A Visual Analytics Approach for Understanding Egocentric Intimacy Network Evolution and Impact Propagation in MMORPGs

Quan Li*[1], Qiaomu Shen†[1], Yao Ming‡[1], Peng Xu§[2], Yun Wang¶[1], Xiaojuan Ma‖[1] and Huamin Qu**[1]

[1]The Hong Kong University of Science and Technology
[2]NetEase, Inc.

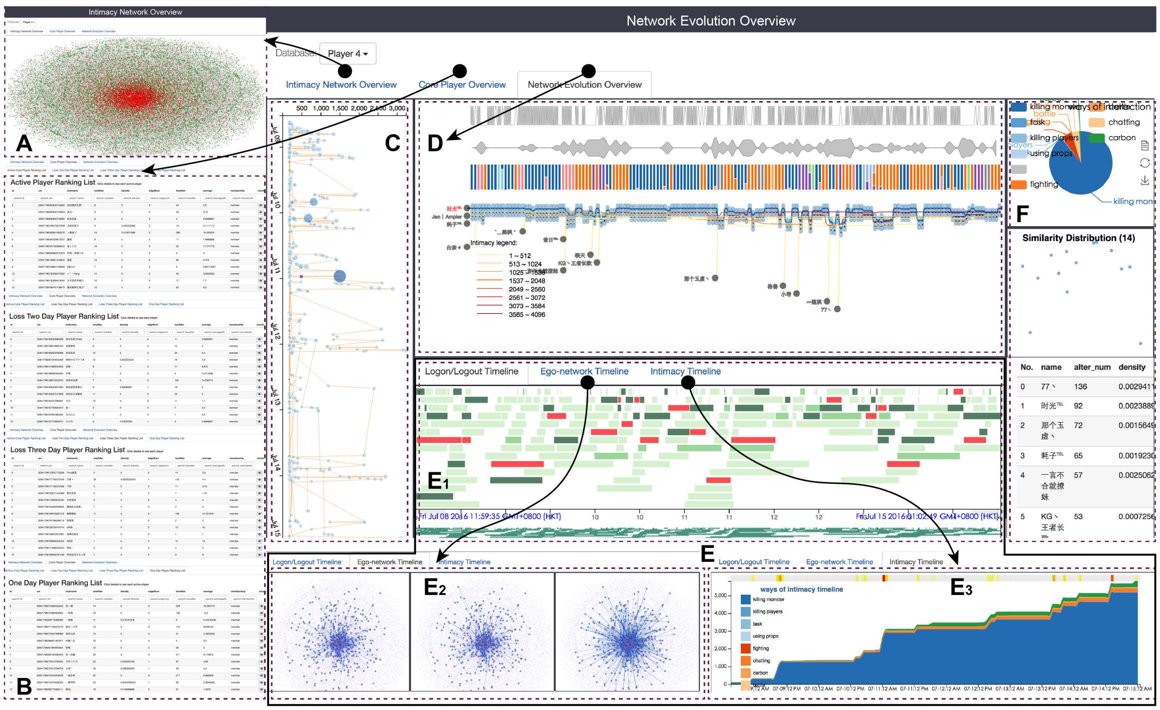

Figure 1: (A) Intimacy Network Overview discloses the distribution of different types of players in the entire network. (B) Ranking lists facilitate users to explore and select different types of players. (C) Summary View of Changes of Alters' Ego-network presents the metric evolutions along with time. (D) Interaction Timeline provides the interaction overview between the ego and the alters. (E) Three timelines include (E_1): Logon/Logout Timeline provides an overview of logon/logout activities of involved players in the corresponding time period; (E_2): Ego-network Timeline maintains an impression of the status of the ego and his/her alters in the entire interaction network; and (E_3): Intimacy Timeline provides a cumulative graph of the intimacy change between an ego and his/her alters. (F) Information View shows the distribution of different types of interaction, similarity distribution of involved players and a table summarizing the detailed attributes of the players.

Abstract

Massively Multiplayer Online Role-playing Games (MMORPGs) feature a large number of players socially interacting with one another in an immersive gaming environment. A successful MMORPG should engage players and meet their needs to achieve different categories of gratifications. Research on the evolution of player social interaction network and the dynamics of inter-player intimacy could provide insights into players' gratification-oriented behaviors in MMORPGs. Such understanding could in turn guide game designs for better engaging existing players and marketing strategies for attracting newcomers. Conventional dynamic network analysis may help investigate game-based social interactions at the macroscopic level. However, current dynamic network visualization techniques mainly focus on illustrating topological changes of the entire network, which are unsuitable for analyzing player-specific social interactions in the virtual world from an egocentric perspective. In general, game designers and operators find it difficult to analyze the way players with different gratification needs may interact with one another and the consequences on their relationships with direct ties, using a decentralized social graph with complicated time-varying structures. In this paper, we present MMOSeer, a visual analytics system for exploring the evolution of egocentric player intimacy

*e-mail: qliba@connect.ust.hk
†e-mail: qshen@connect.ust.hk
‡e-mail: yao.ming@connect.ust.hk
§e-mail: hzxupeng@corp.netease.com
¶e-mail: ywangch@connect.ust.hk
‖e-mail: mxj@cse.ust.hk
**e-mail: huamin@cse.ust.hk

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network. MMOSeer focuses on the relationship between a player (ego) and his/her directly-linked friends (alters). We follow a user-centered design process to develop the system with game analysts and apply novel visualization techniques in conjunction with well-established algorithms to depict the evolution of intimacy egocentric network. We also derive a centrality change metric to infer how the impact of changes in an ego's interactive behaviors may propagate through the intimacy network, reshaping the structure of the alters' social circles at both micro and macro levels. Finally, we validate the usability of MMOSeer by discovering different user interaction patterns and the corresponding ego-network structural changes in a real-world gameplay dataset from a commercial MMORPG.

Index Terms: H.5.2 [INFORMATION INTERFACES AND PRESENTATION]: User Interfaces—Graphical User Interfaces (GUI);

1 Introduction

Massively multiplayer online role-playing games (MMORPG) create immersive and persistent virtual gaming worlds in which a large amount of players socially interact with each other with different characters. Millions of players have invested money and time in different kinds of MMORPGs, which consequently become one of the most valuable markets of the electronic business. The estimated overall revenue of MMORPGs around the world has reached over US$ 11 billion in 2015, and is expected to arise to US$ 13 billion in 2017 [29]. This is also a competitive market, with several popular MMORPGs like World of Warcraft, Diablo III and Tera Online, as well as hundreds of new ones released every year.

To attract and retain players, in gaming business, a well-designed MMORPG should maximize player gratifications, which include: content gratification, fetching new information in games; process gratification, gaining economic benefits during gameplay; social gratification, establishing stable social circle for collective activities; and hedonic gratification, promoting emotional wellbeing through friendships, which is similar to Maslow's hierarchy of needs [27]. These gratifications can be achieved by social interactions through in-game social structures and mechanisms such as friend, team and guild, which are supported by most MMORPGs. For example, players can add friends and form closely cooperated team to conquer highly difficult dungeons or triumph over hostile players to win top equipments and in-game reputations. Thus, understanding the mechanism of in-game social interactions and impact propagation on social network are crucial for developing a MMORPG.

