Mobile Gamer Modelling and Game Performance Preference Measurement

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***Abstract*—With more and more games being played on the mobile phone platform, there is a need to enhance mobile gamer modelling and to improve the understanding of their preferences towards different aspects of game performance. This paper is the first to conduct a large scale study of the US mobile gaming market to collect profiling data and quantify the user-game experience. Our approach utilizes the unsupervised clustering method K-prototypes to classify mobile gamers and successfully identifies five distinctive groups. Moreover, for each of the discovered groups, we quantify gamer's preferences for six device performance factors generalized as: visual smoothness, image quality, battery life, temperature, loading time and touch latency. The results of gamer modelling and their weighted preference scores could contribute to commercial use cases such as mobile game benchmarking and marketing.**

***Index Terms*—mobile gamer modelling, weighted preference, performance factor, clustering, K-prototypes, gamer profiling**

I. Introduction

By the end of 2019 the mobile gaming market had grown to an estimated worth of $65.5Bn and accounted for almost 50% of the total global game market [?]. More and more games which in the past were limited to PC/game consoles, especially high fidelity games [?] such as PUBG, Fortnite and Lineage are being ported onto mobile devices. The shift towards the mobile platform brings significant challenges to game developers and device manufacturers as resources on mobile device are constrained by their nature, with inherent tradeoffs such as maintaining low power consumption and high frame rate. This makes the traditional game performance benchmarking methods originally developed for PC/consoles unsuitable for mobile phones and warrants the development of a new mobile gaming benchmark to measure the performance.

In recognition of this challenge, Samsung proposed a mobile game performance measurement framework [3] in 2019, aiming to develop a gaming performance index that best captures the user-game experience. The new measurement framework is divided into three hierarchical layers. The lowest layer includes the raw performance measures of game session data, this is then generalized into the middle layer of six device performance factors which include visual smoothness, image quality, battery life, temperature, loading time and touch responsiveness, and finally aggregated into the top layer of a single value score called the Game Performance Index (GPI). When combining the six device performance factors into one GPI score, our assumption is that there is no single general weighting strategy that can capture the full gamut of user preferences because different types of gamers have different preferences towards the six performance factors.

To capture the inherent subjective differences among gamers, we adopt a clustering methodology to characterize gamers and discover representative groups rather than assuming just a generalized type for all users and then for each group we quantify their preferences for the six performance factors. This paper is the continuation of Samsung's efforts to further refine the gamer characterization logic as well as the weighted scores to be used for the GPI framework. To collect the required data, a large scale survey is designed and launched by Samsung using SurveyMonkey's Enterprise platform in the US market. 1000 mobile gamers are surveyed collecting their characterizing features including (but not limited to) demographic information, play time patterns, game genre preference, as well as performance preference scores. The gamers are clustered based on these characterizing features with the unsupervised learning technique K-prototypes. Additionally, characteristics of the gamers in each cluster are further examined to better profile each type of gamer and generate useful business insights. To the best of our knowledge this paper is the first to conduct a survey to quantify how device performance factors impact the user preference on mobile devices and generate the weighted preference scores.

II. RELATED WORK

Gamer modelling is a complicated and subjective topic and currently there is no consensus on how best to classify gamers. Researchers have trialled various clustering methods to characterize gamer's data which have been collected from different sources. For example, Gunter Wallner et al. [?] tried to use Twitter data to profile with their tweeting behaviors and playtime. A. Fernández del Río et al. [?] suggested a method to segment players with lifetime, playtime and in-game progression level. Florian Baumann et al. [?] focused specifically on 'hardcore' gamers and classified them into six sub types by using K-means. However, these gamer modelling and profiling studies are either limited to a single type of game or a single type of gamer. What's more, all of the current studies do not distinguish between traditional PC/console games and mobile games. No research work focused solely

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on all mobile games and mobile gamers.

