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Evaluating an AR Experience to Determine Play Strategies

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Abstract

Augmented Reality technology has been advancing at an astonishing rate. Leading to widespread adoption and consequently piquing interest from the world of academia and commerce alike. AR enhanced experiences are also a relatively new body of research. In this report, we evaluate an escape room experience enhanced by augmented reality to determine play strategies, presenting a window into player engagement and design perception. We also build a pipeline to facilitate further research in the area by allowing quick analysis of the play session after the experience.

Introduction

As of now, the video games industry has skyrocketed to be a giant in the entertainment sector overtaking even the movie industry. At the same time, people's engagement with environment, cultural heritage and the community is on the decline. This opens an area of research that piques the interest of the world of academia and commerce alike: What impact can interactive experiences combined with technology have on human emotions, thinking and place attachment?[1] And is being adopted by the top companies[2] to further tweak their existing designs according to the feedback they are inferring from the collected data.

This being a very fresh category of entertainment, there is a relatively small body of research when it comes to Augmented Reality enhanced experiences. This led to the motivation behind this project to study an AR-enhanced escape room experience using a prototype AR game (Ghost Hunt) to determine play strategies, optimizing player engagement and design perceptions all the while building a pipeline to collect, filter and interpret gameplay data opening pathways to further research on this topic.

First section will be looking into a brief of the AR interactive application in discussion – Ghost Hunt, its structure and the main game loop. The following data collection part of the project consists of combining technologies like Unity3D, Google Firebase, Google BigQuery, C#, R programming language and Microsoft Excel to reliably and quickly capture, filter and represent gameplay data.

The analysis part of the project revolves around answering questions related to play strategies and player engagement: Does having high accuracy help in winning more games? How long do players spend looking for relics? Given that we are working with about 4 weeks of data, the conclusions drawn won't be decisive but will give insight into further research paths.

Initial speculations were derived using mathematical techniques such as t-tests, linear regression analysis, standard deviation and graphical analysis. Which hinted towards player engagement being governed by player accuracy and time spent looking for markers.

Ghost Hunt

The Augmented Reality Ghost Hunt Experience is mobile AR app designed to enhance the customer experience at the Old Geelong Gaol and other historic sites around Australia. It uses advanced image recognition, 3D assets and tracking techniques to blend the real-world that users can see, hear and touch with Augmented Reality. It is tied in with the escape room game and it enhances the experience. It also brings in traffic to the old Geelong Gaol and encourages people to interact with and learn about the history and the culture of this historical site.

In brief the main game loop goes as follows:

- People walk in with their devices
- As they enter the jail they are instructed to find relics, which are hidden around the jail.
- Once found the player needs to scan them and on doing so, Augmented Reality ghosts are spawned around the player and the app enters hunt mode with a timer counting down from 30 seconds.
- 10 Augmented reality ghosts are triggered every time a relic is scanned
    - They come in three different rarities (different colours) each taking x number of taps to kill them:
    - Common = 1 Tap
    - Uncommon = 2 Taps
    - Rare = 3 Taps
- Players need to line up the reticule on the screen with the moving ghosts and tap on them to kill them.
- They have 30 secs to shoot all of them. If they fail to do so the ghosts disappear, and the player loses out on scoring points.
- There are in total of 12 relics to be found and scanned with a time limit of 30min.

This app provided a good foundation to construct and conduct the game analysis research which would eventually give a good understanding on how the players were using the app.

Preparation

Questions

The first challenge was knowing what data to collect. A game contains hundreds of variables of data continuously being changed every second. To identify the data which would provide the most information about players is very crucial. To get a clear idea a general direction of figuring out **the trend in player engagement for the duration of each session** was established. This was to check if the players were losing engagement towards the end of the game. To answer if this trend existed a few questions were posed based on observations made during the sessions. This also helped outline the data that needed to be collected.

1. Does having high accuracy help in winning more games?
    - Relic ID
    - Shots taken.
    - Shots hit.
2. How long do players spend to looking for relics?
    - Relic ID.
    - Time spent.

The first question was aimed towards the accuracy trend of each session. Lower accuracy signified low engagement as the players tend to spam fire without taking time to aim. This required us to collect the data for each shot fired and hit in each relic.

The second question was to give an overview on how long players where spending searching for relics and if that played a role in their progression through the game. The data needed for this were the time spent searching for each relic.

Data Collection

Now that the data requirement was set, a pipeline to collect data from the playtimes needed to be established. To facilitate collection, filtration and interpretation of data. The data follows the given path:

1. **Unity3D**
    - Engine used to run the game on iOS and Android.
    - Facilitates the collection of data
    - Sends the data appended with a timestamp to the server whenever an event criterion is met. E.g.: Shot fired, Shot Hit, etc.

2. **Google Firebase**
    - API used to collect custom data and sends it to the cloud in a json data format.

3. **Visual C# (Removed in later stages of the project due to not being as flexible)**
    - Parses the json data to a csv file.
    - Sorts data into individual sessions and individual events.

