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Searching for hidden bridges in co-occurrence networks from Javanese *wayang kulit*

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Abstract

We propose that questions of long-standing interest in the study of *wayang kulit*, Indonesia's centuries-old shadow puppet theatre tradition, can potentially be posed in structural terms and investigated using the tools of network science. Here, we construct weighted character co-occurrence networks based on the Javanese *wayang kulit* incarnation of the Mahabharata epic, supplementing nodes with metadata specifying characters' tribal affiliations and historical origins in either Indian or Javanese traditions. In order to identify characters who play unique structural roles which other approaches may overlook, we generate null model ensembles of artificial networks that share the empirical networks' degree sequences, underlying episodic structures, and node metadata. By ranking nodes by the extent to which their betweenness centrality exceeds a null model's expectations, we reveal characters whose appearances in a story, while not necessarily large in number, tend to serve the specific topological function of bridging groups of other characters. Decomposing betweenness centrality values into their inter-faction components then clarifies how these bridge-like characters are situated among the epic's various social factions. We observe that female characters, despite being few in number and appearing relatively infrequently, appear to dominate these rankings disproportionately. Analyses involving closeness centrality reveal low-closeness outliers whose appearances, although relatively frequent, keep them structurally isolated and distant from the rest of the Mahabharata universe; these include the epic's antagonists, the Korawa. Characters with historical origins in the Javanese tradition are found to be embedded just as closely within the network as are characters from the Indian canon when their degrees are taken into account using null models.

1 Introduction*

1.1 Social complexity in the Javanese *wayang kulit* incarnation of the *Mahabharata*

Like many stories of great historical and cultural importance, the *Mahabharata* is a tale of two warring factions. In Javanese *wayang kulit* shadow puppet theater, one of Southeast Asia's most important theater traditions, the *Mahabharata* is depicted episodically in a series of self-contained but connected stories, with a typical overnight performance covering one story (*lakon*) from the epic. The primary focus of these stories is the power struggle between two groups of adversaries: the *Pandawa* and the *Korawa*. However, the dramatic intrigue of the *Mahabharata* often stems from characters and relationships that straddle these identity lines. Some characters, due to complicated family ties or histories, juggle conflicting loyalties to both of the warring tribes. Deities intercede in the conflict, sometimes even simultaneously aiding members of both tribes against one another without ever decisively taking sides. This complexity is further enriched in the Javanese *wayang kulit* incarnation of the epic through the inclusion of characters and stories of indigeneous Javanese origin. For example, the *Punokawan* are a group of clown-servants with historical origins in pre-Hindu Javanese mythology, assimilated into *Mahabharata* stories to serve as advisors to the protagonist *Pandawa* tribe. Some plot elements, such as the so-called *carangan*

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("branch"') stories, are also understood to represent Javanese additions to the original Indian epic[1].

1.2 Character co-occurrence networks and social complexity

As a recent explosion of research from the digital humanities demonstrates, network representations of stories can bring into sharper focus this notion that characters, rather than simply falling in line with one of two clearly-delineated sides of a conflict, are often bound together in a more complex tapestry of overlapping allegiances and rivalries[2]. By casting this web of relationships in a more tangible form, certain insights that might be missed by traditional scholarship can sometimes be brought to light. Each character and relationship within a fictional universe, while possessing intrinsic traits that are revealed and developed through events depicted in the narrative, can meanwhile also be considered in terms of the structural role it plays within this network. From this structural perspective, a work of fiction can be analyzed in terms of how it joins together — or, conversely, how it keeps separate — its various characters and social factions. Does the story tend to depict a certain faction more often via in-group interactions, or through their encounters with the outside universe? How does the story use certain characters or factions to connect, or to otherwise come between, the other characters and groups that appear within the work's fictional