On the other hand, in the mobile benchmarking market, although there are some approaches or tools to measure game performance such as 3DMark and AnTuTu, all of the current methods can only provide rankings in terms of hardware scores such as GPU and CPU performance. There lacks academic research to link the gamer's subjective user experience to those objective raw hardware performance scores. Therefore, this paper serving as a continuation of our previous game performance framework described in [**?**] aims to fill in the research gap and provides a gamer modelling methodology to quantify how different aspects of mobile game performance will impact the gaming experience and generate the corresponding weighted scores for each performance factor after the gamer clustering.

III. METHODOLOGY

A. Data collection and feature extraction

For data collection, we invited a nationally representative sample of 2456 US respondents with Incidence Response (IR) rate of 40% which gave us 1000 respondents being selected who play mobile games at least once a week on a mobile device. The Margin of Error at 95% confidence level for the sample size of 1000 is 3.1%. The demographics of those participants in terms of age and gender were built to match the 2010 U.S. census data. A variety of questions around the gamer's demographics and playing behaviours, as well as their preference score for each performance factor were asked.

The mobile gamer's features after data pre-processing are comprised of age, gender, the most popular game genre played, weekly total playtime, whether they play high fidelity games, whether they play while commuting, what is their attitude when playing games, and their annual purchasing budget for mobile games. The summary of all the features for modelling a mobile gamer can be found in Table I. In addition, each gamer was asked to allocate 0-100 points in terms of preference across the six device performance factors.This is to enforce a zero-sum game between the factors, capturing the aforementioned performance trade-offs.

TABLE I: Summary of features extracted

Feature name	**Values**
Age	16-24, 25-34, 35-44, 45-54, 55-64, 64+
Gender	Male/Female
Game Genre Affinity	Casual, PCBW (Puzzle, Card, Board, Words), Sports, Strategy, Action, Arcade, Adventure, Role Play, Simulation, Racing. (*Definition obtained from Google Play)
Weekly Total Playtime	How often per week multiply how long each day play, then normalized
Play high fidelity game	Yes/No
Play while commuting	Yes/No
Play Attitude	Immersive (Enjoy immersive playing process, don't care too much about win/lose); Competitive (Obsessed, eager to win the game and very competitive); Time filler (Play mobile game casually, mainly for time filler)
Annual Budget	Non payer($0), Light payer ($\leq$\$200), Heavy payer($>$\$200)

B. Modelling

Clustering unsupervised data is not a straightforward task especially in real business cases where data is typically mixed between categorical and numerical types. In this situation methods based on distance measurement such as K-Means and DBSCAN are not well suited. In this paper, we implement the K-prototypes algorithm which was originally proposed by Z. Huang in [7]. It can cluster mixed types of data.

Unlike supervised learning, it is difficult to accurately determine the 'goodness of fit' of the clustering results from unsupervised learning. In practical applications, the golden rule is still driven by interpretability and meaningfulness with respect to the business use-case. Therefore, we extend the K-prototypes algorithm and utilize a brute force approach described in Algorithm 1 below to search for the best combination of user features summarized in Table I. This allows us to maximum the total Euclidean distance of the six performance factors among different types of gamers which are obtained from the clustering results. From the business perspective, people would like to achieve the largest separation of the weighting preference of each group. As a result, the combination of features of 'weekly total playtime', 'whether play high fidelity game' and 'play while commuting' achieves the largest separation and is used for clustering. The rest of features are used for further characterizing each cluster to enrich the description of each gamer group after the clustering.

Algorithm 1 Brute Force Feature Selection

$F = \{feature_1 \ldots feature_n\}$, *max_distance = 0*
for $r \in 1 \ldots n$ **do**
  for *feature_c* $\in$ *C(F, r)* **do**
    clusters = K_prototypes(*feature_c* $\cap$ *input_data)*
    total = $\sum_{c_i, c_j \in C(clusters, 2)} Euclidean\_dis(c_i, c_j)$
    if $total > max\_distance$ **then**
      max_distance = total
      selected_feature_combination = feature_c
return *selected_feature_combination*

IV. RESULTS AND DISCUSSION

A. Clustering results and analysis

The K-prototypes algorithm is calculated with the number of clusters K set from 3 to 7 respectively which are both meaningful and interpretable for business situation. After evaluation of the total Euclidean distance of the six performance factors among different clusters, the number of clusters K=5 is finally chosen as it achieves the largest separation.