4. **Google Big Query (Replacement for Visual C# parsing functionality)**
    - This API queries the raw data sent by firebase into a tabular format and
    - Exports the data as a .csv file.

5. **R Programming Language**
    - Parses the BigQueryData
    - Divides the data up into sessions and assigns session id's and metadata to enable easy querying.
    - Outlies, duplicates and any erroneous data are removed from the schema.
    - Discards sessions that are less than 10 mins long (as they generally indicate technical problem with the device).
    - Separates data into events allowing use of a query to enable retrieval of correct events.
    - Runs various algorithms to extract required data like, time spent looking for markers, accuracy per marker etc.
    - Draws basic visualisations for the extracted data.
    - Exports the extracted data to csv format.

6. **Excel** (See Appendix A.2 for the excel format of arranging the data).
    - The last stage of the pipeline which parses through the csv file output by R to create quick visualisations using its inbuilt functions (In later stages of the project this step will be integrated into R for more complex visualisations)

Data was collected from the following categories:

- **Start Data** - Collected at the beginning of every play session
    - *Start Data*
        - Start Time - Time at which the play session began

        - Registered every time the player hits play
    - *Ghost Rarity* - The rarity of the ghosts spawned

- **Continuous Data** - Collected at a set interval
    - *Accelerometer* - Measures the acceleration forces on a mobile device - Collected once every second
        - *AverageX* - average acceleration over x axis in 1 sec
        - *AverageY* - average acceleration over y axis in 1 sec
        - *AverageZ* - average acceleration over z axis in 1 sec
        - *AverageMagnitude* - average acceleration magnitude over 1 sec
    - *Compass Data* - reported every minute
        - What direction was the device facing the most over the past 1 minute
    - *Battery Level* - Rate of battery discharge - Collected every two minutes

- **Triggered Data** - Collected when a certain event happens
    - *Relic Scanned* - Every time someone scans a relic and ghosts spawn
        - *Relic ID* - every relic has a fixed id starting from 1 to 12
    - *Relic Cleared* - Every time the player kills all the ghosts or the 30-sec timer is up
        - *Accuracy* - Percentage calculated by dividing no of hits by shots fired
        - *No. of Hits* - No of times player hit the ghost when they fired
        - *Shots fired* - No of times player shot
    - *AppFocus Changed* - Triggered everytime user minimises or maximises the app
    - *End Game* - Fired at the end of the game when if all 12 relics are found
        - *Gameplay Time* - Overall time spent in the play session
        - *Score* - The score based on the number of ghosts caught, accuracy and time remaining.

* Metadata (see appendix A2)

Statistical Analysis

With all the collected data we could begin analyzing and answering the questions laid out in the previous section. This section heavily drew from the Game Developers Conference 2017 talk by Elan Ruskin from Insomniac Games [3]

Question 1 – Does high accuracy lead to wins?

One of the observed trends during sessions was that most players found it easier to just tap on the screen rapidly instead of trying to move around and aim at the ghosts. Each session has 110 ghosts in total, which are a combination of common and uncommon and rare types with an average combination of 63, 33 and 12 respectively. Which means if the player is 100% accurate they would require: $(63 * 1) + (33 * 2) + (12 * 3) \cong \mathbf{165}$ shots to clear the game. However, 100% accuracy may not be possible and sometimes players don't end up shooting down all the ghosts on time. It would be expected for players to miss shots, however according to Table 1 the average total of shots taken in completed games came up to be **1835 - 11.2 times greater than the required shots**. Also note that for unfinished games the shots fired would be less as the players would have played less hunts as compared to the completed games.

Unfinished Games		Finished Games	
Session_ID	Shots Fired	Session_ID	Shots Fired
5 Jan S4	1035	9 Jan S3	1439
9 Jan S2	1754	9 Jan S4	1416
9 Jan S6	1224	12 Jan S2	2172
12 Jan S1	1141	12 Jan S4	2772
19 Jan S7	814	12 Jan S7	1730
19 Jan S9	2305	19 Jan S4	2247
20 Jan S2	1142	28 Jan S1	1069
25 Jan S1	365		
Mean =	**1345**	Mean =	**1962.7**

Table 1

(Note the data in red are outliers and was not considered for the final mean, as the speed of the ghosts were changed after 20th Jan).

This further raised the concern of players spam shooting to win games, hence a deeper look into accuracies was required. With all the data collected for shots fired and shots hit, the accuracy was found through a simple calculation $Accuracy = \frac{Shots\ Hit}{Shots\ Fired}$ which is the standard percent error formula.