In this paper, we investigate the most common social network in MMORPGs – the friendship network, namely the *intimacy network* here, since the level of social interactions between any pair of players is measured by the intimacy degree. Based on the intimacy network, game analysts and operators target to evaluate the effectiveness and stability of the in-game social network. Typical evaluation questions include: Will a player's behavior (e.g., engagement or turnover in games) affect other players in the same game server and how? Can a new player easily establish an effective social network? Because individual players have different own gratification needs, instead of the entire network, it is more effective to study their personal ego-network, which represents the relationship between a specific player (ego) and others (alters) connected to the ego. We focus on two aspects of players' ego-network: evolution (establishment, maintenance, and demolition, etc.) and impact propagation. The former is about network effectiveness and the latter is about interpersonal influence.

Researchers have already developed various analytical methods, e.g., statistical analysis, predicting ties, and detecting alter communities [5, 8, 28, 32] to measure and model different properties of ego-networks. However, to capture the evolutionary pattern of ego-networks in online games induced by ego behaviors is challenging due to highly dynamic network structure. Thus, we adopt visualization techniques to analyze ego-networks in MMORPGs, which follows the Human-in-The-Loop (HTL) approach [17]. Interesting behavior patterns are first identified with human perception, and then verified under further analysis. Although many dynamic graph visualization have been proposed [6, 7, 42], they mainly focus on tracking the changes of the entire graph rather than the ego-networks at a microscopic level. Some have visualized the social network from the egocentric point of view [20, 40], but they merely visualize ego-alter relationships, without investigating evolution of ego-network induced by ego's behaviors. These methods are unable to answer behavior-related questions, such as how ego-alter interactions affect its ego-network, and how ego-network evolves after ego's certain behavior changes. To follow the ego-network evolution, we need to detect not only the changes of corresponding nodes/links, but also the impacts that the ego exerts on their alters.

To address the above concerns, we propose an interactive visual analytics system – MMOSeer, for exploring and analyzing ego-network evolution of players with different gratification needs. MMOSeer provides a holistic exploration of game dataset through three major views: a timeline view of the ego-alter interactions for exploring ego-network evolutions; a microscopic view of in-game activities (e.g., logon/logout, different types of interaction); an overview of the entire intimacy network. These views are seamlessly coordinated with a rich set of interactions, supporting a smooth navigation of the dataset and multi-scope insight discovery in ego-network analysis. To evaluate ego-network's structural changes at both micro and macro level, MMOSeer also incorporates analytical metrics measuring structural changes during network evolution. Our main contributions include:

1. We address the challenges of improving game design and marketing strategy and present the visual design requirements to analyze evolutions of egocentric intimacy network;
2. We develop a suite of interactive visualization techniques enhanced with new features to support visually assisted intimacy network analysis on MMORPG gameplay data, thereby helping game analysts explore ego-alter/alter-alter relationships, and the impact that ego exerts on the evolution of its network;
3. We showcase an experience of iteratively design, evaluate, and deploy a visual analytics system for network evolution analysis in MMORPG with real world game analysts and designers.

2 Background and Requirement Analysis

2.1 Intimacy Network in MMORPGs

MMORPGs provide various systems to facilitate communications between players, such as text/voice chatting and in-game guilds, etc. Friend system is popular in all MMOPRGs. By adding others as friends, a player can get useful information and can easily find suitable teammates for difficult dungeons. Friendship formed in MMORPGs can often be just as intense as those formed offline [16], and often involves collaboration and trust between players. We measure the tightness of friendship using intimacy degrees. Therefore, the friendship network here can be defined as the intimacy network. Different types of interactions between friends in games can contribute a certain amount of value to the intimacy degree between them, such as chatting, conquering dungeons and battles, etc.

2.2 Complexity of Gameplay Data

The gameplay is recorded among different characters with time-varying attributes, such as level, activities and interactions between players. They can be categorized into the following groups:

A.1 Character Interaction. This group includes various types of time-stamped inter-player interactions in the virtual world. Each interaction between players counts as a certain amount of intimacy.

A.2 Character Status. This group contains information on character properties and logon/logout activities that help identify the degree of in-game engagement and turnover.

A.3 Character Social Circle. This group provides player's actions of adding new friends or being admitted into a guild, which enables us to capture details of social network changes in the game.

Timestamp plays the main role in aligning these groups of information. Based on time alignment and data processing outcome, interactive behaviors in different MMORPGs can all be classified into three categories: strength/types of interaction, membership form/demise and character status.

2.3 Working with Domain Experts

We work with a team from NetEase Games[1]: one gaming user experience (GUX) analysts (E.1), one data analyst (E.2), and two game designers (E.3-4) to summarize their need for the intimacy network analysis for a MMORPG. We first illustrate their analysis tasks in conventional practices and then extract user requirements of our system.

The GUX analyst (E.1) operates the game and examines whether the current game product meets the requirements of forming a healthy player social network. In particular, E.1 focuses on analyzing four levels of gratifications of players:

G.1 Content Gratification: the need of fetching new information in games, which may vary among players with different levels of gaming experience. This gratification can be met by *Player Components* design such as in-game text/voice chatting, ranking list and team up platform, etc., which facilitate convenient communications between players.

G.2 Process Gratification: the need of help when facing temporary difficulties in games, or obtaining additional benefits by offering help to others during gameplay. This gratification can be fulfilled by *Story Design Components* including guild/clan system, friend system, home system and even marriage system, etc., which require higher level interactions between players.

G.3 Social Gratification: the need of a stable social circle for collective activities like guild battle and large dungeon challenge. A stable social circle could also maximize the efficiency of goods circulation, and offer protection or revenge when encountering "hostile players". *Challenge Components* design in games such as collective teamwork to conquer dungeons or battles to promote efficient social activities can be utilized to fulfill this gratification.

G.4 Hedonic Gratification: the need of emotional communications between in-game friends. This level of gratification needs essential designs for different game characters, namely *Character Design Components*, i.e., the design of different skill capabilities for different roles, which drives players to seek collaborations and utilize each character's strength to advance in games, helping and relying on each other. Most MMORPGs provide the above elements to support smooth social communication, though different aspects will be emphasized in different games.

On the other hand, the data analyst (E.2) dives into the gameplay data, monitors the entire intimacy network graph evolution (Figure 2), and calculates representative statistics such as the number of communities. Then, typical players are picked up and their interactions with others are studied. Combining the analysis of the GUX analyst (E.1) and the data analyst (E.2), game designers (E.3-4) can discuss how to alter game design/settings to improve interaction experience of players.

2.4 Extracting User Requirement

To study the functionality and development of in-game social network, and which gratifications are met, our main target users, the GUX analyst and data analyst (E.1-2), require the following features:

R.1 Visualization of Ego's Overall Interaction Statistics. Our system should display the statistical changes of ego-alter interactions throughout the observation period. That is, the data analyst (E.2), needs to observe the strength of different types of interactions of the ego well aligned by the time-stamps. Moreover, the ego's status should be reflected in the entire network evolution along with time to provide an overview of ego's network evolution process.

