Social Network Analysis of Gobekli Tepe: Belief Propagation in 10th Millennium BC

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Abstract. For years, we believed that the transition of human communities from simple hunter-gatherer societies to complex sedentary societies occurred due to the expansion of cultivation and the rise of agriculture. Gobekli Tepe, a pre-pottery Neolithic site in Turkey, presents a new explanation that can shed light on the human development to civilization. This archaeological site was constructed through the collaboration of various hunter-gatherer societies as a communal space for ritualistic purposes. Studies show a similarity in architecture, tools, crops and symbolism of some of Gobekli Tepe's neighboring cultures. The commonalities suggest the existence of a shared belief before the construction of the site. Utilizing agent-based modeling and social network analysis tools, this paper investigates the belief propagation to observe the emergence of leaders among the population and examines the network structure of the communities constructing Gobekli Tepe. Most importantly, this site represents a complex adaptive system where the interactions of its components may have caused the emergence of a belief institution.

Keywords: Gobekli Tepe · Social Network Analysis · Leadership · Belief Propagation · Network Structure

1 Introduction

Conducting archaeological research comes with various challenges. These challenges are most prominent in studying the following subjects: a) emergence, communities, and complexity; b) resilience, persistence, transformation, and collapse; c) movement, mobility, and migration, d) cognition, behavior, and identity; and e) human–environment interactions [15]. Other limitations such as the time consuming nature of excavations, project funding, socio-political conflicts, and regional climate affect every stage of an archaeological research. Various modeling approaches are currently utilized by archaeologists to fill in the gaps of yet unattained data and propose possible answers to questions regarding environmental, cultural, social, and biological dynamics [2, 28, 16]. We consider the case of Gobekli Tepe as a test-bed for the study of belief propagation among polities who built the site, the emergence of leaders among the population, and the structure of the social network through computational modeling.

Gobekli Tepe is a Pre-pottery Neolithic (PPN) archaeological site located on a plateau in Upper Mesopotamia and near the town of Sanlurfa in Southeastern

Turkey [23]. Gobekli Tepe was built by a number of hunter-gatherer societies in the region as a communal site for ritualistic purposes [24]. The discovery of this archaeological monument challenged the widely accepted theory of prehistorians who argued that civilization occurred as a result of sedentary lifestyle and agriculture [11, 6]. Archaeologists arguing the opposing side consider Gobekli Tepe as evidence that civilization occurred as a result of the human mind's ability to imagine and believe [24, 9]. These beliefs were the mobilizing sources of the social identity and collective action to built villages, chiefdoms, and states.

Our research utilizes archaeological data and theories to construct an agent-based model (ABM) representative of significant polities in the Urfa region and performs social network analysis (SNA) on the belief propagation among the population. This study intends to investigate the connections among the model population by turning the model into a network of nodes and edges. From this network, data is extracted to perform a SNA. The collected data, methods employed and analysis executed are done to address the central inquiries of the paper. We focus on observing the emergence of leader nodes (agents) from the model and examining the network for a small-world structure and a power-law degree distribution. Diseases and ideas can spread from one person to another, across similar types of networks that connect people, and exhibit very similar structural mechanisms [12]. To this effect, the spread of ideas are sometimes referred to as social contagion. The similarities observed in the susceptible-infected-susceptible (SIS) model in epidemiology and the belief propagation at Gobekli Tepe demonstrate that the propagation of belief follows a scale-free network of node degree distribution that produces a power-law behavior on the macro level. This finding is important, for it paves the path for power-law based examination and analysis of belief propagation models.

2 Related Work

According to the site survey, Gobekli Tepe was constructed in a period of 800 years [23]. The site is not located near any body of water and it bears no evidence of population residence [23]. Animal bones and botanical remains found on the site include wild cattle, wild ass, gazelle, wild pig, wild almond, pistachio, and wild grain [23]. Archaeologist who have excavated various sites in the fertile crescent believe Gobekli Tepe to be a sanctuary built as a collaboration among multiple hunter-gatherer cultures [10, 24, 3]. A communal building for ceremonial purposes constructed by cultures whose artifacts were excavated at the site. Considering the similarities in iconographies at each of these sites, they are assumed to have had similar shamanistic beliefs and rituals. The cultures in the ABM represent the founding polities of Gobekli Tepe.