Table 2 shows accuracy data of all the recorded sessions:

Unfinished Games		Finished Games	
Session_ID	Avg. Accuracy	Session_ID	Avg. Accuracy
5 Jan S4	9	9 Jan S3	12.4
9 Jan S2	12.9	9 Jan S4	15.8
9 Jan S6	2.2	12 Jan S2	10.9
12 Jan S1	10.9	12 Jan S4	8.3
19 Jan S7	11.3	12 Jan S7	11.2
19 Jan S9	6.6	19 Jan S4	8.9
20 Jan S2	14.4	28 Jan S1	13.2
25 Jan S1	28		
Mean =	**9.61**	Mean =	**11.25**

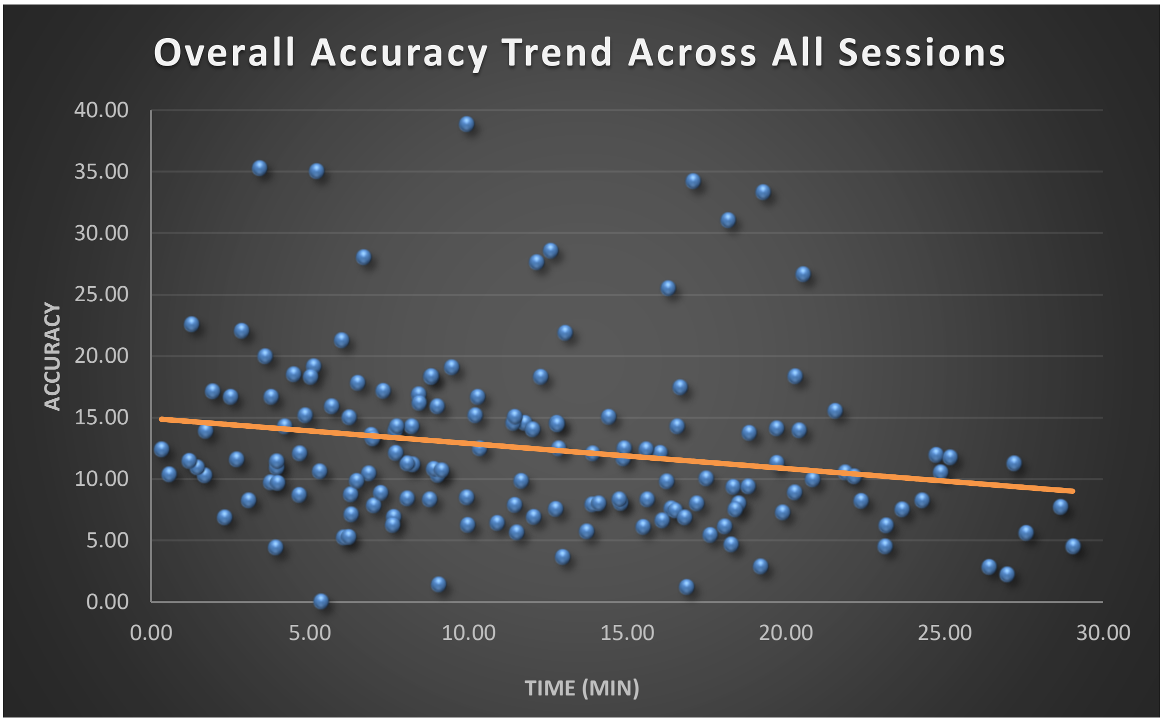
Table 2

Here according to the means the games which were not finished have lower accuracy than games which were completed. This goes against the previous observation from the shots fired data. To find the right answer to this question a t-Test: Using 2-Samples of unequal variances was conducted. For the analysis Student T test was performed on the 2 samples of accuracy data (Unfinished & Finished, excluding the outliers) and the parameters for the test were chosen as follows:

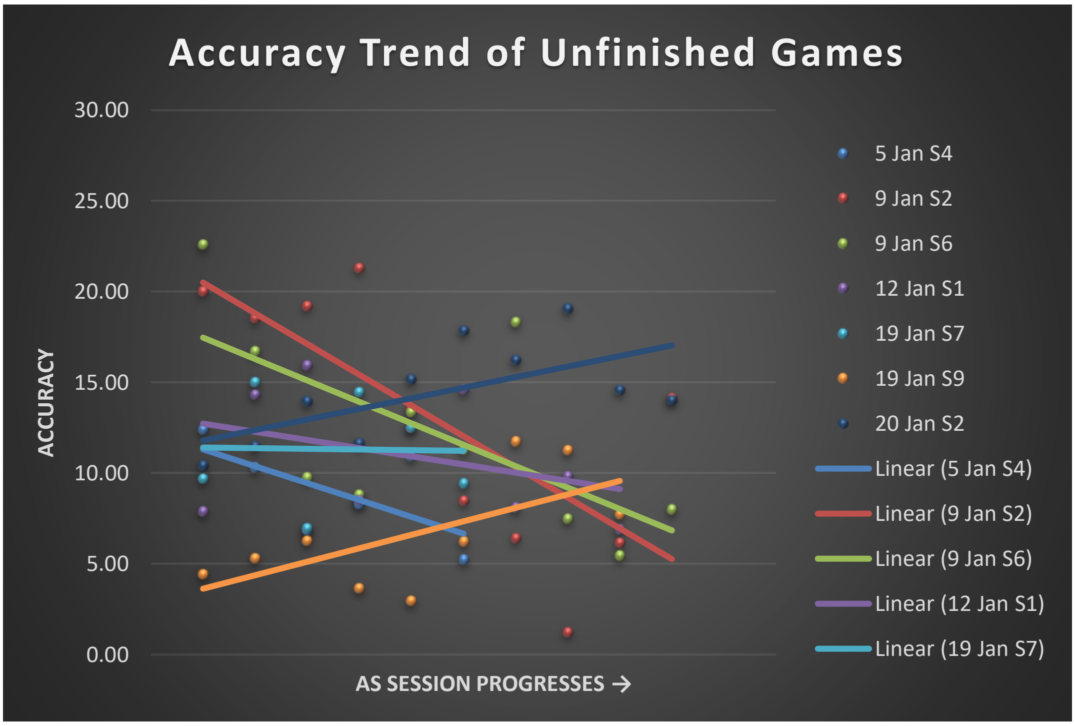
- Null hypothesis $\boldsymbol{H_o}$= Easier to finish with lower accuracy
- Alternate hypothesis $\boldsymbol{H_a}$= Easier to finish with higher accuracy
- A significance value of 0.05 was chosen.

