Structural Characteristics in Historical Networks Reveal Changes in Political Culture: An Example From Northern Song China (960–1127 C.E.)

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Abstract

The mass digitization and datafication of historical records brings about new possibilities to study or re-assess a broad range of individual events. By evaluating microlevel events in a social context simultaneously, insights into the macrolevel dynamics of society can be gained. This paper presents an innovative framework for historical network research that allows the comparison of structural characteristics in networks across different time periods, and illustrates it with an example of the political networks of Northern Song China. By using machine learning models for valence prediction and tracking the changes of structural characteristics related to structural balance, clustering, and connectivity in temporal networks, we reveal that the mid-to-late 11th century, during which political reforms took place, was characterized by political pluralism and even political tolerance, compared to earlier or later periods. The replicable framework proposed in this paper is capable of revealing significant historical changes that would otherwise be obscured, shedding light on the underlying historical dynamics of such changes.

Keywords

social network analysis, structural balance, valence prediction, cultural evolution, Chinese history

1. Introduction

The analysis of structural characteristics of relational data is a widely used approach in network analysis for understanding the dynamics of social relationships and advancing established sociological theories. These theories and characteristics include structural balance [17][6], structural holes [5], and clustering coefficient [32], among others. With the exponential growth of digital data and computing power, researchers can now explore data with an “unprecedented

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breadth and depth and scale" [20, p. 722]. Consequently, recent research efforts have capitalized on the digital traces of online user activities, providing valuable insights into the study of structural network characteristics. For example, Lerner and Lomi used relational event models (REMs) to examine the structural balance in a network based on the activities of Wikipedia editors [21], while Aref et al. proposed a framework that accounts for various levels of structural balance by analyzing multiple networks constructed from online platforms such as Reddit [1].

The born-digital data is not the sole resource that social network analysis can take advantage of. The digitization and datafication of historical records and literary texts has also opened possibilities for researchers to investigate significant macrolevel questions. As stated in the editors' introduction of the *Journal of Historical Network Research*, the last two decades have witnessed a development of network analysis "from a fringe theory into an established methodology in historical research" [28]. Historical network analysis has been applied to a broad range of objects, ranging from first-century Roman fiction [18] to sixteenth-century German religious writing [10]

Particularly, premodern Chinese culture attached great importance to historiography and had a long-standing tradition of recording historical events. Recent efforts to transform these sources into structured data present researchers with an unprecedented opportunity to employ computational approaches to analyze them. Examples of such efforts include digital libraries such as the Chinese Text Project [31], which offers full-text access to historical sources, and databases such as the China Biographical Database (CBDB) [15], which provides relational data on historical figures. In this paper, we examine structural characteristics of a network we built from association data in the CBDB to study the changes in political culture, and the Northern Song period (960–1127, all dates cited in this paper are C.E.) is selected as an example.

The Northern Song (960–1127) marked a significant transition in Chinese history, a time when the aristocracy dissipated and the new ruling elite defined themselves by learning instead of pedigree [7][14]. Historians have recently observed that the political culture was increasingly radicalized and polarized around the mid-eleventh century [19]. In consequence, reconciliations and amicable working relationships between rivals, which were not uncommon in the 1040s, became "politically and ideologically inconceivable" after the 1070s in the Northern Song court [34, p. 210]. To date, many historians have discussed this change by presenting a close reading of historical writings that shed light on topics such as the politics of commemoration [34], the discourses of politics [22], and ritual debates [19].

In contrast, this paper employs quantitative social network analysis methods to reexamine the change in the political culture in the Northern Song. Previous researchers have already studied the social networks in this period [9][29], but our work takes a distinct approach by delving into the structural characteristics of these networks. Furthermore, while we are informed by the triadic balance theory [17][6] widely used in network analysis, this paper also aims to transcend the conventional interpretations of triadic structures that focus mainly on balanced and imbalanced triads. A recent study that employs a similar approach, for example, interprets a higher proportion of imbalanced triads as an indication of political instability [33]. However, it is known that the eleventh-century intellectual landscape was extraordinarily pluralistic, leading to the formation of multiple contending visions in court debates that must not be obscured by the dichotomized language employed by court officials [4].

Therefore, we posit that the four types of triads are all meaningful but indicate different proclivities in the Northern Song political culture. We interpret the four types of triads in the Northern Song political network as follows: "+++" triads stand for "political collegiality" (two actors who have a common friend are also friends with each other), "++−" triads stand for "political tolerance" (two enemies nevertheless are both friends with the same third party), "+−−" triads stand for "political polarization" (two actors who have a common enemy are friends with each other), and "−−−" triads stand for "political plurality" (two actors who have a common enemy also fight between themselves).