R.2 Interactive Filtering to Select Timeframe/Players. The animated graph that data analyst (E.2) uses to investigate players' interactions is time-consuming and causes *change blindness* [35], hampering the detection of changes. Thus, our system must provide an intuitive and clear view to observe with whom the ego interacts, interaction types, and corresponding intimacy values. Simulating the interaction process of the ego helps users understand how the ego socially interacts with his/her alters along with time in one screen. Additionally, user interactions should be provided to select interesting timeframes/players for further investigation.

R.3 Change Summary of Players' Behavior and Evolution of Intimacy Network. Given activities (i.e., logon/logout) that can strongly determine a player's engagement or turnover, our system should display a clear timeline and details of these important events. Meanwhile, to facilitate comparison between ego-network before and after key events, a clear visual clue is needed to indicate when the sudden changes of ego-network occur.

3 Related Work

3.1 Research on MMORPG Player's Behavior

Many studies in player's behavior focus on player's social interactions like teamwork, chatting and trading, etc., which are essential elements that keep players active [3, 15, 16, 19, 31, 41, 44]. Core players rely massively on in-game social interactions and even make offline friends through socialized game activities [16].

One aspect is investigating the player's social roles (e.g. leader, core members and new comers) inside an in-game community. Ang and Zaphiris [3] compared structural characteristics of different social roles in player communities from a social network perspective and showed how social interactions impact players within the social network. Williams et al. [44] conducted interviews with hardcore players and demonstrated the importance of leaders and key structural positions inside a community.

Another aspect focuses on studying the overall relationship of a community. With demographic analysis, Ducheneaut et al. [19] investigated how structures of player communities influence the survival and success of in-game guilds. Chen et al. [15] and Thurau and Bauckhage [41] further investigated the evolution of in-game social structures by mining a vast amount of data from players and groups.

However, the above work analyze player's behavior either in an individual level of player's role or in a macro level of the community network and do not address how social interactions between players affect the community structure evolution.

3.2 Dynamic Network Analysis & Visualization

The challenge of visualizing dynamic networks has inspired many related work in recent years. Most of the proposed techniques can be categorized into animation-based or timeline-based methods [10].

Animation-based techniques simulate the evolution of network by redrawing the network at each time step. Most research in this category focus on solving layout problems to reduce cognitive difficulty and improve efficiency [6, 9, 22, 23, 25, 36]. Foresight layout was introduced and extended by [9, 18, 36] to reduce graph change and preserve the mental map. GPU programming and efficient algorithms were introduced to speed up layout computation [22, 25]. Stepwise transition problems were studied to improve usability of animation visual analytics [6]. Although animation-based techniques are straight forward, it is difficult to reduce user's misinterpretations and the attentions required for the users.

Instead of animating networks as a sequence, timeline-based approaches draw network at each time step simultaneously along a

[1]http://game.163.com/en/

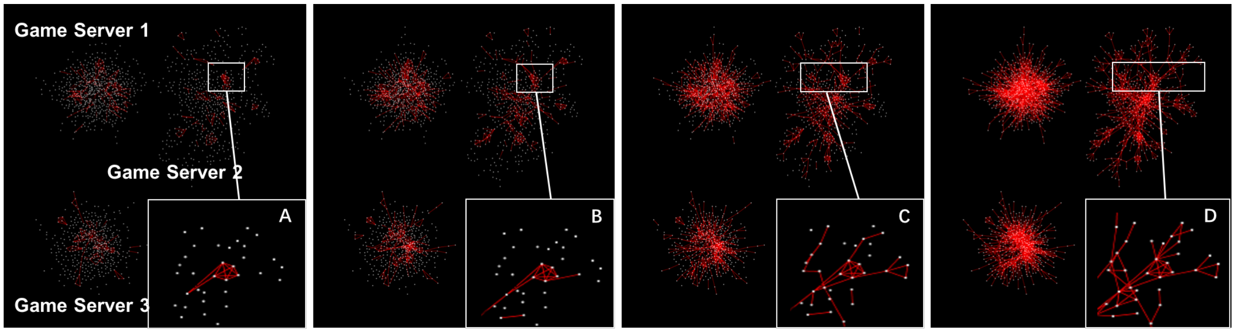

Figure 2: A typical approach by the data analyst (E.2) demonstrates how players' social contacts are established in the largest community of three game servers. The red line indicates those relationships of which the intimacy degree is over 100. A: small groups are established; B: External relationships are formed; C: Small groups begin to merge; D: Groups emerge into a larger community.

timeline. A node-link based diagram was introduced and studied to directly reveal position change of nodes inside the dynamic network [24, 42]. Several others encoded color to adjacency matrices to reveal structural change of large networks in a more readable manner [12, 13]. Despite the readability advantages of timeline-based approaches, one may encounter scalability difficulties since the space is limited for the graphs at each time step.

Both of the animation-based and timeline-based methods focus on visualizing the entire network evolution, which may be difficult when analyzing large networks. One possible solution is to compare structural metrics and visualize their trend over time. Pohl et al. proposed an aggregated structural metrics by measuring variation of the degree centrality [37]. To address local structural change details, Paolo et.al proposed a novel metric for dynamic networks [21], but their application is limited to a small exemplary case.

To enhance the perception of dynamic changes of large networks with an appropriate balance of detail and abstraction, our proposed system provides visualization tools that combine both micro and macro features, i.e., the dynamics of egocentric networks regarding player's behavior and the evolution of player's relationships within an in-game community due to his/her behavior changes.

3.3 Egocentric Network Analysis

Ego-network is a subnetwork which focuses on analyzing the relationship among one focal node (ego) and the alters directly linked to the ego. Prell described three major properties that are typically studied in ego-network analysis: the number of alters (degree), the strengths of ties connecting the ego and alters (closeness), and the number of interconnections between alters (transitivity) [38]. Egocentric analysis has become a widely used approach in analyzing structures of social networks and social interaction patterns.

The application of egocentric network analysis can be found in various areas. Co-authorships of researchers were analyzed using egocentric analysis to investigate variations in researcher's relationships [1,40,45]. Low connection density in ego-networks were found to cause inequity issues and structural hole phenomenon [2, 14]. Intimacy level can be identified by arranging alters' circle in ego-network with hierarchical arrangement [26].

More recent work attempt to use data driven methods to learn overall patterns of specific groups of ego-networks. MacAuley and Leskovec used a node clustering approach to automatically discover circles in ego-network and find high relations between user profile and the circles that they belong [33]. By analyzing large data set from twitter, Arnaboldi et al. investigated how structural properties of ego-networks affect dynamic patterns of the entire network [4].

Most of the above mentioned attempt to combine relational and temporal aspects, which, however, are considered sequentially rather than simultaneously. Either a relational feature (e.g. degree) is computed for each timestamp, and then analyzed over time, or a temporal feature is considered, and then used to compute a structural metric. Besides, they do not consider the impact on the relational consequences of alters' network due to the temporal behavior changes of the ego. In this paper, we aim for an approach that compares subsequent timestamps and take into account both change of ego's behavior and their relational consequences of alters' network.

