Success Factors of Events in Virtual Worlds A Case Study in Second Life

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***Abstract*—In this paper we present results of a study that aims to analyze publicly announced event data in the virtual world of Second Life with the goal to predict whether or not an event will be successful by terms of increasing the average traffic of a region. To that end, we collected in-world position data of avatars visiting events and data from the public accessible calendar of Second Life. Based on statistical analysis of features such as event category, duration, or maturity rating, provided by the Second Life event calendar, we built a simple predictive model that can decide upon the success of an event with an accuracy of over 92 %.**

I. INTRODUCTION

In this research paper we focus on publicly accessible events hosted by residents of a virtual world and their influence on the avatar traffic. We collected event information and combined it with the position information of avatars prior, during and after the event. Overall, we monitored approximately 80,000 events over a period of three months and collected over 110 Million data samples of position information of avatars in the virtual world of Second Life.

With a statistical analysis of the combined data we can answer questions about the success factors of events to increase the average avatar traffic of a particular region in Second Life. In the literature there are many approaches to detect how people behave in the in-world environment of Second Life. One kind of solution to this issue is to deploy in-world sensors that monitor a certain portion of a region to detect what people do or will do in the future [1], [2]. Other approaches intercepted the communication protocol between the client and the server to monitor avatars and objects [3], [4]. Contrary to these methods, our approach is based on the simple idea to monitor the Web-based event calender of Second Life and decide based on the provided features upon the success of an event. To the best of our knowledge this is the first paper that shows that the success of an in event in Second Life can be predicted by relying only on simple Web-based data (=features) such as event category, duration, or maturity rating etc.

II. DATASET

To collect all events from the Second Life Web page we implemented a web-crawler that runs on a daily basis to harvest and store the contents of the Second Life event calendar. We collected information about events from June 2012 to August 2012. To that end, our dataset contains 84,234 data samples of event information of the Second Life event calender. Furthermore, we developed a bot-avatar with the capability to visit events autonomously and to collect data of the present avatars. With this method at hand we could crawl more than 110 Million data samples containing information about the avatar-position and time.

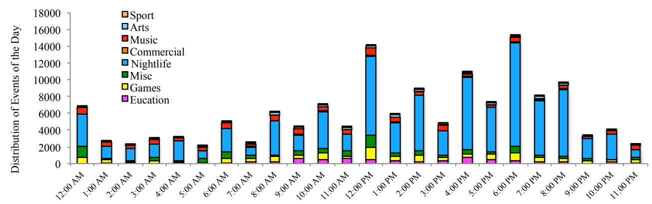

Fig. 1: Distribution of events for different event categories over the day.

III. RESULTS

Events in Second Life can be split up into 10 different categories with five categories containing 94 % of all events: Nightlife/Entertainment 47 %, Live Music 30 %, and Commercial, Games, Contests 7 % each. The duration of events varies from 10 minutes to 720 minutes with 32 % lasting less or equal 60 minutes, 45 % lasting between 61 minutes and 120 minutes, and 10 % of all events lasting 720 minutes. The event-set contains 12.1 % events rated as general accessible, 75.4 % of the events rated as mature and 12.5 % of all events are rated as adult. Figure 1 shows the distribution of events over a day with two peaks at noon and 6:00 pm.

To get a rough overview of the increase of the avatar traffic of a region we compared the average avatar traffic during an event with the average avatar traffic one hour prior the event. We applied a paired students t-test to show the significant difference between the region traffic prior an event (M = 14.07, SE = 13.85) and during the event (M = 19.67, SE = 14.16) ($t(82, 951) = -51.13, p \leq .01$). The average increase of traffic of 33.84 % is computed as the relative change between the avatar traffic prior the event and during the event. Further, we computed a decline of 16.9 % avatars after the event ended (M = 16.29, SE = 13.32). Again, we have a significant difference between the average avatar traffic during the event