The resulting P-Value came out to be **0.893** (See Appendix B). **Since 0.893 > 0.05, the null hypothesis was accepted**. This proved that there is a very high chance that players could easily win games by just tapping the screen.

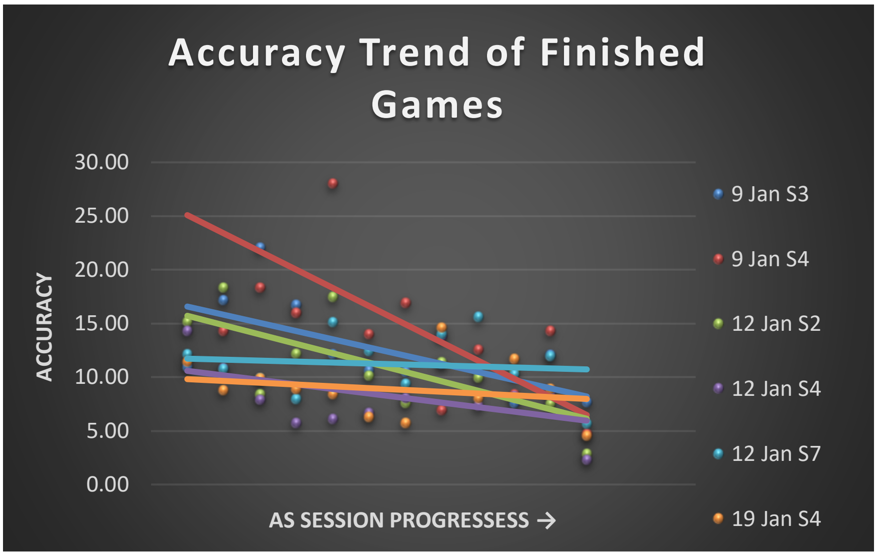
Another trend with accuracy which was noticed was it decreased as players progressed through the game. This may also point towards player disengagement as the game progresses. This is shown clearly through simple linear regression calculated using scatter plot graphs as shown in Graph 1, 2 & 3.



Graph 1



Graph 2



Graph 3

Question 2 – How much time is spent searching for relics?

Graph 4, given below, lists all the unfinished games and the time players spent searching for markers in each game. Each game lasts for 30 minutes and there are a total of 12 markers. Hence the maximum amount of time players can spend shooting down ghosts is 12 x 30 = 360 seconds = 6 minutes. So, if a game couldn't be completed then it can mean that the player spent at least 24 minutes (30 - 6) searching for the relics. However, observing the data in Graph 4 shows only one session where the player spent more than 24 minutes searching. The rest of the sessions are less which means that the players give up and quit. This could likely be due to low player engagement. 7 of 15 games where quit by the player, which is nearly half of the recorded sessions.

Graph 4

Inferring back to the accuracy data further solidifies this assumption as the mean accuracy for unfinished games turned out to be lesser than completed games. Table 3 accumulates all the required data together and shows some very interesting findings.

Note some of the sessions have been excluded due to them being outliers. Session 25 Jan S1 and 28 Jan S1 were excluded on the same grounds as mentioned in the previous section – for having the ghosts speed changed. Session 19 Jan S9 was removed as it was the only session where the player did not quit but did not finish the game either. Therefore, we get two equal sample sizes and increasing the validity of the data.