4 System Overview

MMOSeer consists of two components: Player Classification Module and Visualization Module. The first module integrates essential property data of players, whom are then classified into different categories. Then all relevant data of a selected player will be transferred into the Visualization Module, which contains three subsequent parts: Data Processing, Data Analysis & Modeling and Visualization.

4.1 Player Classification Module

Concretely, friendship data, logon/logout data, and guild relevant data recorded in game are integrated and used to classify players into different categories (i.e., social active players, guild leaders, close in-game friends and isolated players). The entire intimacy network can be constructed as a graph by using the friendship data. Furthermore, the egocentric intimacy network of a player u can then be represented as an undirected graph $G_u = (V_u, E_u)$. Before extracting distinguished players, based on the studies on ego-network and general graph analysis, we adopt the following four essential metrics [45] to characterize an ego u: (1) **number of alters of the ego** u: $n_u = |V_u - \{u\}|$; (2) **number of edges among u's alters**: $L_u = |E_u| - n_u$; (3) **density of u's ego-network** G_u: $den(G_u) = L_u/(n_u(n_u-1)/2)$; and (4) **number of 2-degree alters of the ego** u: $|N(G_u)| = |\{w | w \in V_v, v \in V_u, w \notin V_u\}|$. A feature signature vector of a player in the interaction network is constructed using the above metrics. We then compute pairwise similarity between players using Canberra Distance [11] : $dCan(P,Q) = \sum_i^n \frac{|P_i - Q_i|}{(P_i + Q_i)}$, where P and Q represent the feature signature vectors of two players. The feature signature of each player also serves as a hint for analysts to find interesting players. Then, based on the logon/logout and guild relevant data, we can determine whether a player is continuously engaging in game, or has a turnover and leaves the game, as well as their membership regarding a virtual community (e.g., guild). Given the above information, we then provide the labelling and classification results through Intimacy Network Overview and Core Player View, as shown in Figure 1 (A, B).

4.2 Data Processing in Visualization Module

After exploring and targeting on an interesting player from the Core Player View, raw interaction data of this particular player is then processed prior to further analysis. In particular, to model and visualize the data, we classify and summarize them by their respective features as follows:

F.1 Aligning Interaction Data. We align the specific player's interaction data by timestamps. This provides the complete temporal interaction information of the ego and its corresponding alters.

F.2 Extracting Character Activity/Status. We extract the characters' time stamped logon/logout activities to facilitate the analysis of players' engagement or turnovers in games, and maintain the context (i.e., the status of involved players) in the entire network.

F.3 Summarizing Events. Based on the aggregated game statistics, we construct a table summarizing the relevant information of the ego and his/her alters (e.g., types/strength of interaction and activity summarization), so that we can better understand their distribution.

Besides, when the number of alters that the ego interacts with exceeds over a certain value, the scalability will become a problem, especially for our proposed Interaction Timeline View (Section 4.3.1). After discussion with game experts, we choose an intimacy threshold to filter out those alters with whom the ego has few interactive activities, if the ego has too many alters. However, for the alters' ego-network (Section 4.3.4), we do not apply the intimacy threshold and always keep all the interactive activities to accurately calculate the changes of alters' ego-network.

4.3 Visualization Design

4.3.1 Interaction Timeline View

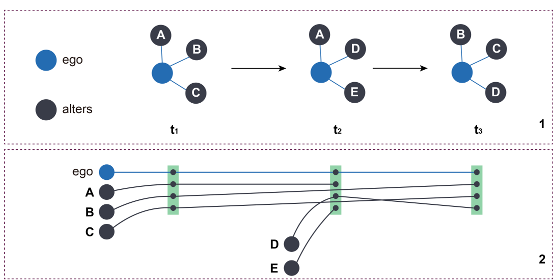

Figure 3: Example of the Interaction Timeline View of a dynamic ego interaction network at three subsequent time steps (t_1, t_2 and t_3): the ego is represented as the red node and the alters as black nodes.

Interaction Timeline View provides the interaction overview between the ego and the alters (Figure 1 (D)) (R.2). For simplicity, we choose a sample interaction data of an ego and its alters to illustrate the basic idea of our method, as shown in Figure 3.

The input data contains an interaction session table and a player table. The interaction session stores the interaction relationships between the ego and its alters and the corresponding timestamp during a certain time period (10 min. in default a session). Each element in the session table has an ID corresponding to that in the player table. The player table describes the information of the involved players. Each element in it represents a player (i.e., the ego and the alters), which contains the following attributes: *ID*, *name* (the nickname of the player), and *type* (ego or alter). Thus, the player table together with the interaction session defines a set of players characterizing the dynamic interaction relationships at different timestamps. We align each interaction session along with time, that is, according to the order of appearance. However, to position the *y*-coordinates of each interaction session to minimize the number of potential link crossing is NP-Hard problem and is difficult to get an exact solution. We therefore, use a heuristics approach staring at the xkcd charts [34]:

Fixed Session Positions and Sorting. In Interaction Timeline View, the input data contains a series of interaction sessions as $S = \{s_0, s_1, s_2, s_3, ..., s_{n-1}\}$. The rounded rectangles are used to present the interaction sessions and in each rectangle the dots are used to present the characters that appear in this session. We align the interaction session in the x direction according to the order of appearance. We also adjust the y-coordinate of each session to minimize the overall curvatures and intersections. The y-coordinate of an interaction session then lies within the y-range of the median session of the players appearing in the session. The sessions are then sorted such that the densest ones are as far away from each other as possible to avoid cluttering and maximize utilization of the space available.

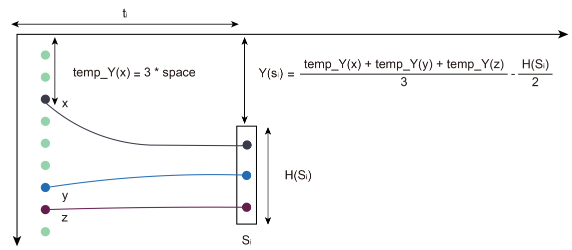

Figure 4: Layout of Interaction Timeline View.

Character Positions within the Session. Let $C = \{c_0, c_1, c_2, ..., c_{n-1}\}$ indicates all the characters appearing in all the interaction sessions. We assign each character c_i in C with an index as *Index(c_i)* according to the order of the appearance of each character. Then we calculate a temp y-coordinate for each character c_i as: $temp_Y(c_i)$=Index(c_i)*space. *Space* is the constant value indicating a vertical gap between two adjacent characters. For each session s_i which contains a character set as $\{c_{i,0}, c_{i,1}, c_{i,2}, ..., c_{i,q-1}\}$, we calculate the y_coordinate of the session box of s_i by: $Y(s_i) = \frac{\sum_{k=0}^{q-1} temp_Y(c_{i,k})}{q} - \frac{H(s_i)}{2}$. With the height and y coordinate of s_i, we then layout the characters containing in s_i evenly in the range of session rectangle according to the order of appearance, as shown in Figure 4.