The research objective of this interdisciplinary paper is to apply network analysis methods from the field of information science to examine the changes in political culture during the Northern Song period in the field of Chinese history. Specifically, our research aims to address two research questions:

1. How did structural characteristics of these networks—especially in relation to structural balance, clustering, and connectivity—vary over time?
2. What do these variations reveal about the changes in Northern Song political culture?

2. Methods

The research framework of this paper includes a data collection stage, a network construction stage, and three data analysis experiments.

2.1. Data Collection and Network Construction

We initially extracted all explicit political associations (including all associations under the categories of "supportive political association", "recommendation and sponsorship", and "oppositional political association") from the CBDB. The CBDB is a renowned relational database with biographical information about over 500,000 individuals. It provides the largest structured dataset on historical figures and their relationships in premodern China and is professionally curated for research purposes, by "systematically harvest[ing] data from biographical indexes, literary collections, and local gazetteers, which document these social interactions using formulaic expressions conducive to semi-automated data extraction" [12, p. 263]. Notably, the data in the CBDB is most comprehensive and well-represented for the Song dynasty (960–1279) [16].

As the majority of association data in the CBDB are not dated (of the 11,393 explicit political associations, only 2,478 or 22% are dated), we utilized officeholding records for reconstructing the political networks in different periods of the Northern Song. We extracted all officeholding records from pertinent tables in the CBDB, generating a list of 5,114 Northern Song officials with an officeholding record between 960 and 1127. We then selected political associations that involve at least one person in this list, resulting in 2,383 political associations of the Northern Song officials.

Treating the Northern Song officials as nodes and their relationships as edges, we then constructed a Northern Song political network based on these 2,383 political associations. We defined "supportive political association" and "recommendation and sponsorship" as positive associations, and "oppositional political association" as negative ones, so that an edge contains either only positive associations (marked as "+"), only negative associations (marked as "−"), or both positive and negative associations (marked as "D", for "duality"). This "officeholding-based" network consists of 1,567 nodes and 1,936 edges. For comparative purposes, we also constructed a "date-based" network consisting of 504 nodes and 538 edges using political associations dated between 960 and 1127. Since most people with a dated association in the Northern Song also have officeholding records, there is significant overlap between the two networks: only 28 nodes (5.6%) and 33 edges (6.1%) in the "date-based" network are not in the "officeholding-based" network.

To track the changes in the Northern Song political culture, we also created 149 temporal networks as the subnetworks of the "officeholding-based" network. These temporal networks are based on political associations involving officials who had an appointment record between 960 and 979 (1st temporal network), between 961 and 980 (2nd temporal network), and all the way up to the period between 1108 and 1127 (149th temporal network). The associations in each network did not necessarily occur within the specified 20-year time window (as there is often no data indicating when the associations took place). Thus, these temporal networks should be interpreted as networks of different cohorts of officials. For instance, the 1st temporal network represents the political network of the 960–979 cohort of officials. The 20-year window is used as it reasonably reflects the span of a cohort of officials.

2.2. Data Analysis

Next, we conducted three data analysis experiments. First, we trained and evaluated machine learning models to classify edge valence. Edge valence, also referred to as edge sign or edge label, signifies whether the relationship between two linked entities is positive ("+"), negative ("−"), or a duality ("D"). We used 13 features identified by the Python library NetworkX [13] for this classification task. These features included five node-level features for each of the two connected vertices, resulting in a total of ten features: local clustering coefficient [32], two measures of structural holes (constraint and effective size) [5], a measure of structural cohesion (k-component with the largest k the vertex belongs to) [26], as well as the size of the component the vertex belongs to. Additionally, we used three edge-level features: a measure of structural holes (local constraint) [5], two measures of connectivity (local node connectivity and local edge connectivity). Notably, these features reveal structural characteristics of unsigned networks. That is, they take into account only the presence or absence of an edge and do not consider edge valence. Thus, they are, by definition, independent of edge valence.

Next, we utilized seven classical machine learning models available in the Python module Scikit-learn [27], namely decision tree, random forest, SVM, logistic regression, perceptron, Naïve Bayes, and LDA. Each model was trained and tested using a 10-fold stratified cross-validation approach on the "officeholding-based" network for both three-class ("+", "−", or "D") and binary ("+" and "−", since the number of instances of "D" is much smaller than the other two classes) classifications. For both tasks, we undersampled the larger classes to balance the size of each class. We repeated the process for the "date-based" network to validate the results. However, due to the small size of the test sets in the temporal networks, we did not use them in the experiment.