The spread of beliefs has been studied in the fields of information diffusion and belief propagation. Belief propagation is a message-passing algorithm that helps draw inference on graphical models such as Bayesian networks and Markov random fields [21]. Information diffusion occurs as a result of information flow from an individual to another in a network [18]. The spread of information is studied through explanatory models and predictive models. Explanatory models include epidemic models (e.g. Susceptible, infected, susceptible) and influence models (e.g. influence maximization) and are used to investigate the behavior of factors that influence others in a network [18]. Information diffusion can be compared to the transmission of a pathogen. The SIS model demonstrates the transmission of a pathogen from an infected individual to a susceptible one [20, 14]. Such networks follow a scale-free nature and result in power-law distributions. Scale-free networks have highly heterogeneous degree distribution that follows a power-law [1]. Most nodes in scale-free networks generally have few neighbors and only a few nodes have a high number of links [1].

Many real-world networks have high clustering and short average path length which are characteristics of small-world networks [30]. Such networks have high modularity, meaning that there are groups of the nodes that are more densely connected to one another than to the rest of the network. Nodes in a small-world network are connected to one another through a chain of acquaintance nodes. Small-world networks are studied to understand the effect of the small clusters on the value of connectivity in the network as a whole [25]. Nodes with the highest connectivity to various clusters are essential to the adaptation and mobilization of each cluster. While such nodes are key to the network information flow, nodes with high connectivity that have kept their state through a simulation, may be key to the preservation of a state in a small-world network. Such nodes may also influence their neighboring nodes in changing their states. Centrality measures are often employed to gain insight on the role of each node [17].

Hunter-gatherer groups seem to share characteristics with small-world networks. These groups were generally formed of kin and family-level members whom, depending on the region, may have been open to exchanging mates, goods, and information with other groups [5, 4]. Historically, living in groups has allowed humans to survive in the most hostile environments with dangerous predators and scarce sources [13]. Hunting, sharing food, and defending the group make the majority of a hunter-gatherer's life [27]. While these acts may seem simple, the collective action that motivates the groups to accomplish them, needs to be organized by a leader [26]. Group movement, group cohesion, and intergroup politics are the main coordination problems a leader had to resolve [27]. It is important to note that in hunter-gatherer societies leadership emerged through the rise of a respected, committed, and connected individual [8]. Using social networks to study the emergence of leadership, allows the identification of patterns of relationships between individuals [29].

3 Data, Model Design, and Analysis Method

The environment of the ABM in the initial stage includes four tribes laid out across a conceptual landscape. Since this is an exploratory model serving the purpose of understanding the agent-agent and agent-environment dynamics, the model was not built according to the exact topological data of the region and time. Therefore, the landscape is simplified to provide equal opportunity for hunting, gathering, cultivation, and encounter and to eliminate the sensitivity of the model to topological factors. Each time-step in the model represents one day. Every tribe in the model has a food property. If an agent does not eat one food unit in 14 days due to the tribe's insufficient food resources, it dies. The agents have the alternative to eat grain that grows in the environment. The more an area is used for gathering of grains and cultivation, the higher its grain yield will be. If an agent from any tribe dies, a new agent will replace it. However, the new agent may be in a different tribe. This is because the tribe can take a new member (whether by joining or replacement), when its current population is less than its initial state, and these current members have a food surplus.

The four clusters, called tribes, each consist of 10 members. The four tribes start in four locations around the landscape. Each tribe is signified by a color. All agents have a ten element array of information concerning their encounters with other agents and the propagation of beliefs in these encounters. These arrays are referred to as the agent's memory in the model. Every tribe member's memory array is initially populated entirely by the culture of its tribe. On each update, there is a 50% chance that the agent may be influenced by agents in its neighborhood. The neighborhood setting of the model follows Moore's [19] definition. The culture of every agent who passed the 50% chance, called the influence rate, is then added to a list referred to as possible belief. Then, the agent chooses the most common belief in its memory array. If there's a tie, the agent's dominant belief is added to the list and then the most common belief is chosen. If there's still a tie, the first item from the possible belief list is used as a tiebreaker. In the end, a new memory is added to the agent's memory, pushing the oldest memory out of the array. The culture with the majority of elements in the agent's memory array is considered to be its dominant belief.

