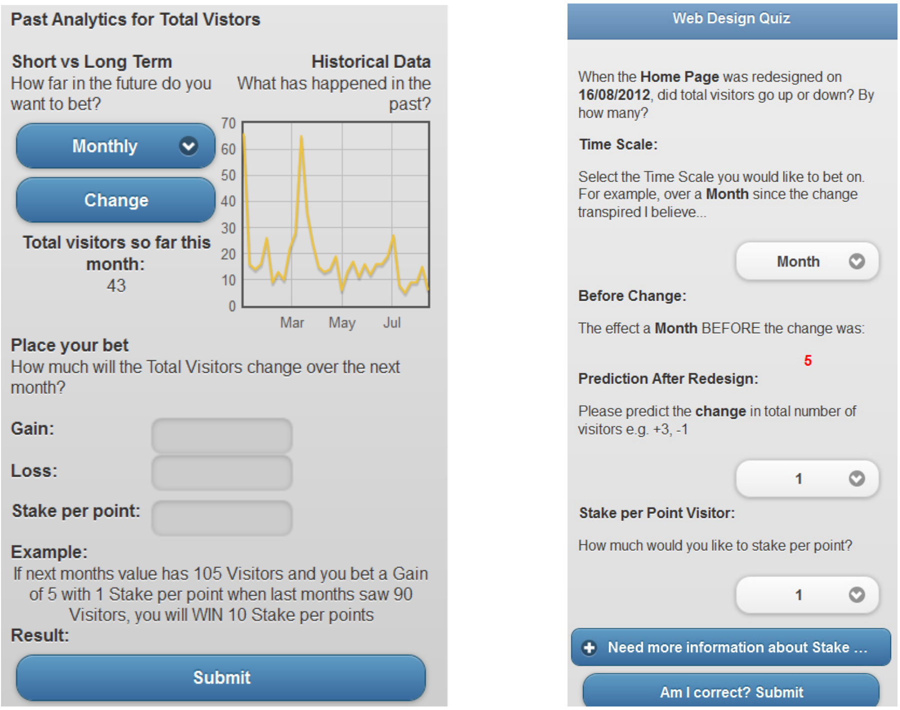

Fig. 3. Web Application (left) and Mobile Game (right)

As can be seen from Figure 1, there is a significant difference between the two versions. The web application provided the user with the necessary past data for the review and investigation of possible outcomes that could allow for a prediction to be made. The user could identify particular trends through the discovery of data. Depending upon the time scale selected, a user would be required to return to receive their success or failure of their prediction much like how spread betting might be used.

The mobile game made use of the web analytics in a different regard to time. Instead of waiting for occurrences to elapse in order to retrieve the verdict of a win or loss, questions would only be asked of the user when online events had already transpired therefore resembling a web design quiz.

6.1 Using Risk and Commodities

The traits regarding risk and commodities have been included within both versions. The fascinating psychological trait to continue to play in the face of risk when winning or losing [18] [19] was intertwined with a commodity known as Stakes per Point. This attempted to create the illusion of the potential to win/lose therefore presenting a level of risk as can be seen in Figure 2.

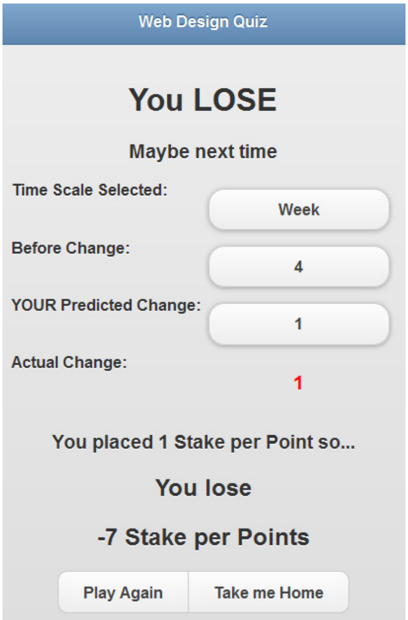

Fig. 4. Risk and Commodities used for a user's win or loss

When a prediction is submitted, a result is presented to the user. Through the form of a win or a loss, the user is rewarded or punished for their prediction. In order to gain the result a calculation was performed.