1 Alan H. Feinstein, Lakon carangan: Ringkasan lakon, vol. 3 (Akademi Seni Karawitan Indonesia, 1986); Laurie Jo Sears, Shadows of empire: Colonial discourse and Javanese tales (Duke University Press, 1996); Sri Mulyono, Wayang, asal-usul, filsafat dan masa depannya (Gunung Agung, 1978); Jacob Kats, De wajang poerwa: een vorm van Javaans toneel, vol. 1 (Foris Publications, 1923); Victoria M. Clara van Groenendael, Wayang Theatre in Indonesia: An Annotated Bibliography (Foris Publications, 1987); James R. Brandon, Pandam Guritno, and Roger A. Long, On thrones of gold: Three Javanese shadow plays (University of Hawaii Press, 1993); Bernard Arps, Tall Tree, Nest of the Wind: The Javanese Shadow-play Dewa Ruci Performed by Ki Anom Soeroto: A Study in Performance Philology (NUS Press, 2016).

2 Aris Xanthos et al., "Visualising the dynamics of character networks," Digital Humanities (2016), 417–419; Michaël C. Waumans, Thibaut Nicodème, and Hugues Bersini, "Topology analysis of social networks extracted from literature," PloS ONE 10, no. 6 (2015): e0126470; Peer Trilcke, Frank Fischer, and Dario Kampkaspar, "Digital network analysis of dramatic texts," Proceedings of the Digital Humanities 6, no. 7 (2015): 8; Seung-Bo Park, Kyeong-Jin Oh, and Geun-Sik Jo, "Social network analysis in a movie using character-net," Multimedia Tools and Applications 59, no. 2 (2012): 601–627; Gyeong-Mi Park, Sung-Hwan Kim, and Hwan-Gue Cho, "Structural analysis on social network constructed from characters in literature texts," Journal of Computers 8, no. 9 (2013): 2442–2447; Frank Fischer et al., "Network Dynamics, Plot Analysis: Approaching the Progressive Structuration of Literary Texts," Digital Humanities 2017 (Montréal, 8–11 August 2017). Book of Abstracts (McGill University, 2017); Yeon-Mu Choi and Hyun-Joo Kim, "A directed network of Greek and Roman mythology," Physica A: Statistical Mechanics and its Applications 382, no. 2 (2007): 665–671.

universe? The quantitative tools provided by network science give scholars a promising framework with which to more systematically explore the deeper complexity beneath a story's most salient binary rivalry.

Character co-occurrence networks provide one such description of the complex scaffolding of character interactions upon which a story is played out. In these networks, the strengths of the connections between character nodes reflect how frequently those characters appear together within some suitably-defined temporal or spatial window. While the choice of co-occurrence window can affect the features of the resulting network, construction of such a network typically requires little or no prior subjective interpretation. Counting co-occurrence events by such a definition does not account for the qualitative aspects of an encounter, nor for the nature of the underlying social tie; co-occurrence may not even necessarily signify a particularly direct exchange between two characters. By no means does a co-occurrence network give a complete description of the fictional universe supposedly revealed by a narrative, which is ultimately too abstract, multifaceted, and subjective to be definitively characterized — let alone quantified — by any single approach. But by representing a story's aggregate of non-simultaneous character encounters as a structural object, a co-occurrence network can capture meaningful information about the patterns of interactions through which a particular realization of a story depicts this underlying universe.

1.3 Comparing distinct retellings of common stories

As the *wayang kulit* tradition has demonstrated to a unique extent for hundreds of years, a single storyline can be told and retold in numerous ways. Historically, *wayang kulit* scholarship has naturally involved comparisons of different realizations of the same set of canonical storylines, whether by comparing Javanese *wayang* to the Indian traditions from which it is understood to have evolved, by studying the evolution of its stories through time, or by comparing its various distinct regional traditions. Differences among different *dhalang* (puppetmasters) in delivering a common story are also of interest, as the ability to present novel re-interpretations of well-known stories is held highly within *wayang* culture. And especially since performances are often deliberately tailored to correspond to local current events, variations between specific performances are also of particular interest within this tradition.

Each of these distinct realizations may emphasize different characters, relationships, and events than another version of the same story does, and these are precisely the types of differences which a co-occurrence network perspective is potentially capable of discriminating. As we will discuss later, direct comparative analyses of multiple distinct realizations of the *Mahabharata* epic, particularly those representing different chronological stages from throughout the historical evolution of its Javanese *wayang kulit* incarnations, may involve certain complications which place them beyond the scope of the current work. However, the potential for these comparative or dynamical historical network analyses in future work motivates our current initial step in that direction.