For the second and third experiments, we used the 149 temporal networks to monitor how the different structural characteristics of these networks changed over time, instead of relying solely on the static networks. In the second experiment, we scrutinized the overall network structure, and tracked the changes in five network-level structural characteristics over the course of the Northern Song: network density, proportion of the nodes in the largest component, transitivity, average clustering coefficient [32], and average node connectivity [2].

In the third experiment, we analyzed closed triads (i.e., three nodes connected by three edges) [6]. For each temporal network, we computed the proportion of all four types of closed triads defined by varying combinations of edge valence: "+++", "++−", "+−−", and "−−−". In contrast to a previous study that excluded edges where both positive and negative associations exist due to the "lack of definitive information to determine valence" [11, p. 345], we calculated the "D" edges twice in our analysis, once as "+", and again as "−". We took this approach in the belief that positive and negative associations between historical figures did not cancel each other out. Building upon these four types of closed triads, we calculated the triadic balance rate for each network, that is, the proportion of "+++" triads and "+−−" triads out of all closed triads.

3. Results and Discussions

In this section, we will report the results from each experiment and offer brief historical interpretations of the results.

3.1. Experiment 1

For the "officeholding-based" network, the SVM model performs best in the three-class classification task, achieving an accuracy of 0.47 and a Cohen's kappa score [8] of 0.21, while the random forest model performs best in the binary classification task, achieving an accuracy of 0.64 and a Cohen's kappa score of 0.29. Given that all classes have an equal number of cases after undersampling in both tasks, a completely random classification would yield an accuracy of 0.33 and a Cohen's kappa of 0 for the three-class classification task, and an accuracy of 0.5 and a Cohen's kappa of 0 for the binary classification task. Therefore, although the performance of the machine learning models is not exceptional, they clearly outperform random classification. This also holds true for the comparison experiment on the "date-based" network, where the three-class classification task achieves an accuracy of 0.57 and a Cohen's kappa of 0.34, while the binary classification task achieves an accuracy of 0.71 and a Cohen's kappa of 0.43.

Because the structural characteristics that are used to train the models are entirely independent of valence, it can thus be concluded that the structural characteristics of the vertices of an edge and of the edge itself in the Northern Song political networks provide meaningful information about the valence of this edge. It is plausible that the structural position of individuals in the Northern Song political networks influenced their decision whether to develop positive or negative relationships with each other. This implies that as a general attribute of the Northern Song political networks, actors were constrained by the structure of their relationships.

3.2. Experiment 2

Figure 1 illustrates the evolution of several network-level structural characteristics in the Northern Song period. Specifically, the proportion of the largest component, the average node con-