Visual Encoding for Timeline. Interaction Timeline View provides a general visualization of the ego's interaction displayed as individual time lines. However, since the interactions between players are not uniformly distributed along with time and can be very sparse or very dense, traditional linear timelines may result in a cluttered graph, which is difficult to understand. In addition, such design uses a suboptimal display space and is problematic for large data. Wang [43] proposed a non-linear time remapping design in an animated narrative visualization for video clickstream data, which is intuitive to serve as a visual cue for the play rate of the animation. We adopt the non-linear spring design, and develop several design alternatives (Figure 5) through an iterative process with our domain experts. For the two designs based on the spring design, the visual encodings of a "looser spring" and a "tenser spring" have the opposite meanings: in Design Alternatives (DA) a, a tenser spring indicates interactions occur within closer subsequent timestamps, and vice versa, while in DA b, interactions occur within closer subsequent timestamps are shown as a looser spring, and vice versa. Although it may be intuitive to encode longer time periods with more spring elements, our analysts have found that the second design alternative is cumbersome as they may tend to illustrate it as there are more activities in the tenser periods, which is not the case. Therefore, we adopt the first one, which could be easily explained by both the interaction activities and the non-linear timeline.

Visual Encoding for Distribution of Intimacy Types. As previously mentioned, there will be a certain amount of intimacy counting for each instance of interaction between the ego and the alters, and the types of interaction may also change. To visualize the evolution of different types of interaction, we design a stacked bar chart along with time to show the percentage of each type of interaction in that particular timestamp (R.1). Intuitively, pie charts may be our first choice. However, due to the limited space between subsequent timestamps, and the fact that if there is no dramatic differences in the types of interaction changes, it is hard to see a clear distribution on a pie chart, we then select the stacked bar as it best suits our case here.

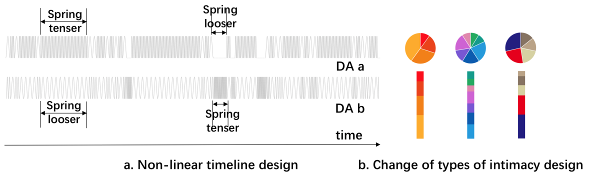

Figure 5: Design alternatives for non-linear timeline (a) and changes of types of intimacy (b).

4.3.2 Ego-network Evolution Metrics

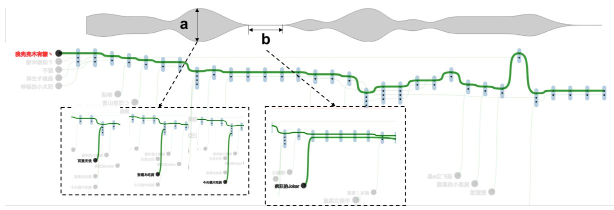

Figure 6: Visualizing the change centrality of an ego-network: (a) The value of the change centrality increases when a sudden change occurs to the ego-network. (b) The value of the change centrality remains the same when no changes occurs to the ego-network.

To measure the evolutionary changes of an ego-network, we introduce a metric named **overall change ratio** (OCR) based on **change centrality** (CC) [21], which considers changing process of a network over a period instead of consequences only. The overall change ratio of an ego-network in a time period is calculated and then visualized as an intuitive stream graph (Figure 6) (R.3). In this section, we first introduce how we derive this metric and then give examples to illustrate it.

Given a discrete-time dynamic ego-network $G = (V, E, T)$, for two consecutive timestamp t_1 and t_2, **n-step change ratio** of a node i is defined as: $r_{t_1,t_2} = \frac{|N^n_{t_1}(i) \Delta N^n_{t_2}(i)|}{|N^n_{t_1}(i) \cup N^n_{t_2}(i)|}$ where $N^n_t(i) = \{v : v \in V, d(v,i) = n\}$ is the set of n-step neighbors of node i at time t. Intuitively, the 1-step change ratio can be considered as the ratio of the number of direct links of node i added and removed, to the number of direct links added, removed and remained. The 1-step change ratio of node i takes minimum value of 0 when the node remains the same 1-step neighbors from t_1 to t_2, and take maximum value of 1 when all the node's neighbors has changed. N-step change ratio follows the same rules. Note that in ego-network here, all the alters are 1-edge distance away from the ego and at most 2-edges distance from other alters, so n can be 0, 1, 2. Also, the default time interval of network changes that we discussed in this paper is 10 minutes, and the interval can be easily modified. In an ego-network, the change centrality of node i between timestamp t_1 and t_2 is defined as: $CC_{t_1,t_2}(i) = \sum_{n=0}^{e_i} a_n r^n_{t_1,t_2}(i)$, where $e_i = max_{t \in t_1,t_2} e_t(i)$ is the maximum eccentricity of node i, and a_n are linear coefficients. Specifically, a_n is a decreasing sequence of n, considering that larger n means farther distance from node i, and hence has lower influence on the centrality. Here we use $a_n = (1/2)^{(n+1)}$, which gives CC the property that $0 < CC < 1$. The change centrality of a node measures the change of its connections over time, taking into account its adjacent nodes, 2-step adjacent nodes and so on [21]. Since we only consider one-alter network for each ego, all the alters contribute the same. Thus, the change centrality of a given node will be equal to zero if no changes have occurred in the connected component that node belongs to. And it will have a value greater than 0.5 if the node is present in only one of the two timestamps. We define the overall change ratio of a ego-network G, between two subsequent timestamps t_1 and t_2 as: $OCR_{t_1,t_2}(G) = \sum_{i=0}^{n} CC_{t_1,t_2}(i)$, where n is the number of nodes in G, including the ego and all the alters in the two subsequent timestamps. This metric is very intuitive for measuring the change (links added and removed) of an ego-network.

Table 1: Calculation of 0/1/2-step change ratios and change centralities between t_1 and t_2 of the example ego-network in Figure 3.

$node$	$r^0_{t_1,t_2}$	$r^1_{t_1,t_2}$	$r^2_{t_1,t_2}$	CC_{t_1,t_2}
ego	$\frac{\lvert\{ego\}\rvert}{\lvert\{ego\}\rvert}$	$\frac{\lvert\{B,C,D,E\}\rvert}{\lvert\{A,B,C,D,E\}\rvert} = 0.8$	0	0.2
A	$\frac{\lvert\emptyset\rvert}{\lvert\{ego\}\rvert}$	$\frac{\lvert\emptyset\rvert}{\lvert\{ego\}\rvert} = 0$	$\frac{\lvert\{D,E,B,C\}\rvert}{\lvert\{D,E,B,C\}\rvert} = 1$	0.125
B	$\frac{\lvert\{B\}\rvert}{\lvert\{B\}\rvert}$	$\frac{\lvert\{ego\}\rvert}{\lvert\{ego\}\rvert} = 1$	$\frac{\lvert\{A,C\}\rvert}{\lvert\{A,C\}\rvert} = 1$	0.875
C	$\frac{\lvert\{C\}\rvert}{\lvert\{C\}\rvert}$	$\frac{\lvert\{ego\}\rvert}{\lvert\{ego\}\rvert} = 1$	$\frac{\lvert\{A,B\}\rvert}{\lvert\{A,B\}\rvert} = 1$	0.875
D	$\frac{\lvert\{D\}\rvert}{\lvert\{D\}\rvert}$	$\frac{\lvert\{ego\}\rvert}{\lvert\{ego\}\rvert} = 1$	$\frac{\lvert\{A,E\}\rvert}{\lvert\{A,E\}\rvert} = 1$	0.875
E	$\frac{\lvert\{E\}\rvert}{\lvert\{E\}\rvert}$	$\frac{\lvert\{ego\}\rvert}{\lvert\{ego\}\rvert} = 1$	$\frac{\lvert\{A,D\}\rvert}{\lvert\{A,D\}\rvert} = 1$	0.875

We present a simple example based on Figure 3. The 0/1/2-step change ratios and change centrality of each node can be computed as in Table.1, in which we observe that the alters with the largest value of change centrality are B, C, D, E (which is present in only one of the two timestamps). The ego has an intermediate value, since it loses two alters but connects two new ones. A is the alter with the lowest change centrality, since A appears in the connection with the ego in both timestamps. Thus, the change centrality of a node measures how much its links change in an ego-network, which is a node-level metric that combines both the local and global features from a relational and dynamic perspective.