1.4 Historical origins and co-occurrence structure in *wayang kulit*

The traditional terminology of *wayang kulit* often carries vivid structural imagery. *Silsilah* (Arabic for "chain" or "linkage") are family trees of characters traditionally included in *wayang* encyclopedias. Even the name of the *carangan* (Javanese for "branch") stories of the Javanese tradition offers a description of their structural function within the epic, casting them as asides of secondary importance deviating from the epic's proper core of *parwa* or *pokok* ("trunk") storylines from the Indian canon. But are the structural claims seemingly implicit in this terminology actually borne out in the scaffolding of character co-occurrences established throughout the course of the stories? Even in lieu of sufficiently detailed data sets which would allow for a more direct observation of how Javanese elements were assimilated into the structure of the Indian *Mahabharata* over time, we propose that co-occurrence structures representing its current incarnations may provide some novel — albeit indirect — insights into the historical processes by which they were formed. Network science provides a clear framework with which to approach the question: How centrally have Javanese innovations to the *Mahabharata* come to be embedded within the epic? This structural perspective could thus complement more traditional approaches to address these issues of long-standing relevance in the study of *wayang kulit* history.

1.5 Scope of the current work

As a first step along these lines, we make an initial network-theoretical venture into the world of *wayang kulit* by constructing weighted, undirected co-occurrence networks based on one representative description of the most popular stories of the Javanese *wayang kulit Mahabharata* tradition[3]. Nodes are endowed with metadata describing characters' affiliations with various social factions based on information which we have compiled in an interactive Digital Wayang Encyclopedia[4]. Viewing this approach as an exploratory framework which may reveal previously unseen patterns within the epic — as a "defamiliarization strategy" with which to glean fresh insights from widely-

3 Purwadi, Kempalan Balungan Lakon Wayang Purwa [Compendium of Classical Wayang Plot Scenarios] (Cendrawasih, 2008).

4 Miguel Escobar Varela, Digital Wayang Encyclopedia (available online under the following URL: https://villaorlado.github.io/wayangnetworks/html, accessed 23 November 2018).

studied works[5] — we seek to identify characters and relationships whose structural roles may not be so immediately visible, even when viewed from other quantitative perspectives. That is, we begin by deliberately seeking out characters whose importance, as quantified by various network centrality measures, cannot simply be explained by how frequently they appear.

The most substantial advantages to be gained through the adoption of a network perspective involve not just superficial renamings of certain quantities (e.g. a character's number of episodes as its "degree"), but rather account for larger-scale structural patterns and chains of non-simultaneous co-occurrence events that extend through a network. Unlike other network-theoretical measures such as degree which only take into account the local environment immediately surrounding a node, higher-order centrality measures such as betweenness[6] and closeness centrality[7] describe a node's position amid extended chains of co-occurrence relationships. Betweenness centrality sums the fractions of shortest paths between node pairs which pass through a given node or link, and closeness is proportional to the inverse sum of the lengths of all shortest paths between a given node and all other nodes. By considering larger-scale patterns that form as the aggregate of non-simultaneous encounters between multiple characters, these measures are uniquely network-theoretical in nature, and so may reveal insights that are invisible to other methods. While the methods used in the current work can be applied to a wide variety of these centrality measures, here we focus specifically on betweenness and closeness centrality because of their intuitive interpretations in the context of co-occurrence networks. They allow us to address specific issues of interest in the study of *wayang kulit*: how various social factions mediate — or otherwise find themselves situated between — the *Pandawa* and *Korawa*, and whether characters with historical origins in the Javanese tradition tend to be closely embedded among other characters within the network, or rather are relegated to peripheral positions or "branches" detached from the network core.