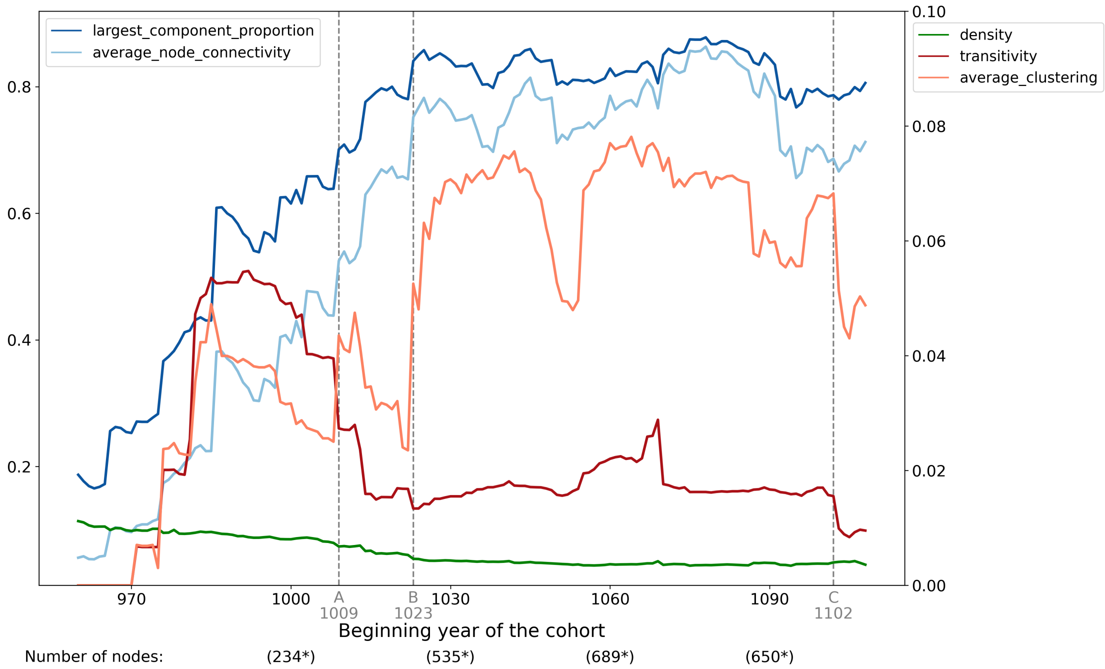

Figure 1: Change of Network-Level Structural Characteristics in the Northern Song. * represents number of nodes in the network. For example, ”234” under year 1000 signifies that there are 234 nodes in the network of the 1000–1019 cohort.

nectivity, and the average clustering coefficient all increased in the first half of the period, remained relatively stable in the 11th century, and decreased slightly in the beginning of the 12th century. The transitivity shows a trend that is similar to the aforementioned features after significant oscillations in the beginning of the Northern Song (the oscillations are likely due to the small size of the networks). Moreover, the density of the networks gradually decreased throughout the entire period.

We added three vertical lines to facilitate the interpretation of the results. The lines A (1009–1028 cohort) and B (1023–1042 cohort) denote the first networks in which two influential officials, Fan Zhongyan and Wang Anshi, respectively, emerged as actors in the networks. Fan and Wang were leaders of highly controversial reforms, the Qingli reform (1043–1045) and the Xining reform (1069–1085) respectively, and political factions formed around them [25, pp. 316–327][30]. Their inclusion introduced intensive political alliances and struggles that significantly increased the degree of network clustering and connectivity. On the contrary, line C (1102–1121 cohort) represents the first network that Zhang Dun’s career in government ended. A plausible interpretation is that Zhang’s downfall paved the way for the rise of Cai Jing, who “established an unchallenged power, inaugurating an era of political stability at court” [23, p. 571], leading to fewer cases of political alliances and struggles and thereby reducing the degree of network clustering and connectivity.