The network data is extracted from the ABM. Various simulations were conducted with the model at initial settings (10 agents per tribe), and with 20 agents per tribe. Then, a data-frame for each time-step was extracted which included the following information for every agent: id, coordinates (x, y), neighbors (in every eight patch surrounding the agent), culture (array of memory), and dominant belief (mode of their culture). The data was used for the SNA pre and post processing. Each node represents an agent in a tribe. An agent will have a set of 10 memory elements that are identical to every other agent in their tribe at the start of the model. The edges develop between nodes based on proximity. If two or more nodes move and situate in close enough geographic proximity that exchange of belief can occur, then an undirected edge between those nodes is established. Then, based on the influence rate, belief exchange may or may not occur between the nodes. Since all nodes can influence each other by a probability, the network is undirected. Therefore, the indegree and outdegree of the edges can't be collected and considered to amplify the importance of a node.

A number of SNA techniques were utilized to examine the central questions of the paper. A leader in this model is a node with high degree centrality over time, who kept a dominant belief for the longest over all the time-steps. To extract the data on the top five nodes with the highest centrality measures, an adjacency matrix was made. Every centrality measure was taken for every time-step and sorted from the highest to the lowest. Using the data-frame, every agent's age and the percentage of each belief as their dominant belief over their lifetime was extracted. By taking the number of times an agent was among the top five for each centrality measure, a list was organized. The normalized centrality measures of each agent was also taken in order to indicate the number of times an agent was among the top five for each centrality measure based on their age. This analysis was used to examine the emergence of leaders from the network.

To test the network for small-world structure, clustering coefficient and average shortest path length were collected for each time-step. The clustering and short average path length were plotted to investigate high clustering in the network. Log-log plots were also created using the network to investigate if the degree of the nodes follows a power-law distribution. The examination of the centrality measures, clustering coefficient, average shortest path length, and log-log plots are reported and explained in the results and discussion sections.

4 Results

Due to the large number of plots, only example graphs and tables for the 40 population are presented in this paper. The nodes are in fixed clusters based on their initial dominant culture. Edges connecting nodes change signifying the connections between agents based on proximity in the ABM. Figure 1.a demonstrates the belief propagation with 40 agents. In this setting all the four beliefs had relatively equal life-spans and they merged into one belief one after another over a short period of time. Figure 1.b demonstrates the belief propagation with 80 agents. While the results for both population settings showed that belief 2 (orange), lasted for the longest time as the dominant belief of the majority of the population and finally took over; at higher population two of the four beliefs had short life-spans and their agents quickly converted to the two remaining beliefs.

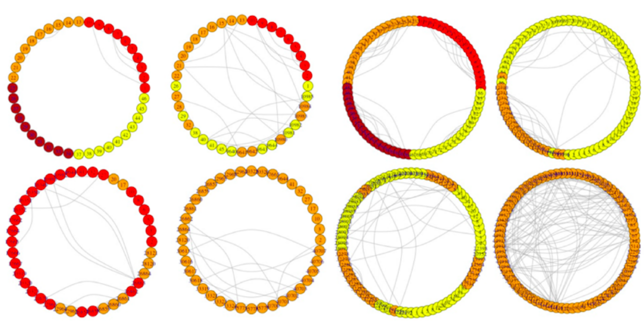

Fig. 1. a. Sample evolution of the network at 40 pop. (left four graphs) [top left: time-step 1, top right: time-step 3,000, bottom left: time-step 7,000, bottom right: time-step 11,000], b. Sample evolution of the network at 80 pop. (right four graphs) [top left: time-step 1, top right: time-step 3,000, bottom left: time-step 7,000, bottom right: time-step 13,300]

Table 1. Degree centrality and belief of leader nodes with 40 population

id	Age	Belief 1	Belief 2	Belief 3	Belief 4	Top Degree	Normalized Top Degree	Longest Belief
4	3461	0.8564	0.0000	0.0000	0.1436	1324	0.3825	1
1	3459	0.8037	0.0124	0.0000	0.1838	860	0.2486	1
5	7101	1.0000	0.0000	0.0000	0.0000	1348	0.1898	1
16	4218	0.0000	1.0000	0.0000	0.0000	659	0.1562	2
7	3461	0.9653	0.0000	0.0000	0.0346	508	0.1467	1

