Temporal Stability and Equilibrium Dynamics in Online Social Interactions: Case Study of a Subreddit Activity Network

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This study investigates the structural evolution of a large online community by analyzing the monthly interaction networks derived from the posts and replies of a Subreddit. Users are represented as nodes and reply relationships as weighted undirected edges, enabling the construction of a time-resolved sequence of social graphs. Using these networks, we compute a range of theoretic measures, including degree distributions, betweenness centrality, clustering coefficients, component structure, and connectivity metrics, to characterize both local and global aspects of the network structure. By examining how these metrics vary across time, we identify persistent structural patterns, shifts in user engagement, and changes in the community's cohesion. The results reveal a highly heterogeneous interaction landscape dominated by sparse, low-clustering regions, with a small but stable core of structurally important users who sustain connectivity across otherwise fragmented subgroups.

1 Introduction

Online social communities generate complex patterns of user interaction that evolve continuously over time. Platforms such as Reddit allow users to participate through posts and replies, providing a rich source of social data that can be modeled as networks and studied using techniques from the domain of Network Science and Graph Theory. The analysis of such networks is essential to understand how communities grow, stabilize, fracture, or reorganize themselves.

In this work, we performed a longitudinal analysis of the temporal dynamics of a specific Subreddit (`r/Documentaries`), between the years 2015 and 2018. To that end, we constructed periodic monthly snapshots of this Subreddit's user interactions in the form of two networks (one directed, one undirected). In these networks, users are represented as nodes and reply events are represented as weighted edges. Edge weights record the number of replies from user u to user v within the snapshot period. While individual comment reply trees are locally acyclic, the month-aggregated directed user-user network may contain reciprocal edges and cycles arising from back-and-forth exchanges.

By computing a suite of structural metrics, such as degree distribution, clustering coefficients, centrality measures, communities, and component structure, and plotting their trajectories across time, we aim to characterize the evolution of user behavioral patterns, identify persistent structural features, and assess the overall stability of this Subreddit's underlying social fabric.

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In addition to the description of the temporal behavior of this Subreddit, we also aim to explore whether this online community exhibits some type of stable signature in their network properties or whether, on the other hand, it evolves unpredictably. To that end, we also created a theoretical network model and measured how it approximated the observed community.

The link to the repository with the source code and the data used in this study is: https://github.com/PFans-201/Social_Net_analysis

2 Data

2.1 Data Source and Choice

The base data for this case study was downloaded as a zip file from ConvoKit, the Cornell Conversation Analysis Toolkit, at https://zissou.infosci.cornell.edu/convokit/datasets/subreddit-corpus/corpus-zipped/. According to their documentation: "This toolkit contains tools to extract conversational features and analyze social phenomena in conversations, using a single unified interface inspired by (and compatible with) scikit-learn. Several large conversational datasets are included together with scripts exemplifying the use of the toolkit on these datasets."

This website includes extracts from multiple Subreddits. Our criteria for selecting the `r/Documentaries` Subreddit as the object of our study were as follows:

(1) **Size of the data set:** At 340 MB, this seemed like a manageable data set that could produce networks with a sufficient number of nodes to derive meaningful results without compromising performance or operational agility. Our aim was to work with networks that contained at least 10 000 nodes.
(2) **Reference in previous work:** The `r/Documentaries` Subreddit was mentioned in the 2018 article "Community Interaction and Conflict on the Web", by S. Kumar, W. L. Hamilton, J. Leskovec, and D. Jurafsky [1]. In their study, the authors identified a group of users from another Subreddit, who mobilized together to initiate a targeted attack against `r/Documentaries`, by posting malicious responses to posts in that Subreddit. Given our intention to analyze the stability and cohesion of an online community over time, the existence of such conflicts that necessarily interfere with regular user activity patterns was of particular interest to us.

2.2 Tabular Data Preparation

The base data set, in tabular format, included data from the time of the Subreddit's creation up to October 2018. Some notes on the structure of the data and nomenclature:

- **Users** are identified by their Reddit username.
- An individual post or a comment is an **utterance**.
- A post and its respective response comments is a **conversation**.
- Users whose profile was deleted had their username replaced with the string `[deleted]`.
- Deleted utterances had their content replaced with the string `[removed]`.