4.3.3 Logon/Logout Timeline

Logon/Logout Timeline provides an overview of logon/logout activities of the involved players in the corresponding time period to unfold the temporal dynamics of the most relevant activity (i.e., logon/logout) (R.3). The x-axis of the view represents the timeline, which can be dynamically filtered/scaled. Each bar indicates the time segment between the timestamp a player logs on and that the player logs out. Therefore, for each involved player, there may exist more than one time segment in the observation period, as long as he/she has logged on the game more than once.

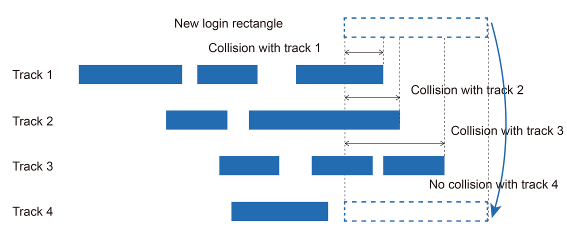

Figure 7: Logon/Logout Timeline shows logon and logout activities of the involved players. Red represents the selected ego, and the darker color indicates the alters with higher intimacy.

This view consists of two bands. The upper band shows the player items within the selected timeline interval. The lower band is the navigation band, which shows the distribution of the logon/logout activities. Click on the lower band and drag will create a brush, facilitating users to select a time interval. We sort all the logon/logout activity items based on their start and end time, and then determine which track it belongs, thus maximizing the space utilization on the limited interface. There are several ways to determine the bars' positions. Here we calculate the positions as follows: Firstly, we sort all the logon rectangles according to the logon time, then we layout them one by one starting from the top track. If we detect that one rectangle collides with the existed rectangles, we move it down to a lower track until we find one position that has no collisions (Figure 7). We use green colors to represent the ultimate intimacies between the ego and the alters, with a lighter one indicating a lower intimacy and vice versa. The *red* color always indicates the ego.

Design Alternatives. In practice, an intuitive design to visualize segments of various owners is to simply stack all the time segments by each owner. The intimacy may be represented by the player's position (nearer to the ego means higher intimacy). However, since the number of involved players in an ego-network can reach 50 to 100, this stack segment design will take a large area from the already limited visualization system. Additionally, the graph will become too sparse and the user has to scroll up and down to explore the view.

4.3.4 Summary View of Changes of Alters' Ego-network

To understand whether the changes of ego's behaviors would affect the alters' ego-network (i.e., impact propagation on the alters' ego-network), we design a summary view of changes of the alters' ego-network (R.3). Inspired by GapMinder [39], we adopt a similar design by considering the alters' ego-network overall change ratio (OCR), the number of players in the alter's ego-network and the summation of intimacy between the alter and players in its ego-network. A simple illustration is shown in Figure 8. We have one ego and five alters, namely A, B, C, D, E across three subsequent timestamps. For each alter $alter_i$, we obtain its ego-network overall change ratio $OCR^i_{t_1}$ and $OCR^i_{t_2}$ in the time gap t_1 - t_2 and t_2 - t_3, respectively by using the algorithm in Section 4.3.2. Also in each timestamp t_i, the summation of the intimacy between the alter and players in its ego-network and the number of players with whom the alter interacts can be calculated, namely as $inti^i_{t_i}$ and $num^i_{t_i}$, respectively. Therefore, for each alter $alter_i$, we have three metrics to measure its changes, in terms of OCR^i_t, $inti^i_t$, and num^i_t, which can be visually encoded into three attributes of Summary View of Changes of Alters' Ego-network: bubble color, positions of x-axis, and bubble size. Y-axis represents the entire gaming period, which is linked with the timelines in other views.

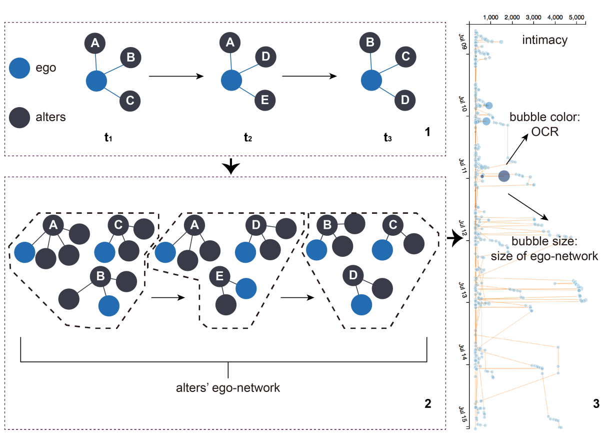

Figure 8: Summary view of changes of alters' ego-networks: (1) the example ego-network evolution; (2) the evolution of alters' ego-networks; and (3) the design of Summary View.

4.3.5 Ego-network & Intimacy Timeline & Information View

To maintain an impression of the status of the ego and his/her alters in the entire interaction network from a global perspective, we provide Ego-network Snapshots to maintain the context information of the whole network (R.1). All the players are rendered as purple nodes and only the edges relevant to the ego-network is displayed in blue. Since the default time period of our data processing is one-week, we only present three phases of the ego-network's evolution: *day one*, *day four* and *day seven* (Figure 1 (E_2)). Users can hover on the nodes to observe the detailed information of the player. This view is also linked with other views, such as Interaction Timeline View to locate a certain player, etc.

Intimacy Timeline provides a cumulative graph of the intimacy change between an ego and his/her alters. As shown in Figure 1 (E_3), various types of intimacy origins (i.e., interactions like chatting, fighting and killing monsters) are encoded with different colors. X-axis represents the time of the entire gaming period and y-axis indicates the intimacy accumulation throughout the time period. The heat map bar on the top indicates the intimacy growth speed, which helps users identify the timestamp when the most active interactions occur.

Information View (Figure 1 (F)) on the right side of the system shows the distribution of different types of interaction, similarity distribution (calculated by the feature signature vector mentioned in Section 4.1) of involved players based on a MDS layout [30] and a table summarizing the detailed attributes of the players (R.2).