Since weighted-network centrality measures inherently tend to take on higher values for more strongly-connected nodes, ranking nodes by their raw centrality values may lead us to conflate a node's overall connection strength with the specific topological features we wish to target when exploring these questions. We account for this using null models, which clarify the extent to which a character's centrality values are explained by its overall number of

5 Franco Moretti, Graphs, maps, trees: abstract models for a literary history (Verso, 2005).

6 Linton C. Freeman, "A set of measures of centrality based on betweenness," Sociometry, 1977, 35–41.

7 Linton C. Freeman, "Centrality in social networks: I. Conceptual clarification," Social networks 1, no. 3 (1978): 215–239.

appearances within the context of the epic, and so allow us to identify nodes whose centrality values can be more rightfully attributed to special, higher-order patterns of co-occurrence established throughout the course of the epic. We then use these insights to guide our explorations of how *wayang kulit* brings together the various social factions of the *Mahabharata* universe.

These explorations reveal several structural features distinguishing the epic's tribal factions: the protagonist *Pandawa* are often depicted in encounters with non-*Pandawa* characters, whereas other tribal factions are most often depicted through encounters with their in-group peers, with one character acting as the community's primary bridge to the rest of the network. While these secondary tribes both form tight-knit structural communities, their differing portrayals are also reflected in the results of null model comparisons: the *Punokawan*, who act as allies to the *Pandawa*, are positioned closer to the rest of the network than are the antagonist *Korawa* tribe. Female characters often emerge as outliers in the search for structural bridges, reflecting common features of their roles within wayang kulit. Characters who were integrated into the *Mahabharata* during the evolution of the Javanese *wayang kulit* tradition from its original Indian roots are shown to be embedded just as centrally within the network (in a sense we will make more precise later) as are canonical Indian characters.

2 Methods

2.1 Constructing co-occurrence networks

We construct weighted, undirected co-occurrence networks based on lists of characters appearing in each scene (*adegan*) from 23 commonly-performed stories (*lakon*) as extracted from a representative compendium of plot synopses from the Javanese *wayang kulit* incarnation of the *Mahabharata*[8]. Since many details of performances are not standardized, no single, definitive source text or recording exists; rather, these synopses outline the key plot points typically depicted in each scene and specify which characters are involved[9]. We thus consider these stories and scenes as the intrinsic narrative units of the epic, and rather than using sliding windows based on clock time within a particular recording or proximity within a particular transcription, we use appearances

8 Purwadi, Kempalan Balungan Lakon Wayang Purwa [Compendium of Classical Wayang Plot Scenarios] (Cendrawasih, 2008).

9 English language synopses for these stories are accessible through our Digital Wayang Encyclopedia (Miguel Escobar Varela, Digital Wayang Encyclopedia (available online under the following URL: https://villaorlado.github.io/wayangnetworks/html, accessed 23 November 2018).

within these traditional subdivisions of the epic to define character co-occurrence. Here, we consider two levels of co-occurrence granularity corresponding to the epic's subdivision into 23 *lakon* and then further into 223 *adegan*. In the following, we focus primarily on the finer-resolution *adegan* co-occurrence network unless otherwise noted, occasionally referring to the coarser *lakon* co-occurrence network to gain insights into how findings are affected by the choice of co-occurrence granularity.

Lists of characters appearing in each episode (that is, in each story or each scene, depending on the choice of co-occurrence window) are used to construct a bipartite character-episode affiliation network $B = (\boldsymbol{C}, \boldsymbol{E}, \boldsymbol{L})$, where $\boldsymbol{C}$ denotes the set of nodes representing characters, $\boldsymbol{E}$ denotes the set of nodes representing episodes, and $\boldsymbol{L}$ denotes the set of links representing character occurrences in these episodes, with the presence of a link $(c, e) \in \boldsymbol{L}$ indicating that character c appears in episode e. A character co-occurrence network G is then constructed as the weighted, unipartite projection of this bipartite network onto the set of character nodes: $G = (C, \boldsymbol{L_E}, w)$, where $\boldsymbol{L_E}$ is a set of co-occurrence links and $w : \boldsymbol{C} \times \boldsymbol{C} \rightarrow \mathbb{N}$ gives the weights for each pair (c_1, c_2) of characters $c_1, c_2 \in \boldsymbol{C}$ as