Table 2. Centrality and normalized measures of leader nodes with 40 population

id	Age	Top Closeness	Top Betweenness	Top Eigenvector	Normalized Top Closeness	Normalized Top Betweenness	Normalized Top Eigenvector	Longest Belief
4	3461	1129	941	971	0.3262	0.2718	0.2805	1
1	3459	625	620	537	0.1806	0.1792	0.1552	1
5	7101	1134	977	975	0.1596	0.1375	0.1373	1
16	4218	574	588	578	0.1360	0.1394	0.1370	2
7	3461	350	345	343	0.1011	0.0996	0.0991	1

4.1 *Emergence of Leaders*

The results of the analysis on the centrality measures demonstrated the emergence of leaders in the network. As previously mentioned, leader in this model is a node with high degree centrality over time, who kept a dominant belief for the longest over all the time-steps. Data collected on the top five leader nodes for both population tests, shows that agents with higher age and degree centrality, will have higher normalized degrees. Tables 1 and 2 demonstrated this correlation. The tables show the occurrences of an agent reaching the top five based on centrality measures gathered over their life-span. Table 2 also shows the percentage of the leaders' life-span that was dedicated to each of the four beliefs. Note that the majority of leaders in both population tests belonged to the beliefs with the longest life-span and not the ones that took over in the end.

4.2 *Small-World Network Structure and Power-Law Degree Distribution*

The results of the analysis demonstrated a small-world network structure and a power-law degree distribution. Both tests showed high clustering coefficient and low average shortest path length which correlated with a small-world network structure. Figure 2 shows a 0.488 average clustering coefficient and an average shortest path of 1.318. Results for 80 population demonstrated a 0.412 average clustering coefficient and an average shortest path of 1.474. The histogram and log-log plots of node degrees showed that the network also follows a power-law distribution. Log-log plots and histograms of degree distribution for both populations are recorded at time-steps near the end of the run for this simulation. Figure 3 shows the results for 40 population.

As sensitivity analysis is generally conducted to find parameters and conditions that the model is sensitive to [22], we conducted this analysis by changing population and influence rate parameter while keeping all the remaining parameters in their initial setting and conducting multiple simulations. The analysis on various simulations shows that population size and influence rate effect the

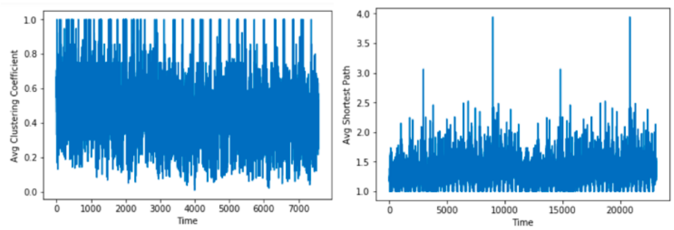

Fig. 2. Average clustering coefficient (left) and average shortest path length (right) for 40 population

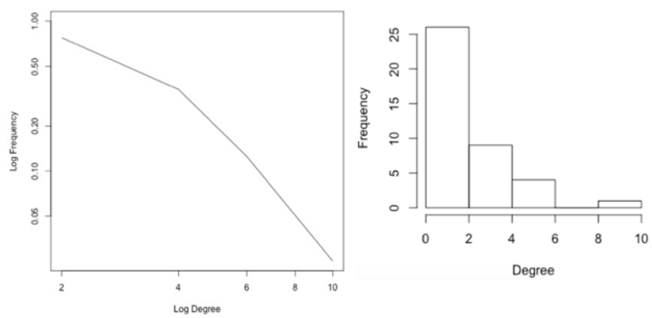

Fig. 3. Log-Log plot of degree distribution for 40 population (left) [time-step 11,256], Histogram of degree distribution for 40 population (right) [time-step 11,256]

speed of the belief propagation but not its occurrence. A larger population results in initial speedy propagation and a later slower propagation, while smaller populations have less of a propagation speed fluctuation.