By analysing the quantitative differences between the 5 clusters we produce qualitative descriptions of each cluster, termed 'gamer profiles'. Fig.1 plots the feature of weekly total play time separated by whether the respondent 'plays high fidelity games' and 'plays while commuting'. Cluster_0 is dominated mainly by high fidelity gamers who play while commuting but also play for the least time. Cluster_1 is dominated with non commuters and non high fidelity gamers. Cluster_2 is comprised of gamers who play while commuting and play the longest time. Cluster_3 consists of gamers who

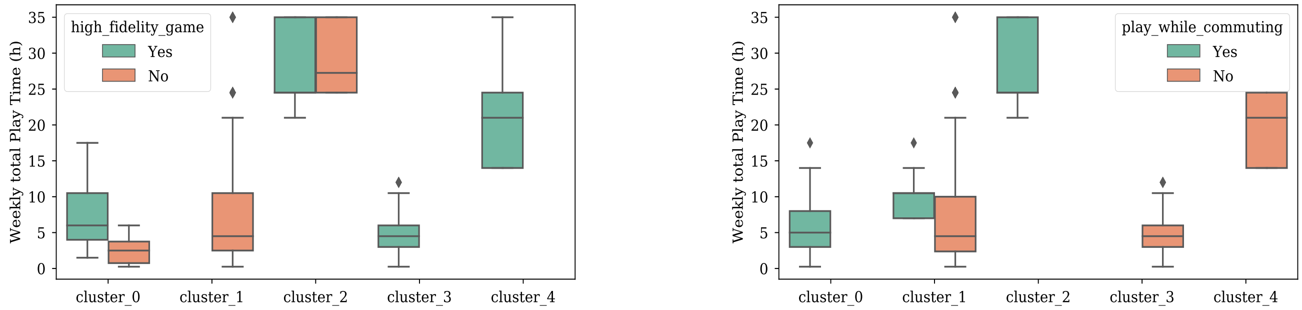

Fig. 1: Weekly total play time separated by whether play high fidelity game and by whether play while commuting

