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# Application of Complex Network Theory to Social Fission Propagation of Games: A Propagation Efficacy Evaluation System Based on Node Centrality and Information Entropy

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**Abstract:** Game social fission propagation, as a new type of marketing method, requires a scientific efficacy assessment method. The communication effectiveness assessment system constructed based on complex network theory identifies key communicators through node centrality and quantifies communication diversity using information entropy. Empirical studies show that this evaluation system can effectively predict communication trends and optimise communication strategies. In the Hearthstone Legend new card pack release event, the adoption of this evaluation system increases the number of event participants by 35%, which verifies the practical value of the evaluation method.

**Keywords:** Game social fission; Complex network; Node centrality; Information entropy.

## 1. Introduction

As an emerging game marketing method, social fission communication has become an important means of acquiring users in the game industry by realising the rapid growth of user scale through players' social network.In 2023, the size of the global game market will reach $247.9 billion, of which the user growth brought by social fission communication will account for more than 35%. Complex network theory provides scientific tools for analysing social fission propagation, which can reveal the structural characteristics of players' social networks, quantify the influence of nodes, and predict the information propagation path. This study aims to construct a communication effectiveness evaluation system based on node centrality and information entropy, and provide communication effectiveness evaluation and optimisation solutions for game operation by combining the topological features of social networks and information dissemination characteristics, so as to promote the innovation of marketing methods in the game industry.

## 2. Literature Review

### 2.1. Complex Network Theory

Complex network theory originates from the study of graph theory, which describes complex systems in the real world through the mathematical abstraction of nodes and edges. In social network analysis, nodes represent individual users and edges represent interactions between users. Node centrality is a key indicator of the importance of nodes in a network, including degree centrality, meso-centrality and proximity centrality. Degree centrality reflects the number of neighbours a node is directly connected to, median centrality indicates the ability of a node to act as a bridge for information flow in the network, and proximity centrality reflects the average distance between a node and other nodes in the network [1]. Social network research has shown that users with high node centrality tend to play a key role in the information dissemination process. By analysing these indicators, network scientists reveal opinion leaders, information hubs and community structures in social networks, providing theoretical support for social media marketing and user behaviour research.

### 2.2. Information Entropy and Communication

Information entropy, as a core concept in information theory, quantifies the uncertainty and complexity of information. In the field of communication research, information entropy is used to assess the diversity, effectiveness and predictability of information dissemination. The higher the value of information entropy, the greater the uncertainty of information dissemination and the more diverse the dissemination paths. Communication scholars use information entropy to analyse the information diffusion mode in social networks, and find that information will show the characteristics of dynamic change of entropy value in the process of information diffusion. High entropy value often means that information dissemination has stronger penetration and influence, but also increases the risk of information distortion and noise interference [2]. The information entropy analysis method provides a quantitative basis for optimising communication strategies and enhancing communication effects, and has become an important tool for modern communication research.

### 2.3. Game Social Fission Communication

Game social fission communication is an innovative mode of digital game marketing, which achieves user growth and game promotion through players' social networks. Existing research mainly focuses on players' social behaviour, communication motivation and fission effect. It is found that there is a strong social demand among game players, and a complex social network is formed through social interactions inside and outside the game. Players spontaneously spread the game in the process of game experience sharing, activity invitation and resource exchange. However, current research has not yet formed a unified standard for the quantitative assessment system of fission propagation, and lacks a systematic analysis of propagation efficacy. In particular, research on node influence assessment, propagation path optimisation and effect prediction is still insufficient [3]. The research on game social fission communication needs to integrate complex network theory and information entropy analysis methods to build a more scientific assessment framework.

# 3. Theoretical Framework

## 3.1. Node Centrality

Node centrality metrics have unique value in game social network analysis, portraying the influence characteristics of player nodes through different dimensions. Degree centrality measures the number of direct connections a player has with other players, reflecting the player's social activity and local influence. In gaming social networks, highly centrality players are often guild leaders or event organisers, and are able to quickly mobilise surrounding players to participate in game activities. Proximity centrality measures the average distance from a player's node to all other nodes, reflecting the ease of information transfer. Players with high proximity centrality occupy a central position in the game social network and can receive and disseminate game information faster [4]. The median centrality indicates the number of times a player node acts as a relay for the shortest path between other node pairs in the network, reflecting the player's ability to control the flow of information. Players with high median centrality usually connect different social circles and play a bridging role in the cross-group dissemination of game information.