4.3.6 Interactions Among the Views

To facilitate performing ego-network evolution analysis from different perspectives and gain deeper insights smoothly, MMOSeer supports a set of intuitive interactions to help users browse the data through the mentioned multiple visualization views: **Filtering and Searching.** Users can interactively select a player of interest in Core Player Overview. In Intimacy Network Overview, users can also find interesting players by hovering and selecting from a global perspective. **Highlighting and Linking.** Most of the visual elements are associated with informative tooltips, indicating the attributes of the hovering players. The highlighting and linking techniques are applied among multiple views. For example, user can hover a player in Interaction Timeline View, and the system automatically highlights the corresponding one in other views, including Logon/Logout Timeline, Ego-network Timeline and Information View. Alternatively, users can browse players through a table in Information View showing the player's attributes, and all other views will indicate the corresponding one. **Brushing and Synchronizing Timeline.** Since the timeline in Interactive Timeline View is non-linear and we need to synchronize it with the other timelines, such as the ones in Logon/Logout Timeline and Intimacy Timeline. When users brush a time period in Logon/Logout Timeline and Intimacy Timeline, the corresponding period will be highlighted by a light grey rectangle, indicating the same piece of timelines.

5 User Cases

5.1 Case One: Social Gratification Satisfaction

The following sequences of activities occur when our GUX analyst and data analyst analyze the players' social behavior and the network structure, which uncover interesting behavior preference patterns and key design issues in the MMORPG.

Observing the Characteristics of the Whole Network. Our data analyst (E.2) first moves to Intimacy Network Overview to get a general idea of the whole intimacy network formulated in a particular game server. He finds that most of the players who joined the game at the first day occupy the central part of the entire network, with the later comers surrounding them ((Figure 1 (A))), mainly locate at the peripheral spaces of the entire network, forming little clusters. Experts comment that this is not a healthy or persistent intimacy network, since new comers are difficult to get involved into a larger player society and tend to turnover easily. Then, he proceeds to Core Player Overview to explore the distribution of different types of players and investigate players in details.

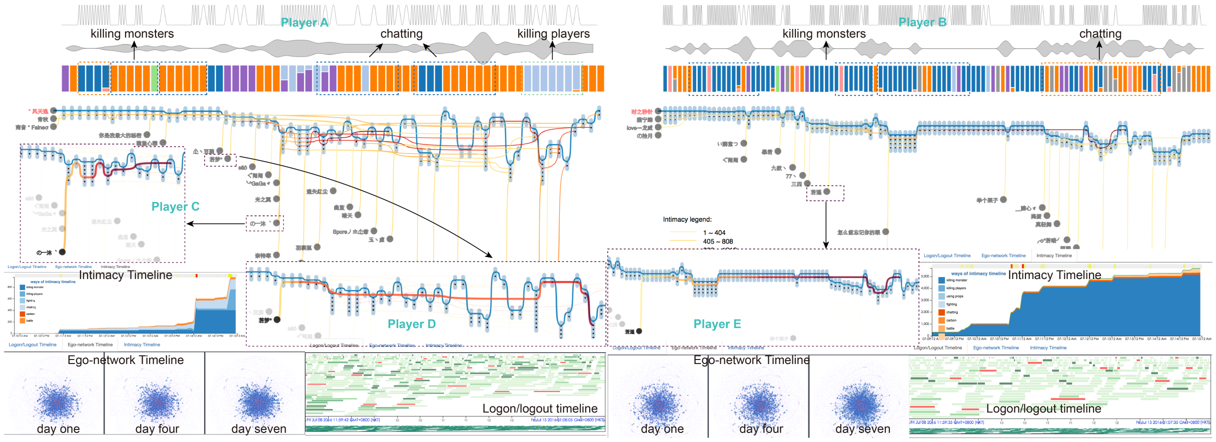

Figure 9: Typical PVP (Player A) and PVE (Player B) players: Both have established a dense ego-network since the first day (Ego-network Timelines). Compared with Player A, Player B has fewer friends with high intimacy, as there are fewer deep green bars in Logon/Logout Timeline of Player B. From the Intimacy Timeline, Player A has more interaction with other players compared with Player B, such as "*killing players*", "*battles*", etc., while Player B mainly focuses on "*killing monsters*".

Observing Behaviors of Different Types of Players. Players can be categorized using their most frequent gameplay activity types, which can be statistically calculated by data analysts, or via phone interview and questionnaire feedbacks, which are conducted by GUX analysts. The attributes of players can be obtained by using the features mentioned in section 4.1. PVP (player versus player) players prefer compete with other players through PK (player killing) and battles. They tend to have a more dynamic intimacy network, keep making new friends along with time (Figure 9 - Player A). The OCR of PVP players' ego-network always holds at a certain level, which means that they keep making new friends. On the other hands, PVE (Player versus Environment) players spend most of the time fighting in-game monsters. Figure 9 (Player B) shows that a typical PVE player's ego-network changes along with time. This player has stable relations with a few friends, chats and kills monsters with them. Unlike PVP players, the OCR changes once in a while and has zero value for several periods, showing he/she doesn't make any new connections actively. It can be inferred that PVE players tend to have a stable intimacy network. They chat to make new friends, play together as relatively long-term teammates to conquer dungeons and kill monsters and bosses (R.2).

One Nation Can't Have Two Queens. One phenomenon that the GUX analyst (E.1) finds is that although friendship exists among those most active players, they do not interact with each other a lot. The "hug her close" is very common, rather than the "strong-strong union". For example, Player A, the most active player in the game server, of whom the most intimate interactions come from Player C and Player D who have relatively much smaller alters. Player B, the second most active player, interacts mostly with Player E, who has only 29 alters (Figure 9).

Summarizing the Takeaways. Resulting from the analysis, game designers conclude the following takeaways for game designs to satisfy player gratifications: **(1) The Smaller, the Stabler:** According to the experts' experience, in online games, a decentralized social network constructed by many small social groups is healthier than a centralized network led by a core community. A centralized network such as in Figure 1 (A) creates a barrier for newcomers to blend in the center part. Thus, to facilitate small social groups, designers are suggested to develop small-team gameplays such as 3/5-players dungeons, which also help build relations among small groups. Moreover, a mentoring system among experienced players and new ones can help the latter have a better gaming experience and build tighter relations. **(2) Advanced Social Interaction Systems:** Due to different behavior patterns of PVE/PVP players, different social interaction systems can be developed to enhance their gaming experience. Since PVE players have a stable ego-network and relatively long-term friendships, designs like extra reward for intimate friends, and automatic recommending collective dungeons/battles for intimate friends will build a closer connections. While for PVP players who chat intensively, a versatile and easy-accessible voice/text chatting system is a must.

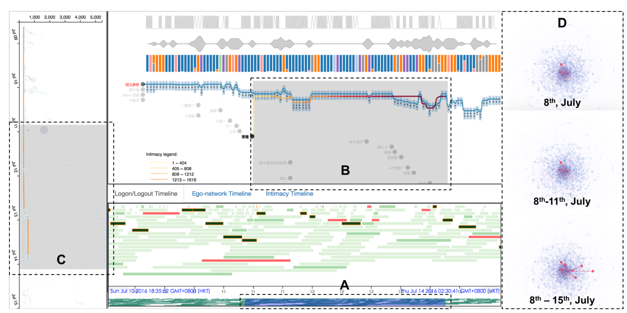

Figure 10: High impact on inactive player by a very active one.