Our data preprocessing pipeline started with the loading of the conversation and utterance data sets, which we called **posts** and **comments**, respectively. We then performed a series of preprocessing operations, namely:

- **Parsing conversation timestamps:** The timestamp of the start of a conversation was converted from a unix-timestamp to a datetime object.
- **Parsing utterance timestamps:** The timestamp in which an utterance was produced was converted from a unix-timestamp to a datetime object. When the original timestamp could not be parsed, the records were dropped from the data set. In the remaining records, we created four derived features based on the timestamp: the week-of-year, the month-of-year, the year, and the string concatenation of year and month

in "YYYY-MM" format. These new features enabled us to identify which utterances belonged to each network snapshot in later steps of the analysis.

- **Excluding invalid utterances based on user details:** To prevent skewing the results, we excluded all utterances where the user was identified as `[deleted]` or was left undefined. If these utterances had been left in the data set, they would have produced user nodes in the networks with a substantially higher degree than the others, as they would have aggregated the activity from an unknown number of users. For the same reason, we also excluded all utterances where the reply-to user was undefined (note: the first utterance in a conversation is considered to be a self-reply, so this field should not be empty under normal circumstances).
- **Excluding invalid utterances based on text:** Our goal was to derive new attributes from the utterance text that could be used to characterize the network and communities found therein. As such, we excluded all utterances in which the text was unavailable.
- **Calculating the sentiment analysis score for each utterance:** We used the VADER SentimentIntensityAnalyzer model to calculate the sentiment score for each utterance. This was an example of an attribute that could be extracted from the text of the utterances that could be used to characterize communities of users. Other attributes considered were a controlled subset of topics, but due to time constraints, these were not implemented.

During the analysis of the data, we detected that there were a number of bots among the Subreddit users. We consider that the presence of these bots could potentially skew the results of the study, however, due to time constraints and the difficulty in correctly identifying which utterances were produced by a bot, these data points were left in the data set.

2.3 Network Preparation

With the base data preprocessed and formatted, the next step in our process was to create user-user networks based on the tabular utterance data. Our algorithm worked by taking as input the number of snapshots per year to be created and the temporal granularity of the data (weekly or monthly). For the purpose of the results presented in this report, we generated four monthly snapshot networks according to the following process:

(1) **Selection of snapshot periods:** Given the granularity and yearly number of snapshots to create, we determined a set of candidate dates for the creation of a network. For each candidate date, we then estimated the number of nodes comprising the giant connected component (GCC) of the resulting network, in order to exclude networks that did not meet our criterion for a minimum of 10 000 nodes. The remaining dates were selected for network creation.

(2) **Selection of utterances within each snapshot period:** For each date, we selected the utterances that were produced within that period. For example, a snapshot for the date of January 2018 (with monthly granularity) should include all utterances made from January 1 until January 31 of that year.

(3) **Identification of replied-to users and edges:** The utterances data set identifies the previous comment in a conversation by its utterance ID. In order for us to identify the user who produced that utterance, we created a map between utterance ID and users. By applying this map to the utterances data set, we were able to identify which users/nodes should be connected by an edge in our network and which weight that edge should have. The edge weight was calculated as the count of utterances between those two users within the snapshot period. We once again excluded data points where the replied-to users had deleted their profile or were not defined. We also excluded self-replies: the first utterance in a conversation, i.e. a Reddit post, is always considered a self-reply since it is not a direct reply to any previous utterance.

(4) **Creation of undirected and directed weighted graphs:** For each snapshot, we constructed an undirected and a directed graph. Edges in the undirected graph connect users who replied to each other, without

specifying who replied to whom. In the directed graph, each directed edge $u \rightarrow v$ indicates that user u replied to user v within the snapshot window. In both directed and undirected graphs, the edge weight equals the count of replies in that window. We explicitly avoid labeling the aggregated directed networks as DAGs, because reciprocal replies and cross-thread activity can produce directed cycles at the user level.