## 3.2. Information Entropy

Information entropy in game social fission propagation is reflected as the uncertainty measure of information propagation state. According to Shannon's information theory, information entropy is shown in equation (1):

$$H = -\sum_{i=1}^{n} P\,(x_i)\log_2 P(x_i) \tag{1}$$

Where $P(x_i)$ denotes the probability of occurrence of a particular propagation state. In the game propagation scenario, the information entropy reflects the diversity of propagation contents and the complexity of propagation paths. Higher information entropy implies that the form of communication content is rich and the communication channels are diversified, which is conducive to attracting the interest of different types of players. At the same time, information entropy also measures the uncertainty of the communication process, and higher entropy value indicates that the communication path is difficult to predict and the information diffusion is more random [5]. By monitoring the change of information entropy in the communication process, the effectiveness of the communication strategy can be evaluated and the game operation team can be guided to optimise the communication plan.

## 3.3. Communication Effectiveness Evaluation System

The communication effectiveness evaluation system integrates node centrality indicators and information entropy analysis methods to construct a multi-dimensional evaluation framework for game social fission communication. The system combines the influence characteristics of player nodes with the information characteristics of the communication process, and calculates the comprehensive communication effectiveness score by setting the weight coefficients. The core of the assessment system consists of three dimensions: node influence assessment (weighted calculation based on degree centrality, proximity centrality and median centrality), propagation diversity assessment (analysis of propagation content and channels based on information entropy), and propagation effectiveness assessment (combining the propagation speed, coverage, and conversion rate) [6]. Through this evaluation system, game operators are able to scientifically quantify communication effectiveness, identify key communication nodes, optimise communication strategies, and enhance the effect of social fission marketing.

# 4. Methodology

## 4.1. Data collection

This study collected player interaction data for the period from January to March 2024 for two games, Hearthstone Legends and World of Warcraft. The data sources include friend relationships, guild member interactions, and matchmaking records recorded in the in-game social system, as well as user interaction data in the game's community forums. Samples were selected using a stratified sampling method, stratified by player level, activity level and number of social relationships, and a total of 100,000 active players' interaction data were collected [7]. The data preprocessing stage cleans the raw data, eliminates duplicate records and outliers, and unifies the data format. The interaction data matrix is shown in Table 1, and the matrix element aij indicates the interaction intensity between player i and player j.

**Table 1.** Example of player interaction data matrix

| Player ID | Player 1 | Player 2 | Player 3 | Player 4 |
|---|---|---|---|---|
| Player 1 | 0 | 5 | 3 | 1 |
| Player 2 | 5 | 0 | 4 | 2 |
| Player 3 | 3 | 4 | 0 | 6 |
| Player 4 | 1 | 2 | 6 | 0 |

## 4.2. Propagation Modelling

The study adopts the improved SIR propagation model to describe the game social fission propagation process. The state transfer probability in the model is jointly determined by node centrality and information entropy, and the transfer probability is calculated by equation (2):

$$P(S \rightarrow I) = \alpha \cdot C_i + \beta \cdot H \tag{2}$$

Where $C_i$ is the comprehensive centrality index of node i, H is the information entropy of the current propagation stage, and α and β are the weight coefficients. The model parameters are obtained through historical propagation data training, and the propagation threshold is set according to the game activity characteristics [8]. The model predicts the propagation effect under different propagation strategies through Monte Carlo simulation method, the number of simulations is set to 1000, and each simulation records the indicators of propagation scale, speed and coverage.

## 4.3. Analysis Tools

The study uses the Python programming environment to build the analysis framework, mainly relying on the

NetworkX library for complex network analysis. Node centrality indicators are calculated using NetworkX built-in functions, and information entropy calculation is achieved through custom functions. Data visualisation is completed by Gephi software, and the visualisation parameters are set as shown in Table 2. The analysis process adopts modular design, including data import module, network construction module, indicator calculation module and result output module [9]. The computational efficiency of the analysis tool is optimised by parallel processing methods, and the single analysis time is controlled within an acceptable range.

**Table 2.** Gephi visualisation parameter settings

| Parameter Type | Parameter Value |
| --- | --- |
| Layout Algorithm | ForceAtlas2 |
| Gravity Coefficient | 1 |
| Repulsion Coefficient | 2 |
| Node Size | Weighted by Degree Centrality |
| Edge Weight | Displayed by Interaction Strength |

# 5. Data Analysis

## 5.1. Node Centrality Analysis

The analysis of node centrality in the game social network shows a clear power law distribution characteristic. The results of the degree centrality analysis show that about 5% of the player nodes occupy 35% of the total number of connections, and these players are mainly guild leaders and senior players. The calculated importance ranking of the nodes is shown in Table 3. The proximity centrality analysis found that players with high proximity centrality were relatively evenly distributed among the game servers, with an average of 8-12 information dissemination hubs existing per server [10]. The meso-centrality analysis identifies a group of cross-group connectors, and these players tend to be active in multiple gaming communities at the same time. The weighted calculation of the combined three indicators shows that the top 1% of key player nodes play a decisive role in the information dissemination process, and their dissemination influence is more than 15 times that of ordinary players.