	Sessions	GH01	GH02	GH03	GH04	GH05	GH06	GH07	GH08	GH09	GH10	GH11	GH12	Relics Cleared	Total Time Spent	Avg. Time Spent On Each Relic	Z Score	Avg. Accuracy	Z Score
Unfinished	5 Jan S4	1.6	0.4	0	0	0.1	0.1	0.3	1	0	0	0	0	6	3.5	0.58	-1.03	9	-0.261
	9 Jan S2	5.5	0.4	1.2	0.7	2.3	0.4	0.1	0.6	0.4	3.1	0	0	10	14.7	1.47	0.06	12.9	0.648
	9 Jan S6	0.6	0.4	0.6	0.5	2	0	0.8	0.7	7.2	0.8	0.2	0	10	13.8	1.38	-0.05	2.2	-1.846
	12 Jan S1	0	0.4	0.4	2.5	0.9	0	0.7	6.5	0.1	0.9	0.1	0	9	12.5	1.39	-0.04	10.9	0.182
	19 Jan S7	3.7	0	5	0	3.7	1.1	1.9	0	0	2.1	0	0	6	17.5	2.92	1.85	11.3	0.275
	20 Jan S2	0.1	1.7	0.1	1.4	0.1	1.6	1.6	0	0.8	0.5	0.2	0	10	8.1	0.81	-0.75	14.4	0.998
															Mean =	1.42		10.12	
															STDEV =	0.81		4.29	
Finished	9 Jan S3	3.2	0.4	0.1	1	0.6	0.2	0.5	0.9	0.5	1	0.9	1.1	12	10.4	0.87	-1.32	12.4	0.426
	9 Jan S4	2.3	0.5	0.5	0.7	0.3	0.3	0.2	0.3	0.2	2.9	3.1	0.1	12	11.4	0.95	-1.12	15.8	1.685
	12 Jan S2	1.8	0.5	0.7	2	1.3	0.8	0.3	0.3	0.9	0.7	9.7	1.3	12	20.3	1.69	0.65	10.9	-0.130
	12 Jan S4	2.1	0.6	0.5	1.8	1.5	1.4	0.1	7.2	1.2	2.2	0.7	1.2	12	20.5	1.71	0.69	8.3	-1.093
	12 Jan S7	2	0.9	0.1	2.4	2.4	1.7	0.3	7.2	0.7	1.8	0.9	1.8	12	22.2	1.85	1.02	11.2	-0.019
	19 Jan S4	1.5	0.7	3.5	1.1	0.3	0.9	0.3	4.9	0.9	1	0.5	1.6	12	17.2	1.43	0.03	8.9	-0.870
															Mean =	1.42		11.25	
															STDEV =	0.42		2.70	
Overall time spent searching the relic		24.4	6.9	12.7	14.1	15.5	8.5	7.1	29.6	12.9	17	16.3	7.1						

Table 3

Data on 'Average Time Spent On Each Relic' (found by = $\frac{No.of\ Relics\ Cleared}{Total\ Time\ Spent\ Looking\ for\ Relics}$) and data on the 'Avg Accuracy' was put through a correlation test for both Unfinished and Finished tests. The results from the test (Table 4 & 5) showed that there was positive correlation for the unfinished sessions and a negative correlation for finished sessions. This may indicate that there may be no causality between these two values also given the reason the sample size may be too small to draw any conclusions.

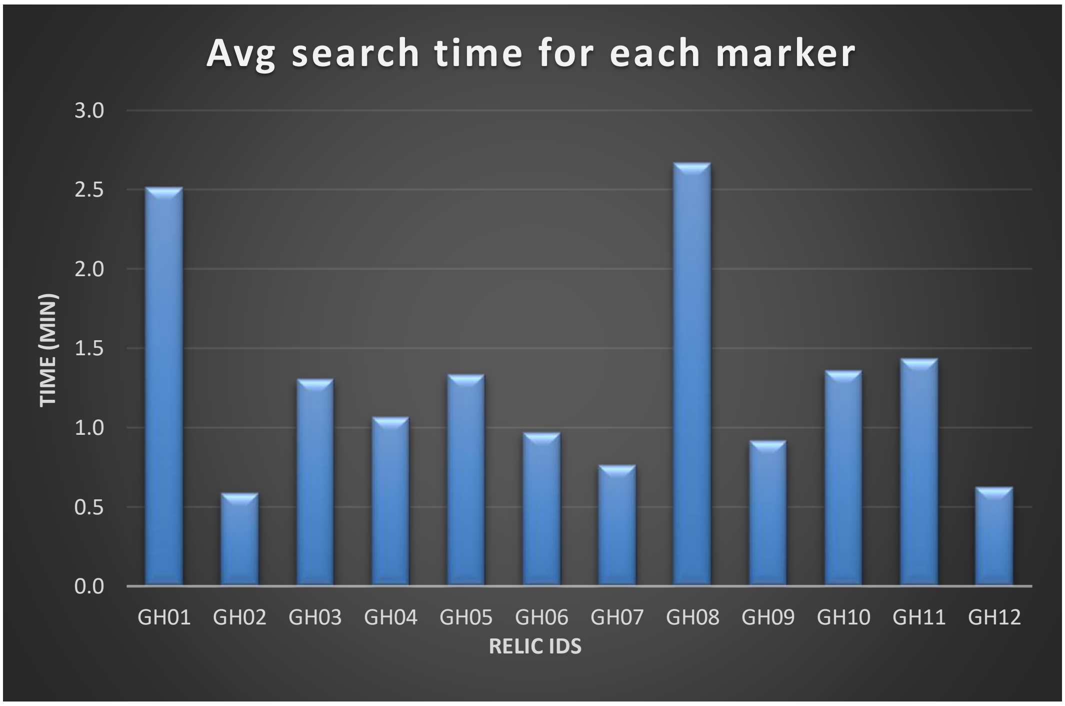
Unfinished		
	Avg. Time Spent On Each Relic	*Avg. Accuracy*
Avg. Time Spent On Each Relic	1	
Avg. Accuracy	0.260196439	1