This process produced a total of 30 networks (15 directed and 15 undirected), from April 2015 to October 2018. The months considered over this period were January, April, July and October. These networks are further characterized in the "Results and Discussion" section.

3 Methodology

After the creation of the network snapshots, we proceeded to analyze them according to a number of metrics. We started by applying a community detection algorithm to each snapshot that returned a correspondence between node and the community it belonged to. Based on the network snapshots and the results of that community detection algorithm, we then calculated some network metrics for each temporal snapshot over the following entities:

- Full network;
- Subgraph of the snapshot's GCC;
- Subgraph of the snapshot's largest identified community.

3.1 Community Detection

We decided to first use the Louvain algorithm due to its good performance and the fact that it identifies non-overlapping communities. This was an important attribute to have in our first analysis, as working with a 1-N relationship between node and community ID would make the process to compute certain metrics on a community basis more complex.

Directed vs. undirected processing. Many community detection algorithms, like Louvain or BigCLAM, expect undirected graphs as input. In those cases, we use the snapshot's undirected view (NetworkX's `to_undirected()`), preserving edge weights by summing reciprocated weights where necessary. Metrics that rely on directionality (in-degree, reciprocity, directed motifs) are computed on the original directed, weighted snapshots.

The Louvain algorithm was applied independently to each network snapshot. Therefore, we take note that there is no guarantee that the community ID generated by the algorithm refer to the same entity in all the snapshots.

3.2 Metrics

Given the number and size of the networks produced, we tried to separate the metrics calculation step from the interpretation step as much as possible. This allowed us to better automate the computation process and improve the performance of our code. We pre-calculated the following metrics:

- Total utterances count per snapshot;
- Unique user count per snapshot;
- Unique posts with replies per snapshot;
- Total utterances without text per snapshot;
- Total utterances that are replies per snapshot;
- Valid user-to-user replies per snapshot;
- Unique user-to-user reply pairs per snapshot;
- Average user reply counts per snapshot;
- Maximum user reply counts per snapshot;

- Median conversations per user per snapshot;
- Median users per conversation per snapshot;
- Ratio of users commenting on multiple conversations per snapshot;
- Ratio of conversations with multiple users per snapshot;
- Total node count per snapshot, per snapshot GCC and per snapshot's largest identified community;
- Total edge count per snapshot, per snapshot GCC and per snapshot's largest identified community;
- Network density per snapshot, per snapshot GCC and per snapshot's largest identified community;
- Network assortativity per snapshot, per snapshot GCC and per snapshot's largest identified community;
- Count of communities identified per snapshot;
- Community modularity metric per snapshot;
- Average community internal vs external edge ratio per snapshot;
- Network diameter per snapshot GCC;
- Average shortest path per snapshot GCC.

In addition to these numerical metrics, we also collected data for the following distributions:

- Network degree distribution per snapshot, per snapshot GCC and per snapshot's largest identified community;
- Sizes of the connected components per snapshot, per snapshot GCC and per snapshot's largest identified community;
- Network clustering coefficients per snapshot, per snapshot GCC and per snapshot's largest identified community;
- Network betweenness centrality measures per snapshot, per snapshot GCC and per snapshot's largest identified community;
- Total users per community per snapshot;
- Median utterance sentiment score per community per snapshot;
- Average utterance sentiment score per community per snapshot;
- Standard deviation of the utterance sentiment score per community per snapshot.

4 Results and Discussion

4.1 Observed Network

An analysis of the temporal snapshots of the networks that represent user-user interactions in the (`r/Documentaries`) Subreddit reveals some patterns of instability.

Although the total number of users interacting in this Subreddit displays a generally rising trend up until late 2017, there are periods when the number of users appeared to abruptly decline. Throughout the year of 2018, the analysis of the network sizes also suggests that the user base's trend of growth started to reverse (Figure 1a).

It should be noted that the networks' largest connected component is very close in size to the size of the full network on all snapshots (Figure 1b). The other connected components include only a minimal fraction of the nodes of the overall network. In association with the analysis of the degree distribution of the network (Figure 2a), the small diameter and low value of the average shortest path of the network's giant connected component (Figure 2b), this is supporting evidence that this network presents small-world properties.