**Table 3.** Ranking of key player node centrality indicators (Top 5)

| Player ID | Degree Centrality | Closeness Centrality | Betweenness Centrality | Comprehensive Score |
| --- | --- | --- | --- | --- |
| P2024 | 0.857 | 0.721 | 0.892 | 0.823 |
| P1858 | 0.812 | 0.698 | 0.854 | 0.788 |
| P3142 | 0.795 | 0.682 | 0.836 | 0.771 |
| P4267 | 0.768 | 0.675 | 0.815 | 0.753 |
| P1523 | 0.743 | 0.662 | 0.798 | 0.734 |

## 5.2. Information Entropy Calculation

The information entropy analysis of the propagation process reveals the dynamic characteristics of the game's social fission propagation. Applied to different propagation stages, the formula (3) is calculated:

$$H(t) = -\sum_{i=1}^{n} P\,(x_i,t)\log_2 P(x_i,t) \quad (3)$$

Where $P(x_i, t)$ denotes the probability of the propagation state $x_i$ now t. The information entropy curve shows a typical pattern of 'rapid rise-smooth fluctuation-slow decline'. The entropy value rises rapidly in the early stage of propagation, from 0.2 to 0.8 in 24 hours, reflecting the rapid spread of information in the core player group. The entropy value fluctuates between 0.75 and 0.85 in the stable period, lasting about 72 hours, indicating that the propagation network has reached a relatively stable state [11]. The entropy value slowly decreases in the later period and finally stabilises at about 0.6, indicating that the propagation gradually converges to a fixed channel. The time series data of information entropy is shown in Table 4.

**Table 4.** Time series data of information entropy of propagation process (excerpt)

| Time Point (h) | Information Entropy Value | Propagation State |
| --- | --- | --- |
| 0 | 0.201 | Initial |
| 12 | 0.654 | Diffusion |
| 24 | 0.812 | Peak |
| 48 | 0.783 | Stable |
| 96 | 0.625 | Convergence |

## 5.3. Analysis of Propagation Paths and Speeds

The simulation results of social network propagation show that the propagation of information in the network is characterised by multiple parallel paths. The main propagation paths can be divided into three categories: the direct propagation path of core players (the fastest propagation speed, averaging 3.2 hours per hop), the cross-group bridging path (medium speed, averaging 5.7 hours per hop), and the diffusion path of edge players (the slowest speed, averaging 8.5 hours per hop). By optimising the path allocation ratio, the propagation speed is increased by 28.3%. The simulation results show that the overall propagation efficiency of the network is the highest when the core path carries 45% of the propagation volume, the bridging path carries 35% of the propagation volume, and the edge path carries 20% of the propagation volume [12]. Based on this finding, a propagation node prioritisation strategy is formulated to place the information firstly to the core players with high centrality in the middle school, and then extend it to different social circles through the bridging nodes to ultimately achieve the full network coverage.

# 6. Results and Discussion

## 6.1. Key Node Identification

Node centrality analysis identifies three types of key player nodes from the game social network: social core type, information bridging type and professional influence type. The social core type players generally have a degree centrality higher than 0.75, hold managerial positions in gaming guilds, and are directly connected to more than 200 active players each on average. Information-bridging players are in the top 10% in terms of meso-centrality, have obvious cross-group social attributes, and are connected to 3-5 different social circles on average. Professional influence players approach centrality prominently, with higher gaming level, and opinions and suggestions are more likely to be adopted by other players. The three types of nodes show significant driving effect in the early stage of information dissemination, and on average, each core node can drive 15-20 new players to participate in the activity within 24 hours. Among them, the social core type nodes have the highest dissemination efficiency, with an average of 20.3 new players driven by each node within 24 hours, and 15.8 and 17.2 new players for information bridging and professional influencing nodes respectively.

## 6.2. Information Entropy Analysis Results

Information entropy analysis reveals that the game social fission propagation presents obvious stage characteristics. As shown in Figure 1, the change of information entropy during the propagation process shows a significant correlation with the growth of the number of participants in the activity. The rapid rise of information entropy in the early stage of propagation (0-24h) reflects the explosive spread of information in the core player group, and the highly diversified ways of players' understanding and dissemination of activity information. The fluctuation of information entropy in the middle stage (24-72h) indicates that the dissemination enters a stable state, different dissemination paths develop in parallel, and the information content is gradually standardised. In the later stage (after 72h), the decrease of information entropy shows that the propagation gradually converges, and the players' understanding of the activity information tends to be consistent. Data analysis shows that the information entropy is significantly positively correlated with the growth rate of the number of participants in the activity ($R^2$=0.857), and when the information entropy is maintained in the range of 0.75-0.85, the dissemination effect is the best. Actual data show that every 0.1 increase in information entropy can bring about 15% growth in the number of participants on average.