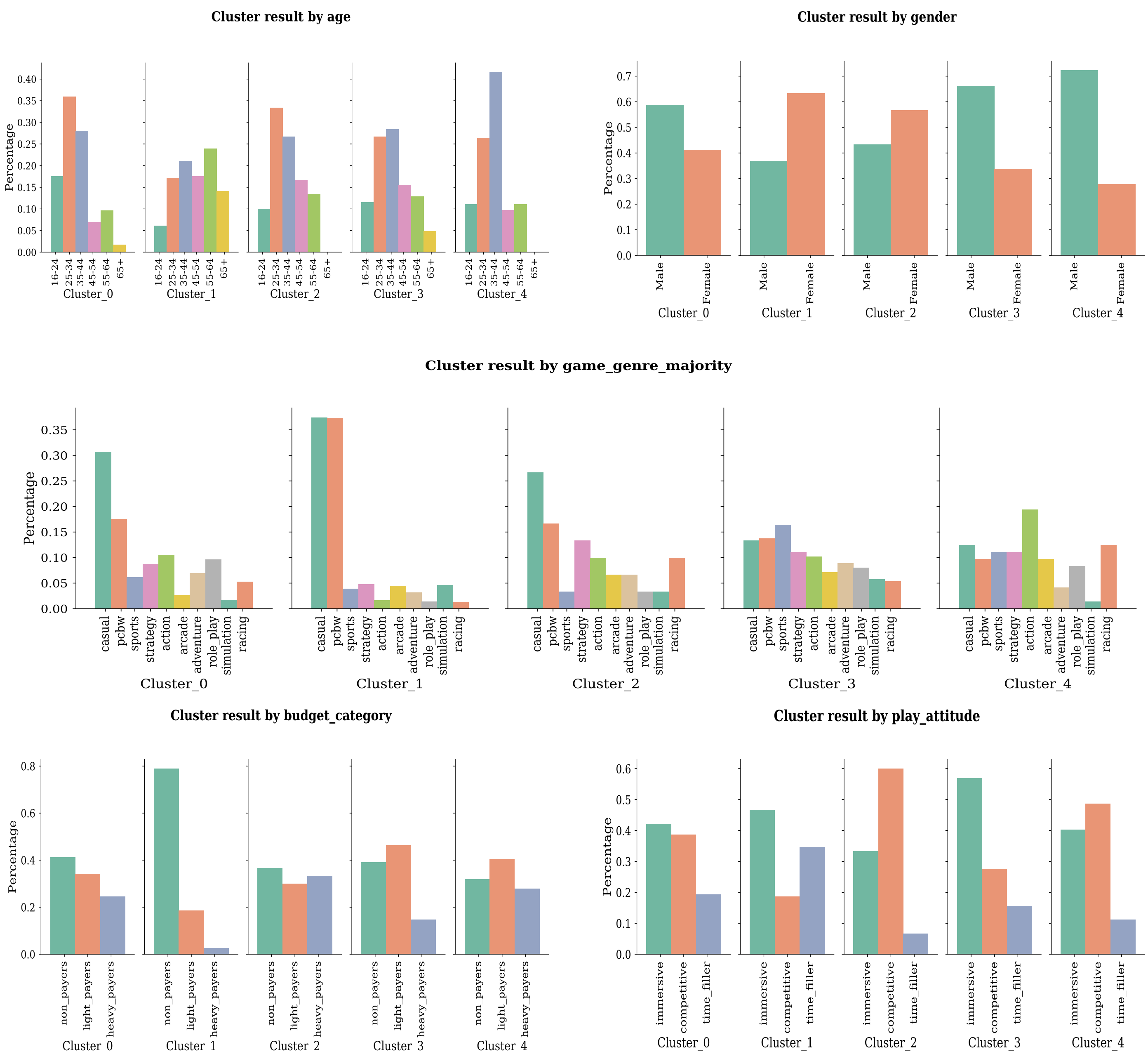

Fig. 2: Cluster results further profiled by features including age, gender, game genre affinity, budget and play attitude.

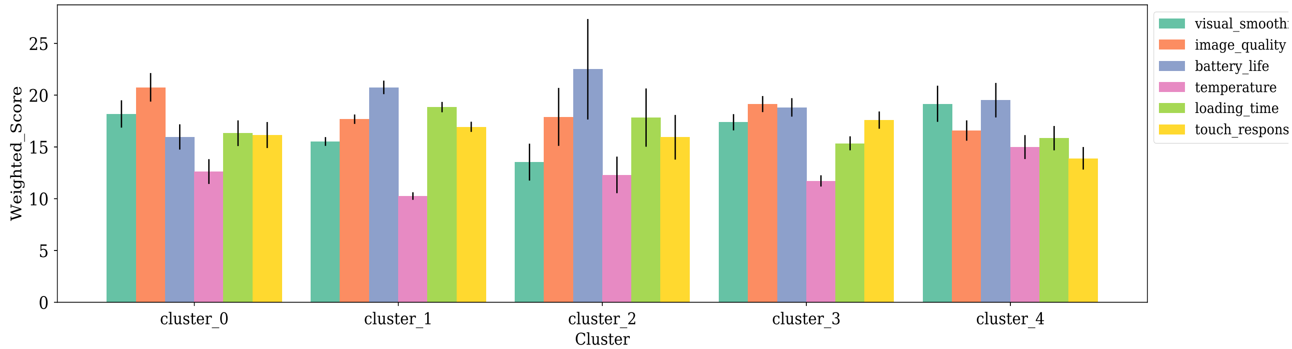

Fig. 3: Weighted preference scores towards six performance factors for each cluster

play high fidelity games, but don't play while commuting. Cluster_4 is similar to cluster_3 but longer play time.

Fig.2 further examines each cluster separated by their categorical features which includes age, gender, game genre affinity, budget and play attitude. The resulting qualitative descriptors for each group are shown in Table II, along with rudimentary names assigned to them. Loosely aligning the profiles with recognised terms in the gaming industry we identify the following: 'Young Commuter', 'Casual', 'Hardcore', 'Premium', and 'Hardcore Commuter'.