A look at the distribution of the clustering coefficients of the network in the April 2015 and October 2018 snapshot (Figure 3) reveals other notable features:

- There is a strong right skew, with the majority of nodes having clustering coefficients near zero. This indicates that, for most users, their neighbors are not connected to each other. The network may be considered sparse and dominated by weakly connected local structures.
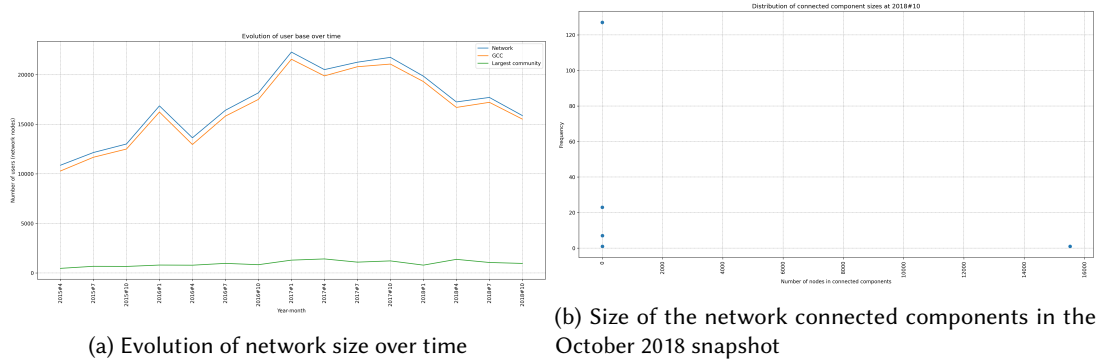
(a) Evolution of network size over time

(b) Size of the network connected components in the October 2018 snapshot

Fig. 1. Network and connected component sizes

(a) Network degree distribution (log-scaled) in the October 2018 snapshot

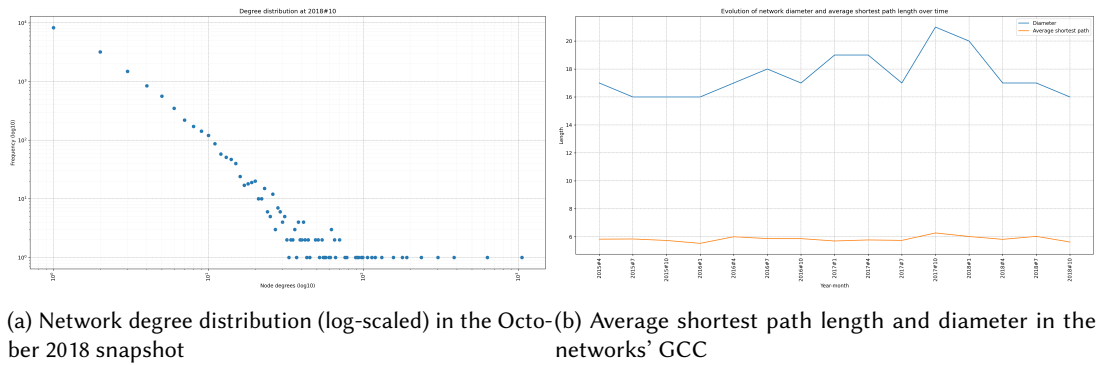(b) Average shortest path length and diameter in the networks' GCC

Fig. 2. Network degree distribution and average shortest path lengths

- A relatively small number of nodes achieve moderate or high clustering coefficients, suggesting that while most users participate sparsely, a minority are involved within more cohesive conversational clusters. These may be, for example, core regular Subreddit users who frequently interact with one another.
- Many unique clustering-coefficient values appear only once, forming a band of frequency = 1, especially in the low-clustering region. This suggests there is no strong grouping within low-clustering nodes; instead, they form a broadly dispersed continuum.