$$w\big((c_1, c_2)\big) = \|\{e \in \boldsymbol{E} \mid (c_1, e), (c_2, e) \in \boldsymbol{L}\}\| , \tag{1}$$

with $\| \cdot \|$ indicating the number of elements in the set. Here, $(c_1, c_2) \in \boldsymbol{L_E}$ only if $w\big((c_1, c_2)\big) > 0$. Link weights thus represent the number of distinct episodes in which both of the linked characters appear. In the following, we refer to a node's number of links within the character-affiliation network B (that is, the total number of episodes in which the corresponding character appears) as its *degree*, as distinct from the total sum of its link weights within the character co-occurrence network G, which we refer to as its *node strength*.

2.2 Identifying centrality outliers

When identifying the shortest paths between pairs of nodes, weighted-network generalizations of centrality measures often define the distance associated with the traversal of a link as the reciprocal of the link's weight[10]. In fictional co-occurrence networks, a densely-interconnected core of main characters is typically surrounded by numerous peripheral characters within a network of small diameter. These frequently co-occurring main characters tend to share links that have weights of a higher order of magnitude than those of peripheral characters, and so inherently tend to support the majority of shortest paths between nodes in the network. Large-degree nodes will thus tend to exhibit the

10 Mark E. J. Newman, "Scientific collaboration networks. II. Shortest paths, weighted networks, and centrality," Physical Review E 64, no. 1 (2001): 016132.

highest centrality values, even when their primary structural roles — as characterized by the topological "shape" of their connections, and not just by overall magnitudes of their link weights — may not correspond to the features which one wishes to target using a certain centrality measure. We thus wish to systematically identify characters whose appearances, though possibly few in number, are arranged to serve a specific structural role targeted by the centrality measure.

In order to identify nodes whose centrality measures are higher or lower than expected given the overall strengths of their connections, we uses ensemble null models. By averaging centrality values of each character over an ensemble of artificial networks, each of which gives characters the same levels of overall prominence that they exhibit in the actual network, we can estimate the ranges of centrality values that are expected to result from the network's combination of node degrees. A variety of approaches exist for estimating the weights of each link within a weighted network given only a specified degree sequence[11,12]. In the current context, however, link weights count discrete co-occurrence events, and so are constrained to take values in the natural numbers (Equation 1). So, we design our null model to reflect the co-occurrence network's origins as the weighted projection of an unweighted affiliation network, in addition to reproducing its degree sequences and any relevant node metadata.

We consider two methods for generating these artificial networks. First, we use a *rewired* model in which networks are generated by iteratively rewiring the empirical character-episode affiliation network $B = (\boldsymbol{C}, \boldsymbol{E}, \boldsymbol{L})$. To produce each artificial network realization B'_i of an ensemble B', we begin with a copy of the empirical link set, $\boldsymbol{L'}_{\boldsymbol{i}} = L$. At each step of an iterated process, a randomly-selected pair of distinct links $(c_1, e_1), (c_2, e_2) \in \boldsymbol{L'}_{\boldsymbol{i}}$ is removed and replaced with $(c_1, e_2), (c_2, e_1) \in \boldsymbol{L'}_{\boldsymbol{i}}$ until a set number of iterations (here, $50\|\boldsymbol{L}\|$) is reached. The resulting rewired link set $\boldsymbol{L'}_{\boldsymbol{i}}$ defines a new network realization $B'_i = (\boldsymbol{C}, \boldsymbol{E}, \boldsymbol{L'}_{\boldsymbol{i}})$, the degree sequences of which are identical to those of the original network.

We also consider a *configuration model*[13], adapted here for the bipartite network context at hand. Given a character-episode affiliation network B with target character degree sequence $\{m_c\}$ and episode degree sequence $\{n_e\}$, we

11 Iacopo Mastromatteo, Elia Zarinelli, and Matteo Marsili, "Reconstruction of financial networks for robust estimation of systemic risk," Journal of Statistical Mechanics: Theory and Experiment 2012, no. 03 (2012): P03011

12 Giulio Cimini et al., "Estimating topological properties of weighted networks from limited information," Physical Review E 92, no. 4 (2015): 040802.