B. Weighted preference scores

After clustering the data we go on to investigate how gamers in the different groups weigh the six performance factors in terms of their impact on the gaming experience. Fig.3 plots the weighted scores for the groups showing they each have a distinct distribution, in simple terms valuing different aspects of the gaming experience. For example, Cluster_3 four performance factors: image quality, battery life, visual smoothness and touch latency being of near equal value, while in Cluster_2 battery life is seen as the most important factor. All of the groups leave temperature (overheating) as the least important factor, although gamers in Cluster_4 evaluate it relatively high compared with the gamers in other clusters. Key performance factors for each of 5 profile groups are also shown in Table II.

C. Summary

By means of clustering on characterising features, we categorise gamers into 5 distinctive groups. Qualitative descriptions of groups are then made to produce 'gamer profiles' which are seen to have some overlaps with more traditional expectations in industry. This is then tied to performance preference data to produce weighted preference scores which reveal the associations between the discovered types of mobile gamers and their values with regards to the game experience.

V. CONCLUSION

In this paper we have introduced an approach to characterising mobile gamers based on data collected from a large scale survey, and in doing so have discovered natural groupings based on a variety of informative characteristics. Through our extension of the K-prototypes clustering algorithm, we tune the model by maximising distinct preferences in performance factors. Results show distinctive groups as described by their gamer characteristics and performance preferences which provide strong quantitative guidance to a number of real business cases including mobile game performance benchmarking, and understanding of the mobile gaming market.

TABLE II: Summary of the five mobile gamer profiles

Cluster	Gamer Profiling	Preference
0 (n=14) Young Commuter	Low-level play time; Play while commuting; Young people; Love to play a variety of game genres, especially Role play game; Play mainly to enjoy the experience and care about results;	Image Quality, Visual Smoothness
1 (n=559) Casual	Low-level play time; Don't play high fidelity games; Most people don't play while commuting; Higher ratio of 45+ people; Female dominant; Mainly play Casual/PCBW games; Unwilling to pay; Play mainly for time filling;	Battery Life, Loading Time
2 (n=30) Hardcore Commuter	High-level play time; Mixed preference towards high fidelity game; Specifically like Strategy, Action, and Racing game; Highest ratio of heavy payers; Mainly play to win the game;	Battery Life
3 (n=225) Premium	Low-level play time; Like to play high fidelity games; Not play while commuting; Male dominant; Balanced preference among different game genres; Willing to pay light amount; Play mainly to enjoy the immersive experience;	Balancing pattern of preferences
4 (n=72) Hardcore	Mid-level play time; Like to play high fidelity game; Higher ratio of 35-44 mid-age people; Specifically like Action, Racing and Role play game; Highest ratio of light payers; Care about winning/losing the game;	Battery Life, Visual Smoothness.

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REFERENCES

[1] https://influencermarketinghub.com/mobile-gaming-statistics/

[2] https://community.arm.com/developer/tools-software/graphics/b/blog/posts/the-rise-of-high-fidelity-mobile-gaming

[3] H. Dar, J. Kwan, Y. Liu, O. Pantazis, R. Sharp, "The game performance index for mobile phones," arXiv:1910.13872, 2019.

[4] G.Wallner, "Tweeting your Destiny: Profiling Users in the Twitter Landscape around an Online Game," 2019 IEEE Conference on Games.

[5] A. Fernández del Río, P.P. Chen, Á. Periáñez, "Profiling Players with Engagement Predictions," 2019 IEEE Conference on Games.

[6] F.Baumann, D.Emmert, H.Baumgartl, "Hardcore Gamer Profiling: Results from an unsupervised learning approach to playing behavior on the Steam platform," International Conference on Knowledge Based and Intelligent Information and Engineering Systems.

[7] F.Z. Huang, "Clustering Large Data Sets with Mixed Numeric and Categorical Values," Pacific-Asia Conference on Knowledge Discovery and Data Mining, 1997.