We analyzed the distribution of the betweenness centrality measures of the network at the start and end of the temporal analysis (Figure 4). The plots reveal common features at both points in time:

- In line with the previous observation of network sparsity, most network nodes have near-zero betweenness. This indicates most users play no bridging role in the global flow of interaction, and their presence or absence does not strongly affect connectivity between different parts of the network.
- There is a visible tail extending towards higher betweenness values. A few users act as central connectors, playing an important role in the network's cohesion and information flow, possibly because they participate widely across different threads or maintain persistent cross-user engagement.

We applied the Population Stability Index (PSI), a metric frequently used to detect instances of data drift, to measure the stability of the node degree distributions and of the betweenness centrality distributions across
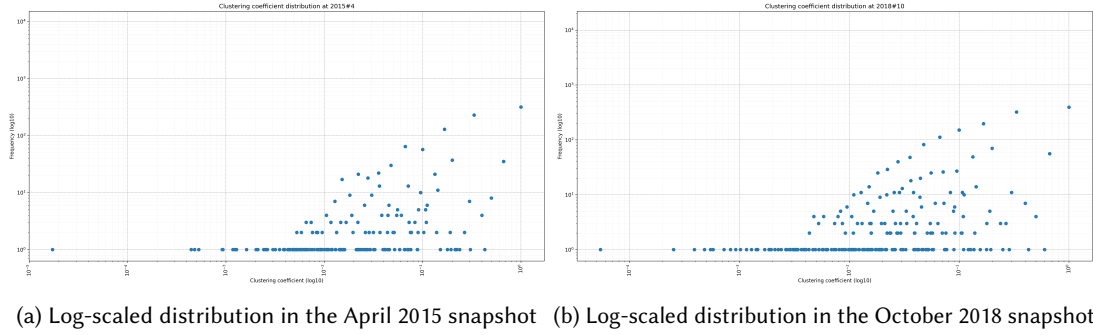
(a) Log-scaled distribution in the April 2015 snapshot (b) Log-scaled distribution in the October 2018 snapshot

Fig. 3. Network clustering coefficient distributions

(a) Log-scaled distribution in the April 2015 snapshot (b) Log-scaled distribution in the October 2018 snapshot
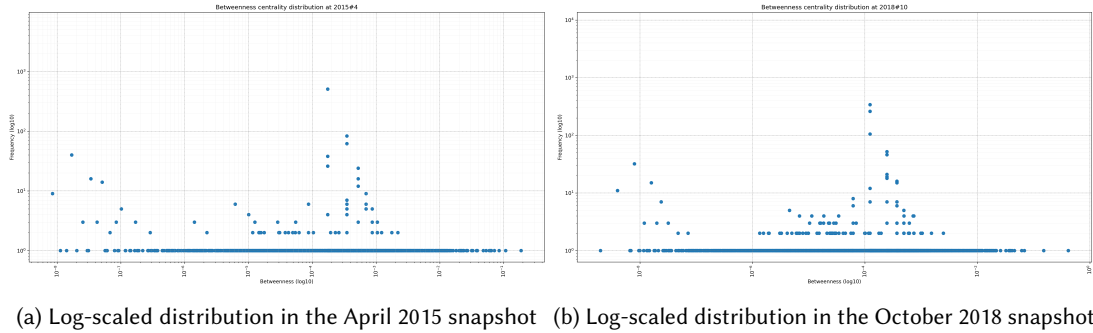
Fig. 4. Network betweenness centrality distributions

snapshots (Figure 5). Using the April 2015 snapshot as a baseline, we compared the distributions of the two features in the subsequent snapshots with the baseline to determine whether there were significant changes in the composition of the network. We found that, while the degree distributions are quite stable (PSI < 0.2 for all snapshots), the betweenness centrality PSI values oscillated between 0.24 and 0.34, indicating a greater level of instability.

4.2 Diagnosis: A "Liquid" Network Driven by Content

The analysis of r/Documentaries reveals a network characterized by extreme instability at the micro-level. Unlike traditional social networks where connections are stabilized by persistent interpersonal bonds this Subreddit functions as a **"Liquid" Network**.

The dynamics resemble a busy transport hub rather than a community center: the aggregate crowd volume remains constant, but the specific individuals interacting change almost entirely from one time step to the next.