Simply, the calculation is represented by three key aspects in order to provide a result. As stated within (1) the overall outcome (a), the difference between the prediction and the actual outcome (b) and the commodity placed (c) is required to provide a result (d).

$$((a) - (b)) \text{ x } c = d \quad (1)$$

The calculation can be broken down further as stated within (2). An overall outcome is gained by subtracting from the value that occurred within the time frame prior to the prediction (b). For example, the user places a prediction within a certain week therefore the week before shall be used. This value is subtracted from the actual value (a) that transpired within the time frame selected.

As stated within (3) the prediction (c) is comprised of the actual value (a) in addition to the predicted change (f). The actual value (a) can then be subtracted from the prediction (b). The value of this process is then multiplied by the commodity (d) to provide the result (e) as shown below:

$$((a - b) - ((c) - a)) \times d = e \tag{2}$$

$$((a - b) - ((a + f) - a)) \times d = e \tag{3}$$

7 Methodology

The need to measure the success or failure of each version requires the collection of qualitative as well as quantitative data. A usability methodology was employed due to its inherent logical nature. Specifically, the Common Industry Format (CIF) to aid testing as a formal methodology making it applicable for testing with users and software [26].

At certain stages of the development process, formative feedback would be gained from certain users in order to refine the design through RAD. At the summative stage, a field based empirical evaluation allowed for the constant reporting of quantitative measurements to be gained. Building the necessary features into each version, certain metrics such as time spent, success and path of the user could be concluded. In conjunction, survey evaluation was utilized to cover the qualitative aspect of testing after a user's completion of tasks within an electronic format. This entire process began when a participant showed an interest to take part within the study; an electronic email was sent to them including the necessary instructions to carry out the tasks.

In the same way that a user will make use of a website, an application or game where the developer will not determine who necessarily uses it, random sampling was used. As conveyed by its name, it acted as an appropriate means to keep testing random and therefore unbiased.

The web application was tested against two random samples of five participants. In order to test the validity of risk in regards to winning and losing, the calculation mentioned was offset to cause five participants of each outcome. Whether this caused an effect to continue playing or not when winning or losing would be reflected within the summative feedback provided within the survey evaluation.

The mobile game was tested against a singular group of five participants in accordance to the previous versions methodology for consistency and reduced bias of results. As such, the main difference within testing was the design of each version.

8 Findings

8.1 The Web Application

Testing of the web application began to build an image of a possible user group or demographic to aim this type of concept towards. A preliminary examination of both winning (1) and losing (2) groups saw nine out of ten participants succeed at the tasks. The one participant that failed withdrew from testing expressing feelings of complication and an unlikely use for the web application. Follow-up interviews with the participant revealed comments of "it's not something that I would use regularly". When seeking an explanation for this feedback, another participant expressed similar issues where the duration to complete tasks were substantial with 687 seconds compared to the average 431.8. When comparing the participants, eight out the ten were between eighteen and twenty four years with a university education considering themselves to have a certain level of proficiency with technology. The two participants that opposed the web application were between the age range of forty six and fifty five years with a school education considering themselves to be novices in regards to technology. This preliminary examination of the results demonstrates a possible correlation towards an analytics game being accepted amongst younger age ranges that are more familiar with mobile technology.

When comparing both web application groups, initially it can be seen that the mean durations are very similar with the winning group (431.8 seconds) and losing group (490.2 seconds). When carrying out statistical analysis through an independent t-test, no significance can be found between winning (M = 431.8, S.D. = 209.17) and losing (M = 490.2, S.D. = 30.88), where the participants is predetermined to win ($t(10) = 0.554$; $p > 0.05$) or lose ($t(10) = 0.569$; $p > 0.05$). In regards to duration the participant is not affected or influenced by gaining a loss compared to a win. Essentially the participant does not take a more prolonged or shorter amount of time as a result of a certain verdict.