5 Discussion

Configurations of edges affect nodes connected to them by shaping behavior and affecting processes such as diffusion. Centrality measures were examined as a part of static measures. The degree of the nodes represent the number of edges they are connected to and can signify the importance of a node in a network. Degree centrality is an important measure for finding local leaders through direct influence. Betweenness centrality is helpful in finding brokers of information and collaboration. In this case, the agents with high betweenness centrality were among agents on the edge of their tribe who were in proximity to encounter agents of other tribes. Closeness centrality allows for the detection of the nodes that are at the center of a propagation. Finally, eigenvector centrality is important in finding global leaders through connected neighboring nodes.

Similar to disease spread, the diffusion process of this network is simple contagion because each connected node can influence/infect a node by some probability. The model is dynamic and not random because the nodes are connected to one another based on proximity and influenced by a percentage based on a process of belief exchange. The results demonstrate that at lower population, all the tribes had an equal opportunity to move around the landscape, hunt, gather, and spread their beliefs. The low population and surplus of food allows agents to provide food for themselves and their tribe members. Therefore, mortality rates are lower. The relatively equal life-span of the beliefs in this setting resemble a cultural coexistence that is observed in human societies of the lower population.

At higher population, two beliefs disappear relatively quickly and their members all take on a new beliefs. Mortality rate at this setting is high. This is due to the scarcity of food and the high demand for it. The sufficiency of food production keeps them from moving around the landscape and running into people of the other belief. However, even when they encounter others, due to their memory containing a majority of their own belief elements, it takes each individual multiple encounters to be converted to a new belief. Note that agents also always return to their tribes. Therefore, even if they gain a few new beliefs in their memory, it can quickly be overridden by the neighbors of their belief. The higher population presents a dynamic of resistance towards accepting a new belief. The network shows that when there are equal people in two competing beliefs with a high population, propagation occurs over a longer period. Note that in both population tests, the belief which propagated was not the one with the longest life-span. This can be due to the effect of nodes with high centrality measures.

5.1 *Emergence of Leaders*

In this network, a leader is considered to be a node with high degree centrality over time, who kept a dominant belief for the longest over all the time-steps. The majority of leaders in both population tests belonged to the beliefs with the longest life-span and not the ones that finally took over. This suggests a correlation between the leaders and the beliefs with the longest life-span. It is possible to suggest that population variation does not affect the emergence of leaders and their association with beliefs that lasted the longest. This possible correlation can ease the process of finding one from another. The resistance showed at higher population results in beliefs holding the same dominance ratio.

5.2 *Small-World Network Structure and Power-Law Degree Distribution*

Both population test results demonstrated the structure of the network to be small-world and the degree distribution to follow a power-law. The histogram and log-log plots of node degrees verify these findings. Meaning that while the probability of high-degree nodes gradually declines, such nodes will exist as leaders on the fat tail of the power-law distribution. Power-law mechanism shows node growth, which means that on average older nodes have more edges and preferential attachment meaning new nodes tend to connect to well-connected nodes. These tests show high clustering coefficient and low average shortest path length. The histograms and log-log plots for all time-steps show that for most simulations, the majority of nodes have low degree centralities while a minority of the nodes have high degree centralities.

Verification and validation are processes that confirm the accuracy and robustness of a model [7]. The verification process of the model was conducted by checking the functioning of the code and comparing the model results at various states to the expected model results. Validation was examined by strengthening the assumptions of the model, such as food sources with thorough research on nutritional and environmental data from the region. The state after one belief propagates through the system can also be studied and compared to the state before it, which increases our understanding of the processes leading to the cooperation, management, and production at Gobekli Tepe.

6 Conclusion

Utilizing social network analysis and agent-based modeling as our methods, we simulated the case of belief propagation that possibly lead to the construction of Gobekli Tepe. The analysis showed that population increase, decreases the propagation of belief in the network. Leaders emerge from the networks. The length of the life-span of a belief is correlated with the dominant belief of the top five leaders. High clustering coefficient and low average shortest path length confirm that the network has a small-world structure. The histograms and log-log plots of node degrees follow a power-law distribution.

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