4.3 Analysis of Hubs: "15 Minutes of Fame"

The analysis identifies a phenomenon of "15 Minutes of Fame" regarding network influence.

- **High Turnover:** The "survival rate" of hubs (central nodes) across time periods is exceptionally low, fluctuating between 5% and 8%.

(a) Stability across degree distributions over time

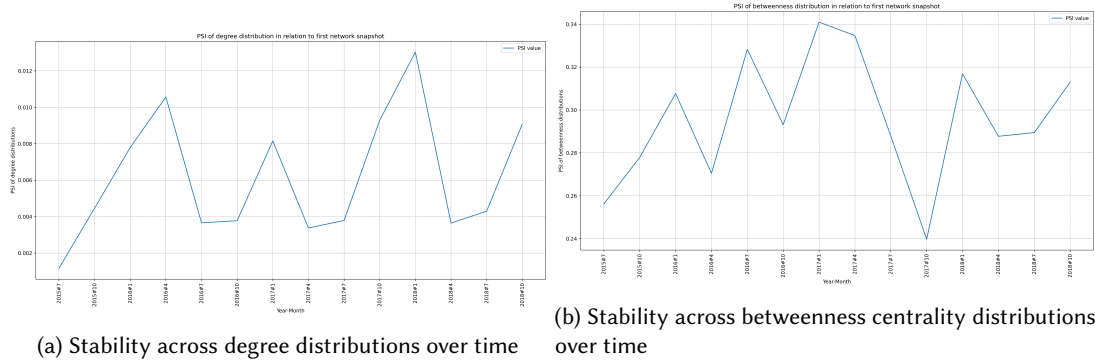(b) Stability across betweenness centrality distributions over time

Fig. 5. Population Stability Index (PSI) values for key network metrics

- **Interpretation:** Being a "Hub" is a temporary state, not a permanent rank. High centrality likely correlates to a user posting a viral documentary or a top comment. Once the content fades from the "Hot" page, the user's hub status vanishes.
- **The Infrastructure Constant:** The only "Evergreen Hub" present across all 15 analyzed periods is the **AutoModerator**.
  - *Significance:* This confirms the absence of a "human oligarchy" or stable group of influencers. The network structure is maintained by technical infrastructure (bots) and content flow, not by social leaders.

4.4 Analysis of User Fidelity: The "Nomad" Effect

User behavior metrics indicate a lack of cohesive social groupings, pointing instead to interest-based, transient interactions.

- **Zero Loyalty:** The **Global Average Fidelity is** 0.004. If a user interacts with a specific group in Period t, the probability of them interacting with that same group in Period $t + 3$ is effectively zero.
- **100% Switching Rate:** In nearly every period transition, 99.6% to 100% of users are flagged as "switching communities."
- **Implication:** In this dataset, a "Community" is a proxy for a **Topic** or a **Thread**, not a social clique. Users do not migrate together. A user might engage with a "History" cluster in January and a "Nature" cluster in February, with no continuity in their peers.

4.5 Conclusion: Equilibrium Dynamics & Evolution

These results provide definitive answers regarding the equilibrium and evolutionary properties of the network.

Does Macroscopic Stability emerge from Microscopic Instability? **YES.** While the micro-level population is in a state of constant flux (extreme instability), the macroscopic structural properties remain robust.

Evidence: The quantity of Hubs remains relatively stable (fluctuating between ∼ 130 and ∼ 240) even as the *identity* of those hubs changes completely. The network maintains a consistent topological "shape," despite being composed of a completely fluid population.

How do communities evolve? They do not "evolve" in the biological sense (splitting, merging, or growing over time). Instead, they **dissolve and reform**.

This dynamic suggests that social bonding models are ill-suited for this network. Instead, an **Independent Cascade** model or a **Resource-Based** model (where "attention" is the finite resource) provides a more accurate fit.

Theoretical Implication: The Fitness Model. The rapid appearance and disappearance of hubs impacts the choice of simulation models.