The subjective feedback gained from the survey evaluation indicated a negative picture for the web application. With fifteen questions allowing for an indication of feedback between one and five there is a potential of 525 points from each group. Each group received roughly one half of the total values available with the winning group accounting for 249 (47.4%) and the losing group providing 229 (43.6%). Whilst the overall values reveal very little, the individual identification and comparison of some questions demonstrate a possible consensus of opinion. In particular, questions relating to the addiction of playing were scored extremely low (Group 1 = 9 / 25.7%, Group 2 = 8 / 22.8 %). Similarly, the results from questions such as participants 'would happily use the application again' (Group 1 = 12 / 34.2%) (Group 2 = 10 / 28.5%) and the 'application being playful' (Group 1 = 15 / 42.8%) (Group 2 = 12 / 34.2%) indicated a lack of enjoyment. Alternatively, this could indicate a number of issues. When reviewing the qualitative data to identify an explanation, statements of "wasn't too sure on how to bet or what I was meant to do" and "a lot to look at, too much to take on" emphasized an overcomplicating of the web application. The intended functionality of user's being able to review data as a form of discovery clearly proved overwhelming and complicated. This reoccurring feedback of participants being unaware of what they were doing suggests the need to guide the user [27] through certain stages to make a prediction and gain results.

8.2 The Mobile Game

Learning from the issues of the web application, the mobile game was designed to include an intuitive guide to step the user through making a prediction. Differences applied like this and the alternate use of analytics in regard to time discussed previously, opens versions to be scrutinized comparatively.

Testing of the mobile game saw the five participant's progress through each task quicker than the last with individual means between 120 and 166 seconds whilst gaining an accumulative mean of 386.6 seconds. It indicated participants learning through repetition from the guided stages. It demonstrates that the mobile game was accepted once the initial workings were understood. A design that is hard to use may not exhibit this quality which may have been indicative of the web application.

When comparing the mobile game's participant group against that of the web application in order to identify participants taking a risk when winning ($t(10 = 0.869$; $p > 0.05$) or losing ($t(10 = 1.131$; $p > 0.05$), there is no significance for the tasks carried out. Within both accounts of each version, a significance cannot be found to prove a possibility that users are drawn to play a game due to their trend of winning or losing.

The survey evaluations overall total for the mobile game (257 / 56.4%) and the web application (Group 1 = 249 / 47.5%, Group 2 = 229 / 43.6%) provides the game with a lead of 10.9%. It generally highlighted a higher level of satisfaction with the mobile game compared to the web application. Additionally, an independent t-test between the winning group for the web application against the mobile game has found significances for certain questions regarding 'addiction' ($t(10) = -2.530$; $p < 0.05$) and the 'ability to find results' ($t(10) = -3.939$; $p < 0.05$). Both the 'addiction' (M = 2.60, S.D. = 0.548) and 'finding results' (M = 5.80, S.D. 1.304) for the mobile game were significantly higher than the web application (M = 2.80, S.D. = 1.095) (M = 1.80, S.D. = 0.447). It demonstrated a general preference to use the mobile game as well as finding it easier to find results and play when guided through a staged design.

9 Conclusion

The design and development of two distinctive versions making use of web analytics in a playful manner with prediction has identified:

- A potential demographic profile (18 – 24 and an expert user) has been formed of a user that is most likely to find this type of mobile game playful.
- Confusion was associated with the web application. A method of guiding the user through the stages as seen by the mobile game is required in order to simplify the design and therefore encourage use.

- The literature [19] based around a win or a loss having the potential to encourage further risks to be taken has been disproven.
- A mobile game making use of web analytics from events that have elapsed rather than having the user return to gain an answer appears to be the most suitable.

The findings have supported the feasibility of a web analytics mobile game. This research has demonstrated that web analytics can be broken out of its predefined purpose and used for more unique and creative means.

Whilst some of the features identified to encourage use such as risk were disproven for suitability, it was only tested against small participant groups. Carrying out additional tests could elaborate on aspects and potentials that placing predictions on web analytics can bring for the user.

The findings present a strong basis for future research. Already, testing has begun using an extensive dataset from Kingston University's live web analytics to provide questions and answers to drive predictions made from the mobile game. With a larger scale of participants across the mobile marketplace, this research leaves the question, what other contexts can web analytics be used for?

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