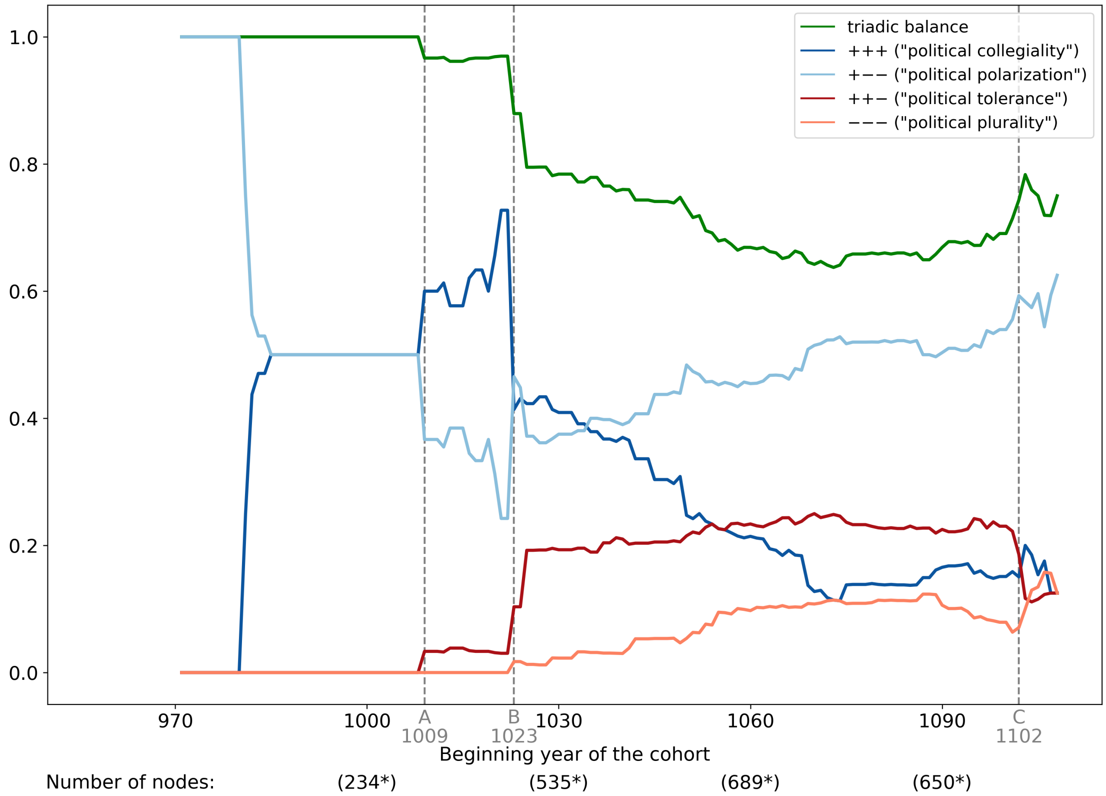

Figure 2: Change of Triadic Balance in the Northern Song

3.3. Experiment 3

Figure 2 shows considerable changes in the distribution of different types of closed triads over the Northern Song period. Due to the absence of closed triads in the earlier networks, the lines on the graph start only with the 971–990 cohort. The triadic balance rate shows a sharp decline during the first half of the 11th century, due to the increasing proportion of "++−" and "−−−" triads. However, in the early 12th century, the triadic balance rate shows a slight rebound, thanks to the decreasing proportion of "++−" triad. Furthermore, the two types of balanced triads ("+++" and "+−−") headed in opposite directions, although this does not have an impact on the triadic balance rate. Once again, we added to Figure 2 the same three vertical lines, as we did in Figure 1, to help interpret the results.

The inclusion of Fan Zhongyan's political associations (line A) resulted in an increase in "political collegiality" ("+++") and a decrease in "political polarization" ("+−−"), while the inclusion of Wang Anshi's political associations (line B) led to opposite changes. This corresponds to a change in political culture: while an amicable relationship between political rivals was still very possible in Fan's times, the Fan group introduced a moralistic language of politics that laid the ground for factional struggle that is believed to have intensified in Wang's times.

Besides, despite the sustained low levels of "political plurality" ("−−−"), line B notably exhibits a relative increase in its value, which should be closely related to the increasing diversity of the intellectual landscape that formed around Wang Anshi, Sima Guang, Su Shi, Cheng Yi, among others [3, pp. 161–163], as well as a somewhat unexpected increase in "political tolerance" ("++−"). "Political tolerance" remained at a relatively high level until line C, when "political polarization" increased due to the failure of "factional conciliation" [23, p. 566].

4. Conclusion

Our findings from Experiment 1 indicate that the structural characteristics of a network correlated with the behavior of the actors in the Northern Song political networks. In Experiments 2 and 3, we explored the changes in the degree of network clustering and connectivity, and the triadic balance rate. Our results show that they all increased in the first half of the 11th century and slightly decreased in the beginning of the 12th century. These findings challenge the traditional view of Northern Song politics as a dichotomy between reformers and conservatives [24] and reinforce the more recent view that highlights a pluralistic political culture [4], but from a macro-level perspective. Our data suggest that, while the political reforms in the 11th century generated intensive political struggles, they did not result in political polarization. Rather, the period was characterized by strong political pluralism and even a degree of political tolerance.

The future research will go into three directions. First, we intend to examine the specific associations that caused the changes in the structural characteristics of the political network, especially the unexpected political tolerance observed during the 11th century when political reforms took place. Through a close reading of the historical sources, we aim to gain deeper understanding of the underlying dynamics that contributed to the changes in Northern Song political culture. Second, we plan to enhance our machine learning approach by incorporating additional features, encompassing both characteristics associated with personal traits external to the network and supplementary network attributes that are independent of edge valence. By assessing which attributes exhibit the highest explanatory power in our models, we aim to gain a deeper understanding of actor behavior in the Northern Song political networks and the underlying political culture of the period. Third, we aim to conduct further time series analysis, using statistical approaches to scrutinize significant changes in the curves on both Figure 2 and Figure 3. This will enable us to compile a comprehensive list of rapid changes in network measures in supplement to the three changes marked by the vertical lines.

In conclusion, this interdisciplinary paper contributes to three fields. First, to the field of Chinese history, it provides a quantitative assessment that helps historians better understand changes in the Northern Song political culture. Second, to the field of social network analysis, it extends the application of quantitative analysis of network structures to historical data. Finally, to digital humanities and information science, it demonstrates the interpretative power of computational methods on important domain-specific questions, such as cultural evolution.

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