- **Standard Barabási-Albert (BA):** This model is likely insufficient. In a standard BA network, the oldest nodes tend to become the largest (preferential attachment based on age/accumulation).
- **Bianconi-Barabási (Fitness Model):** The data strongly suggests this extension of the BA model is required. In the Fitness Model, nodes have an intrinsic "fitness" (quality of content). A new node with high fitness (a viral post) can rapidly overtake older nodes. This aligns perfectly with the observation that new content constantly supersedes old content in the network rankings.

4.6 Comparison with Theoretical Model

To validate our hypothesis that the network dynamics are driven by a "Price + Fitness + Activity" mechanism rather than a standard Barabási-Albert growth model, we implemented a generative simulation. The simulator couples a Markovian lifecycle model (governing user churn, birth, and resurrection, observed in Figure 6) with a modified preferential attachment mechanism that accounts for node fitness (virality) and explicit reciprocity.
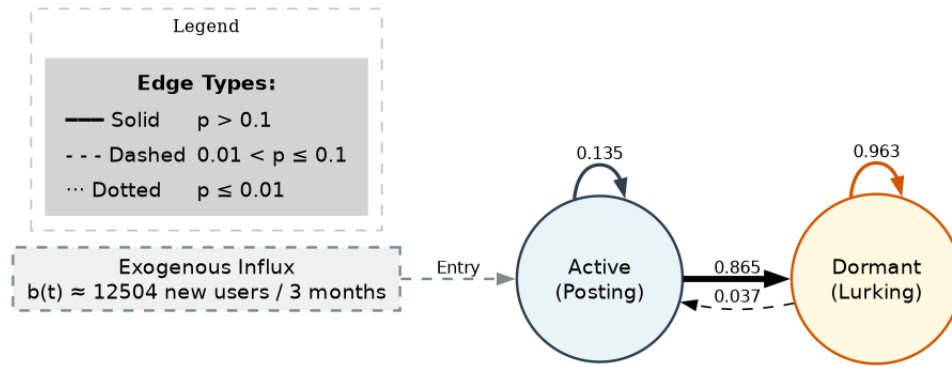
Fig. 6. Markovian Lifecycle Model. Visualizing the transition probabilities between user states (Active, Dormant) and the exogenous influx of new users.

We trained the model parameters on the first 80% of the snapshots (2015–2017) and tested its predictive power on the remaining 20% (2018). Figure 7 illustrates the comparison between the empirical data (Real) and the simulation (Simulated) across six key metrics.

The simulation results demonstrate a strong fit for macroscopic properties. As shown in Table 1, the model achieves an overall accuracy score of approximately 81% on the test set. The simulation closely tracks the Reciprocity ($R \approx 0.34$) and the Power-Law fit quality ($R^2 > 0.9$), confirming that the underlying "physics" of the Reddit network—high churn combined with fitness-based attachment—are well-represented by our theoretical framework.

While the node and edge counts in the simulation are slightly higher than the observed values in the test period, the structural signatures (Reciprocity and Alpha) remain consistent. This discrepancy suggests that while the *volume* of activity in the real subreddit began to decline in 2018 (as noted in Section 5.1), the *structure* of interactions remains governed by the same generative rules identified in the training period.

Table 1. Validation Metrics for the Test Set (2018)

Time	Phase	Nodes (Real)	Nodes (Sim)	Edges (Real)	Edges (Sim)	Recip (Real)	Recip (Sim)	JS Div	α (Real)	α (Sim)	Score
2018#4	Test	17,256	19,762	29,298	39,653	0.333	0.338	0.212	2.585	2.443	0.804
2018#7	Test	17,710	20,331	30,667	39,882	0.346	0.354	0.173	2.583	2.306	0.834
2018#10	Test	15,880	19,653	28,254	39,625	0.348	0.338	0.197	2.612	2.523	0.792