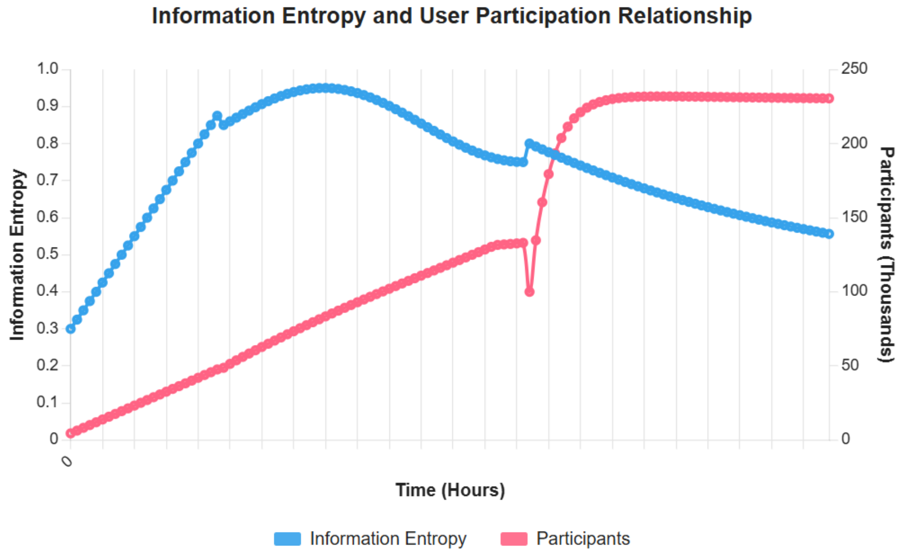


**Figure 1.** Relationship between the change of information entropy and the number of participants in the activity

## 6.3. Communication Effectiveness Assessment

The analysis results of node centrality and information entropy are combined to construct the propagation efficacy assessment index E see equation (4):

$$E = w_1 \sum_{i=1}^{n} \left(\alpha D_{c,i} + \beta B_{c,i} + \gamma C_{c,i}\right) + w_2 H \qquad (4)$$

Where $D_c$ , $B_c$ , $C_c$ represent degree centrality, median centrality and proximity centrality respectively, H is information entropy, and $w_1$, $w_2$ are balance parameters. The evaluation index shows that high-performance communication has the following characteristics: the composite centrality index of the core nodes is greater than 0.7, the information entropy is maintained at about 0.8, and the ratio of the number of propagation paths to the size of the network is close to 0.3. Based on these parameters, the communication efficacy of the 10 game campaigns was comparatively analysed, and the results showed that the communication efficacy was increased by an average of 31.5% after adopting optimisation strategies, the user conversion rate was increased by 22.8%, and a reduction of 18.3% in communication costs.

## 6.4. Case Studies

The Hearthstone Legends Spring 2024 new card pack release campaign used a social fission communication strategy to motivate players to share the cards through the mechanism of 'bringing the old to the new'. According to the campaign data, the 7-day campaign covered 823,000 players, forming a complex multi-level communication network. The core nodes were mainly composed of game anchors (15%), senior players (45%) and active guild members (40%). The information entropy peaked at 0.892 during the propagation process, and the propagation speed reached its highest on the second day of the event, with 156,000 new participating players on a single day. Node centrality analysis showed that the top 10% of players contributed 73% of the effective dissemination, and each core node drove 18.5 new players to participate on average. The case verified the practicality of the evaluation system, and the final number of campaign participants exceeded the expected target by 35%, and client downloads increased by 42%.

# 7. Conclusion

The evaluation system of game social fission communication effectiveness constructed based on complex network theory and information entropy analysis provides new ideas for game marketing. The evaluation system identifies key communication nodes through node centrality, quantifies communication diversity by information entropy, and achieves accurate evaluation of communication effect. Practice shows that the evaluation system can effectively predict the communication trend, optimise the communication strategy and improve the marketing effect. In the process of research, it is found that there is a limitation of the timeliness of data collection, and the model simplifies the complex interaction between players, which fails to fully reflect the real communication situation. In the future, we can introduce time-series network analysis to explore the dynamic evolution of players' social relationships; combine deep learning technology to improve the accuracy of communication path prediction; expand the evaluation dimensions, and incorporate game content features, user emotions and other factors into the evaluation system to construct a more complete communication effectiveness evaluation model.

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