Table 4

Finished		
	Avg. Time Spent On Each Relic	*Avg. Accuracy*
Avg. Time Spent On Each Relic	1	
Avg. Accuracy	-0.671130293	1

Table 5

One definite observation these values gave is the relic which proved to be the hardest to find as compared to all the others. This found by simply summation of all the times of each relic. GH08 was found to be the most difficult marker to find, the second being GH01 (See Graph 5). This was an important result as looking for hidden relics makes up for the main part of the escape room experience. This sheds more light on the designs of each relic.



Graph 5

Discussion

One of the biggest challenges faced by Game Analytics is trying to find the right method to map the complexity of human emotions into ordinal inferable data. It hard to expect any practical ways trying to label human data as perfect [4]. Given the limited amount of data sizes it was a challenge to confidently draw conclusions from the observed data.

The main direction of checking if low engagement existed according to the collected data, led us to answer the two main questions - if low accuracy leads to wins? and how much time is spent searching for relics.

The conclusion from answering the first question does strongly point towards depleting engagement from players which was also observed during game sessions. After all the very definition of a game according to Sid Meier (See Appendix C) means a serious of meaningful choices. The design allows the player to adopt this sort of playstyle and there are no clear defined incentives or penalties to inform the user to use a different strategy. When players are not making meaningful decisions, it can only point towards loss of immersion and connection from the experience and this builds up disengagement as the game progresses. The T-test too clearly gives us a high probabilistic outcome that playing in a such a way the players are likely to win and the players certainly feel the same way too. This informs us that the hunt design needs to be restructured to make it more engaging to the player. Once more data is collected, it would be easy to identify clear normal distributions and cross verify the hypothesis of low accuracies leading to a high likelihood of winning the game. Or if normal distributions are not recognizable, the Mann Whitney test would be the next best option. This can be later cross-referenced using acceleration data to check if the players are actively moving their phones while aiming.

The analysis for the second question did not result in any consequential verdict. The correlation analysis gave mixed results and the means turns out to be peculiarly the same for both unfinished and finished games, hence performing any hypothesis tests would have not yielded correct results. This may have very well been due to the small sample sizes, given a bigger sample size there is a good probability that the means would not be the same. More clear patterns can also surface when handling large data sets. One conclusive evidence which was revealed was which relic was hardest to find by the players. That information can be used to reconfigure the harder relics and make it bit more easier and more balanced.

Conclusion

The main goal of this report was more focused towards a technical point of view of establishing a data collection pipeline for an interactive experience and demonstrating a few methods how the collected data could be inferred to understand the design and its player interactions. Although there weren't many significant findings, it proved how the potential of Game Analytics could be tapped to further strengthen design decisions.

Taking this project further the next goal would be to make this process more dynamical and create a database dashboard system which designers could easily open and instantly view all the statistics of any required group of data. The analysis would be further re-enforced with a large population and sample sizes and more tests such as Mann-Whitney test, AB testing and other regression analysis etc. The environment also needs to be controlled more strictly to allow low chances of data pollution. This would be also coupled with phycological models and short player questionnaire's which could be used to categorize players into groups according to their characteristics such as age, familiarity of their age and technology etc.