References

[1] Jure Leskovec Srijan Kumar, William L. Hamilton and Dan Jurafsky. 2018. Community Interaction and Conflict on the Web. *WWW '18: Proceedings of the 2018 World Wide Web Conference* (April 2018), 933–943. doi:10.1145/3178876.3186141
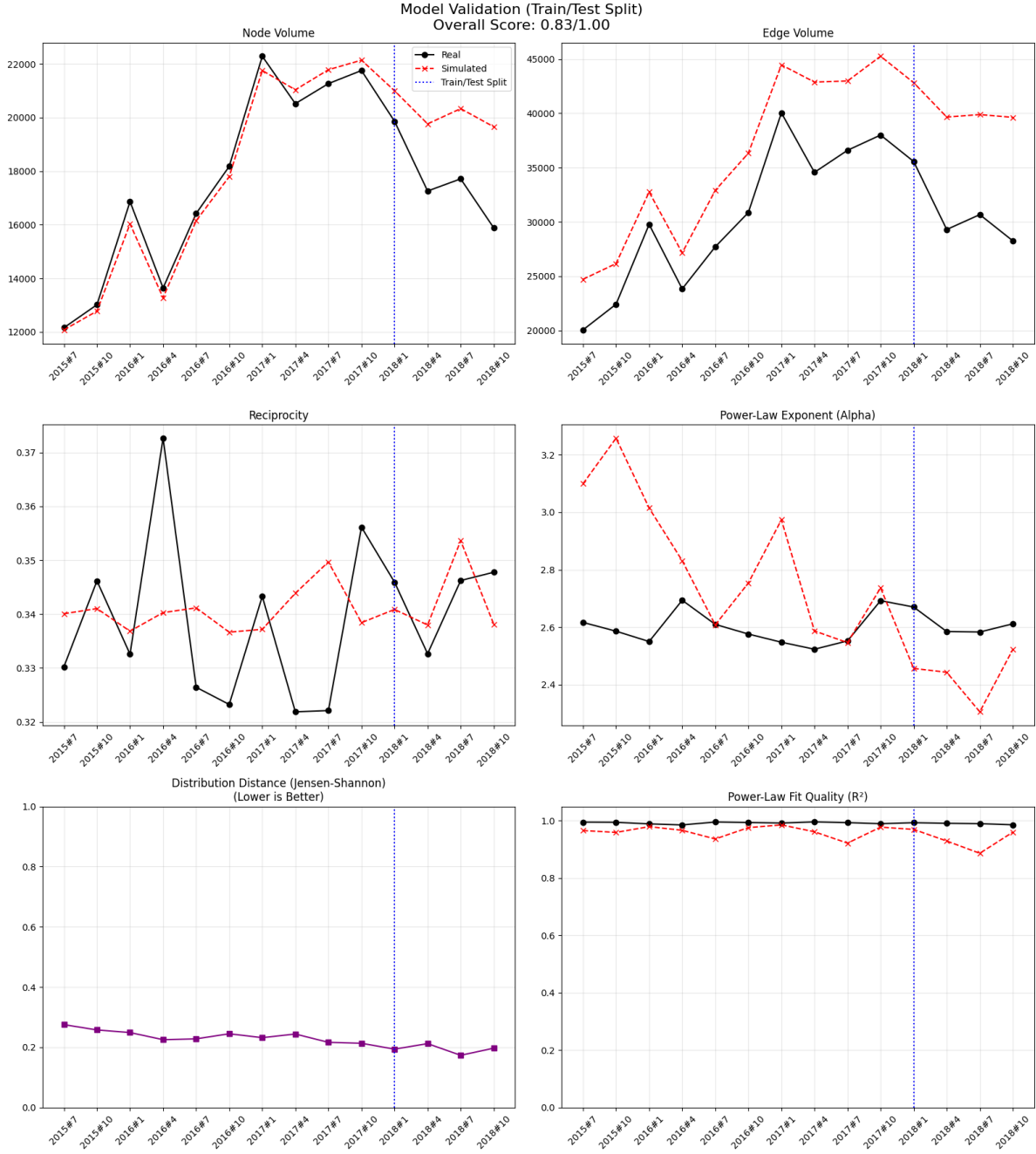
Fig. 7. Model Validation (Train/Test Split). The vertical blue line marks the split between the training phase (parameter estimation) and the testing phase (forecasting). The model successfully captures the trends in edge volume and reciprocity, and approximates the power-law exponent (α).