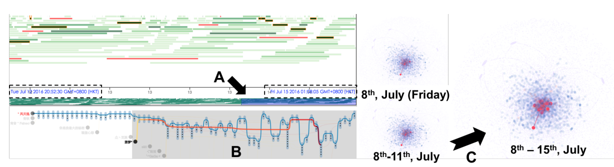

Figure 11: Another example of high impact on inactive player by a very active one: (A) Adjusting the time slide. (B) Select the player with the largest intimacy. (C) The player's ego-network expands significantly after the interaction with the ego, who is a very active player.

5.2 Case Two: Visual Tracking of Impact propagation

This case demonstrates the efficiency of MMOSeer for visually tracking and understanding how the impact of ego-alter interactions may potentially affect the evolution of alters' ego-networks (R.1, R.3).

High-impact on Inactive Players by Active One. The data analyst first gets interested in the most interactive player with the ego (red bars) and selects that player (dark green bars) *a* as in Figure 10. Most of their interactions are "killing monsters" together as a team. He then adjusts the time scale slide (A) to match their interaction session. Then the timelines in Interactive Timeline View (B) and Summary View of Changes of Alters' Ego-network (C) are highlighted by grey rectangles. The data analyst (E.2) observes a slight increase in the summation of intimacy of a's ego-network and several unchanged bubbles, indicating that the number of alters remains the same. In Ego-network Timeline (D), he interestingly finds that a's ego-network remains unchanged from 8^{th} to 11^{th}, July and then dramatically expands to a larger scale and establishes more connections from 12^{th} to 15^{th}. The only person a contacted after 11^{th}, July is the ego, with whom a has the highest intimacy. The data analyst also discovers similar *active-promote-inactive* phenomenons among many other players (such as Figure 11). He explains that it might be the collaboratice *PVE* activities that enlarge this player's social contact and help establish connections with other players.

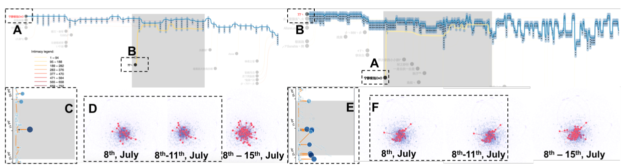

Figure 12: Two active players interact with each other from different perspective: A as the ego and B as the alter; A as the alter and B as the ego.

Low-impact between Active Ones. In the previous case study, the *one nation can't have two queens* catches the data analyst's interest and he takes a detailed analysis on interrelationships between the very active players. He selects several players with a large number of one-degree alters, namely over 100 connections, and finds the interactions between two randomly chosen active players have little impact on each other's ego-network (Figure 12). During their interaction session, although they have a lot of interaction with their own ego-network (C and E), their ego-networks (D and F) do not expand significantly. This also applies to many other similar investigated cases.

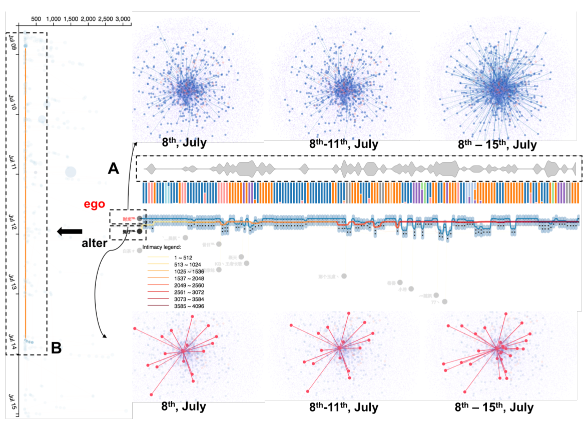

Figure 13: The ego's network from $8^{th} - 11^{th}$ does not change significantly. The OCR metric (A) of ego-network is relatively stable. During the entire interaction with the ego, the alter's ego-network does not change significantly, either. The summary view (B) displays a smooth curve of the alter, indicating that the alter only interacts with the ego.

Impact Between Inactive Players: The GUX analyst then wonders *"what about two relatively inactive players? Will their interactions affect their own ego-network's structure?"* He then finds interesting pattern between two relatively inactive players. Although interactions may expand ego-networks of corresponding players to some extent, if the two players interact too tightly with each other, they tend to less interact with other strangers. Their ego-networks remain the same for a relatively long period. For example, as in Figure 13, the alter's ego-network remains nearly unchanged during the whole interaction period with the ego – "intimate friend" in the game.

5.3 Experts Review and Discussion

System Usability. We conducted a semi-structured interview with our experts. They were excited by MMOSeer to visually and interactively explore and compare different types of players. The GUX analyst (E.1) prefers the effectiveness of using the system to reduce his workload in MMORPG social requirement evaluation. Previously, he needed to go through the game and gather all the social-relevant gameplay, function, and system designs in the game and took notes. Meanwhile, he had to consult several players to gather feedback and user experience, which is labor intensive and time consuming. With our system, he can easily explore and select interesting players in the Core Player Overview and Intimacy Network Overview. The data analyst (E.2) can explore different but interconnected information about an individual player in various views. He commented that *"MMOSeer is very useful because it provides a novel and highly interactive way to uncover the dynamics of ego-network and its impact propagation patterns."* Once they become familiar with the interactions in the system, they start to develop a path through the system for behavior inspection and ego-network evolution analysis, which boosts their analysis efficiency.

Visual design and interactions. All the experts were impressed by the simple but effective visual designs and interactions. They like the Interaction Timeline which provides intuitive representation of ego-alter interaction details, which largely overwhelms the traditional dynamic graphs approaches. The game designers (E.3-4) said *"We can compare the analysis results obtained from each type of player and establish a consensus on the possible reasons behind it."* Moreover, the data analyst (E.2) enjoys our system to deliver compelling stories of statistical findings to the game designers. Before this, he had been using statistical methods to extract latent features that are abstract to understand. Comparing different types of player in a comprehensive system does facilitate our analysts to conduct a better comparison of different players.

Suggestions. All the experts agree that our system can be easily extended to other MMORPGs by making minor modification, since social structures in MMORPGs are quite similar. For improvements, they suggest to integrate recommendation system to summarize similar players for more comprehensive analysis in a larger scale.

6 Conclusion and Future Work

In this paper, we present a visual analytic system for understanding the egocentric intimacy network in MMORPGs. It provides a suite of novel visualization tools for analyzing the in-game ego-network evolution and impact propagation. Through case studies, we validate the system's effectiveness in identifying patterns of different player behavioral preferences and impact propagation. We also provide several solid suggestions for designing a MMORPG. For future development, we plan to provide a comparison between multiple game servers and extend the gaming periods to a larger time scale, supporting research on game version comparison and players' behavior evolution analysis. We also plan to add other types of in-game social networks, such as guilds/clan community and aggregate multiple players into one display. This kind of work will cope with the challenge of solving the display of increasing game data in terms of its volume and dimensions.

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