Appendices

- **Appendix A1:**

Session_ID	event_timestamp	event_name	key	relic_id	value	z_score	mean	median	mode	sd
5 Jan S4	1.54666E+15	zone_cleared	accuracy	GH05	12.39	-0.01	12.47	11.07	16.67	7.03
20190105_4	1.54666E+15	zone_cleared	accuracy	GH08	10.29	-0.31	12.47	11.07	16.67	7.03
20190105_4	1.54666E+15	zone_cleared	accuracy	GH06	6.83	-0.80	12.47	11.07	16.67	7.03
20190105_4	1.54666E+15	zone_cleared	accuracy	GH07	8.25	-0.60	12.47	11.07	16.67	7.03
20190105_4	1.54666E+15	zone_cleared	accuracy	GH02	10.92	-0.22	12.47	11.07	16.67	7.03
20190105_4	1.54666E+15	zone_cleared	accuracy	GH01	5.22	-1.03	12.47	11.07	16.67	7.03
9 Jan S2	1.54701E+15	zone_cleared	accuracy	GH10	20.00	1.07	12.47	11.07	16.67	7.03
20190109_2	1.54701E+15	zone_cleared	accuracy	GH06	18.52	0.86	12.47	11.07	16.67	7.03
20190109_2	1.54701E+15	zone_cleared	accuracy	GH07	19.18	0.95	12.47	11.07	16.67	7.03
20190109_2	1.54701E+15	zone_cleared	accuracy	GH02	21.28	1.25	12.47	11.07	16.67	7.03
20190109_2	1.54701E+15	zone_cleared	accuracy	GH09	13.56	0.15	12.47	11.07	16.67	7.03
20190109_2	1.54701E+15	zone_cleared	accuracy	GH08	8.44	-0.57	12.47	11.07	16.67	7.03
20190109_2	1.54701E+15	zone_cleared	accuracy	GH05	6.40	-0.86	12.47	11.07	16.67	7.03
20190109_2	1.54701E+15	zone_cleared	accuracy	GH01	1.22	-1.60	12.47	11.07	16.67	7.03
20190109_2	1.54701E+15	zone_cleared	accuracy	GH04	6.12	-0.90	12.47	11.07	16.67	7.03
20190109_2	1.54701E+15	zone_cleared	accuracy	GH03	14.10	0.23	12.47	11.07	16.67	7.03
9 Jan S3	1.54701E+15	zone_cleared	accuracy	GH08	10.92	-0.22	12.47	11.07	16.67	7.03
20190109_3	1.54701E+15	zone_cleared	accuracy	GH06	17.11	0.66	12.47	11.07	16.67	7.03
20190109_3	1.54701E+15	zone_cleared	accuracy	GH07	22.03	1.36	12.47	11.07	16.67	7.03
20190109_3	1.54701E+15	zone_cleared	accuracy	GH02	16.67	0.60	12.47	11.07	16.67	7.03
20190109_3	1.54701E+15	zone_cleared	accuracy	GH09	12.07	-0.06	12.47	11.07	16.67	7.03
20190109_3	1.54701E+15	zone_cleared	accuracy	GH03	10.61	-0.27	12.47	11.07	16.67	7.03
20190109_3	1.54701E+15	zone_cleared	accuracy	GH10	10.45	-0.29	12.47	11.07	16.67	7.03
20190109_3	1.54701E+15	zone_cleared	accuracy	GH11	11.21	-0.18	12.47	11.07	16.67	7.03
20190109_3	1.54701E+15	zone_cleared	accuracy	GH05	10.34	-0.30	12.47	11.07	16.67	7.03
20190109_3	1.54701E+15	zone_cleared	accuracy	GH01	7.56	-0.70	12.47	11.07	16.67	7.03
20190109_3	1.54701E+15	zone_cleared	accuracy	GH04	12.04	-0.06	12.47	11.07	16.67	7.03
20190109_3	1.54701E+15	zone_cleared	accuracy	GH12	7.60	-0.69	12.47	11.07	16.67	7.03
9 Jan S4	1.54701E+15	zone_cleared	accuracy	GH10	35.29	3.25	12.47	11.07	16.67	7.03
20190109_4	1.54701E+15	zone_cleared	accuracy	GH08	14.29	0.26	12.47	11.07	16.67	7.03
20190109_4	1.54701E+15	zone_cleared	accuracy	GH06	18.31	0.83	12.47	11.07	16.67	7.03
20190109_4	1.54701E+15	zone_cleared	accuracy	GH07	15.93	0.49	12.47	11.07	16.67	7.03
20190109_4	1.54701E+15	zone_cleared	accuracy	GH02	28.00	2.21	12.47	11.07	16.67	7.03
20190109_4	1.54701E+15	zone_cleared	accuracy	GH03	13.92	0.21	12.47	11.07	16.67	7.03
20190109_4	1.54701E+15	zone_cleared	accuracy	GH09	16.88	0.63	12.47	11.07	16.67	7.03
20190109_4	1.54701E+15	zone_cleared	accuracy	GH11	6.90	-0.79	12.47	11.07	16.67	7.03
20190109_4	1.54701E+15	zone_cleared	accuracy	GH05	12.50	0.00	12.47	11.07	16.67	7.03
20190109_4	1.54701E+15	zone_cleared	accuracy	GH01	8.33	-0.59	12.47	11.07	16.67	7.03
20190109_4	1.54701E+15	zone_cleared	accuracy	GH04	14.29	0.26	12.47	11.07	16.67	7.03
20190109_4	1.54701E+15	zone_cleared	accuracy	GH12	4.69	-1.11	12.47	11.07	16.67	7.03

- ## Appendix A2:

Field name	Data type	Description
App		
app_info	RECORD	A record of information on the app.
app_info.id	STRING	The package name or bundle ID of the app.
app_info.firebase_app_id	STRING	The Firebase App ID

		associated with the app
app_info.install_source	STRING	The store that installed the app.
app_info.version	STRING	The app's versionName (Android) or short bundle version.
Device		
device	RECORD	A record of device information.
device.category	STRING	The device category (mobile, tablet, desktop).
device.mobile_brand_name	STRING	The device brand name.
device.mobile_model_name	STRING	The device model name.
device.mobile_marketing_name	STRING	The device marketing name.
device.mobile_os_hardware_model	STRING	The device model information retrieved directly from the operating system.
device.operating_system	STRING	The operating system of the device.