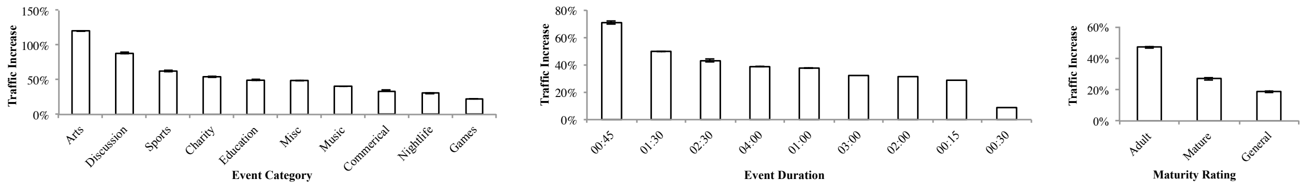

Fig. 2: The average avatar traffic increase during an event segmented into different event categories, event durations, and maturity ratings.

and after the event ended ($t(82, 951) = 35.42, p \leq .01$). For a more detailed analysis we split the events according to their categories, duration, and maturity to see the implications on the avatar traffic. Figure 2 shows the average avatar traffic increase during an event for different features. All features show a significant increase of traffic during the event. Further, one can see from the figures that for example events with category "Arts" increases the event traffic by over 120 % whereas "Games" increase it only by 20 %.

What we also noticed during our analysis on the dataset is the fact that not all kinds of events have a positive effect on the traffic gain for a region. In particular, we observed that 40.6 % of all events had a positive effect on the traffic of a region and 59,4 % of all events had a negative effect. A good explanation for this could be that people leave a region or go offline because the event is not of their interest. Based on this observation and the features depicted in Figure 2 the question arises, if it is possible to build a model (= train a classifier) to correctly identify successful (= events that increase the traffic of a regions) and unsuccessful events (= events that decrease the traffic of a region). More formally, given a list of events as input samples for our model $E = \{e_1(...), e_2(...), ..., e_n(...)\}$, we want to learn the function $f : E \rightarrow C$ which maps each event $e_i(...)$ correctly to the corresponding class $C = \{successful, unsuccessful\}$.

To find the best learning algorithm we performed a number of experiments using for instance supervised machine learning techniques. To find the best learning method we compared the average F1-scores and AUC (=Area Under Curve) values of all approaches with each other. As best classifier we could identify a Naive Bayes classifier which we used for our final model. To analyze the performance of each of our classifiers a 10-fold cross validation approach was chosen.

In Table I, we show the performance of our model based on different features. As presented, the features *Maturity* (=maturity rating of an event), *Duration*, *Weekday* (= the day of the week an event takes place) and *Start* (= the time of a day a event takes place) *alone* have very low classification power, *i.e.* F1 score and AUC are close to the baseline. The feature Category performs slightly better. However, if we combine all these features (= Combined), we can see that we significantly outperform the baseline, which means that we classify an event as successful or unsuccessful in 83.4 % of the cases correctly if we look at the AUC value.

Apart from the standard features, we also checked the features *Host* (= name of the host), *Pre Event* (= max. number of avatars one hour before an event takes place) and Region. As shown, in Table I the highest classification power can be archived with the number of avatars prior an event. Interestingly, if we combine all features of the table (= All) the Pre Event feature is nearly as good as all features together. All in all, we can predict 92.9 % of all events correctly with this model.

Feature	Precision	Recall	F1	AUC
Baseline	0.353	0.594	0.442	0.5
Category	0.618	0.627	0.619	0.601
Maturity	0.353	0.594	0.442	0.54
Duration	0.38	0.585	0.439	0.55
Weekday	0.353	0.594	0.442	0.521
Start	0.562	0.593	0.518	0.599
Combined	**0.766**	**0.765**	**0.766**	**0.834**
Pre Event	0.86	0.853	0.849	0.921
Region	0.758	0.76	0.758	0.835
Host	0.73	0.729	0.717	0.791
All	**0.846**	**0.845**	**0.845**	**0.929**

TABLE I: Results of the event prediction experiment using our best performing Naive Bayes classifier.

IV. Conclusion and Outlook

In this research paper we focused on public accessible events hosted by residents of the virtual world Second Life and their influence on the traffic of a region. For that purpose, we collected event information of the Second Life event calendar and combined it with the in-world position information of avatars prior, during and after an event. Based on statistical analysis of features such as event category, duration, or maturity rating, provided by the Second Life event calendar, we built a simple predictive model that can decide upon the success of an event with an accuracy of over 92 %.

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