device.operating_system_version	STRING	The OS version.
device.vendor_id	STRING	IDFV (present only if IDFA is not collected).
device.advertising_id	STRING	Advertising ID/IDFA.
device.language	STRING	The OS language.
device.time_zone_offset_seconds	INTEGER	The offset from GMT in seconds.
device.is_limited_ad_tracking	BOOLEAN	The device's Limit Ad Tracking setting.
Stream and platform		
stream_id	STRING	The numeric ID of the stream.
platform	STRING	The platform on which the app was built.
User		
user_first_touch_timestamp	INTEGER	The time (in microseconds) at which the user first opened the app.
user_id	STRING	The user ID set via the setUserId API.
user_pseudo_id	STRING	The pseudonymous id (e.g., app instance ID) for the user.

user_properties	RECORD	A repeated record of user properties set with the setUserProperty API.
user_properties.key	STRING	The name of the user property.
user_properties.value	RECORD	A record for the user property value.
user_properties.value.string_value	STRING	The string value of the user property.
user_properties.value.int_value	INTEGER	The integer value of the user property.
user_properties.value.double_value	FLOAT	The double value of the user property.
user_properties.value.float_value	FLOAT	This field is currently unused.
user_properties.value.set_timestamp_micros	INTEGER	The time (in microseconds) at which the user property was last set.
user_ltv	RECORD	A record of Lifetime Value information about the user. This field is not populated in intraday tables.

user_ltv.revenue	FLOAT	The Lifetime Value (revenue) of the user. This field is not populated in intraday tables.
user_ltv.currency	STRING	The Lifetime Value (currency) of the user. This field is not populated in intraday tables.
Campaign		Note: traffic_source attribution is based on cross-channel last click. traffic_source values do not change if the user interacts with subsequent campaigns after installation.
traffic_source	RECORD	Name of the traffic source that first acquired the user. This field is not populated in intraday tables.
traffic_source.name	STRING	Name of the marketing campaign that first acquired the

		user. This field is not populated in intraday tables.
traffic_source.medium	STRING	Name of the medium (paid search, organic search, email, etc.) that first acquired the user. This field is not populated in intraday tables.
traffic_source.source	STRING	Name of the network that first acquired the user. This field is not populated in intraday tables.
Geo		
geo	RECORD	A record of the user's geographic information.
geo.continent	STRING	The continent from which events were reported, based on IP address.
geo.sub_continent	STRING	The subcontinent from which events were

		reported, based on IP address.
geo.country	STRING	The country from which events were reported, based on IP address.
geo.region	STRING	The region from which events were reported, based on IP address.
geo.metro	STRING	The metro from which events were reported, based on IP address.
geo.city	STRING	The city from which events were reported, based on IP address.
Event		
event_date	STRING	The date on which the event was logged (YYYYMMDD format in the registered timezone of your app).
event_timestamp	INTEGER	The time (in microseconds, UTC) at which the event was

		logged on the client.
event_previous_timestamp	INTEGER	The time (in microseconds, UTC) at which the event was previously logged on the client.
event_name	STRING	The name of the event.
event_params	RECORD	A repeated record of the parameters associated with this event.
event_params.key	STRING	The event parameter's key.
event_params.value	RECORD	A record of the event parameter's value.
event_params.value.string_value	STRING	The string value of the event parameter.
event_params.value.int_value	INTEGER	The integer value of the event parameter.
event_params.value.double_value	FLOAT	The double value of the event parameter.
event_params.value.float_value	FLOAT	The float value of the event

		parameter. This field is currently unused.
event_value_in_usd	FLOAT	The currency-converted value (in USD) of the event's "value" parameter.
event_bundle_sequence_id	INTEGER	The sequential ID of the bundle in which these events were uploaded.
event_server_timestamp_offset	INTEGER	Timestamp offset between collection time and upload time in micros.
Web		
web_info	RECORD	A record of information for web data.
web_info.hostname	STRING	The hostname associated with the logged event.
web_info.browser	STRING	The browser in which the user viewed content.
web_info.browser_version	STRING	

- **Appendix B:**

t-Test: Two-Sample Assuming Unequal Variances

Accuracy Data		
	Variable 1	*Variable 2*
Mean	11.041	11.244
Variance	6.675	7.275
Observations	7.000	6.000
Hypothesized Mean Difference	0.000	
df	11.000	
t Stat	-0.138	
P(T<=t) one-tail	0.446	
t Critical one-tail	1.796	
P(T<=t) two-tail	0.893	
t Critical two-tail	2.201	

- ## Appendix C:

  Sid Meier (14): One of the most highly regarded computer game designers working today, Meier has been responsible for Civilization (the computer version, not the board game version, although there is now a board game version of the computer game), Pirates!, and Gettysburg.

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