13 Fan Chung and Linyuan Lu, "The average distance in a random graph with given expected degrees," Internet Mathematics 1, no. 1 (2004): 91–113.

generate each network $B'_i \in B'$ by allowing each potential link affiliating a character node c with an episode node e to be realized with a probability

$$P\big((c,e) \in \mathrm{L}\big) = \frac{m_c n_e}{\|L\|}\,. \qquad (2)$$

The degree sequences of each individual network may not attain their exact target values in each B'_i, but their mean values in the ensemble B' approach those of the target sequences as the total number of network realizations increases. As a result, nodes with low total strength in the empirical network will remain disconnected from any network realizations wherein no links are realized for that node under the probabilistic generation of links in accord with Equation 2. These disconnected nodes will be excluded from the shortest path counting used to compute centrality values for all other nodes.

Projection of each artificial character-episode affiliation network $B'_i \in B'$ onto C then yields an ensemble of the corresponding co-occurrence networks $G'_i \in G'$ upon which the measures of interest are computed. In the following, we present results for the *adegan* co-occurrence network based on *rewired* and *configuration* model ensembles of 1000 network realizations each, as well as a 500-network rewired ensemble and an 800-network configuration model ensemble for the *lakon* co-occurrence network.

For a centrality measure b measured on a node c in G, the expected value of $b_G(c)$ according to a null model ensemble of network realizations $G' = \{G'_1, G'_2, \dots\}$ is given by

$$\langle b_{G'}(c)\rangle_{G' \in G'} = \frac{1}{\|G'\|} \sum_{G' \in G'} b_{G'}(c)\,. \qquad (3)$$

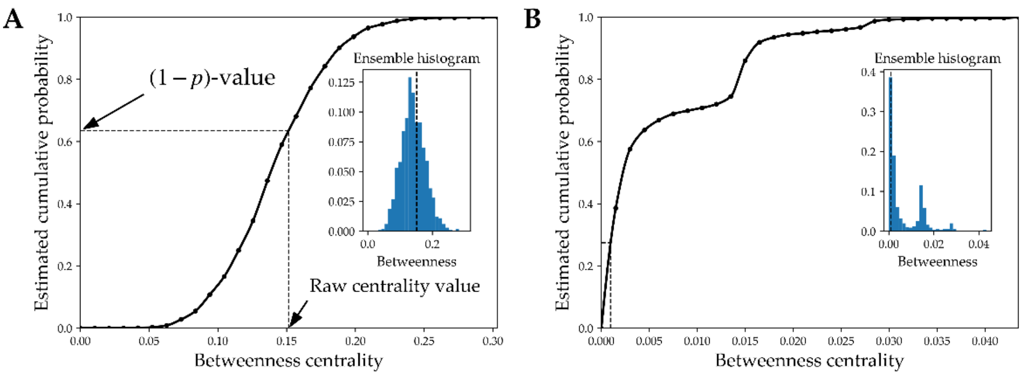
Bootstrapping from histograms based on the set of null model values $\left\{b_{G'_1}(c), b_{G'_2}(c), \dots\right\}$, we estimate the relative values of the probability distribution $P\big(b_{G'}(c)\big)$ at histogram bin centers, and interpolate these to estimate a corresponding continuous cumulative probability distribution $P\big(x < b_{G'}(c)\big)$. The "p-value"[14] corresponding to the empirical network value $b_G(c)$ is given by

$$p\big(b_G(c)\big) = 1 - P\big(b_G(c) < b_{G'}(c)\big)\,, \qquad (4)$$

14 We refer to these as "p-values" in a slight deviation from the usual statistics terminology; here, p = .05 would indicate a 5% chance that the null model network would achieve a value greater than the empirical value, while p = .95 would indicate a 5% chance that a null model network achieves a value less than than empirical value.

as illustrated in Figure 1. The p-values corresponding to node and link betweenness centrality, closeness centrality, and global network metrics are computed similarly. In the following rankings, we sort nodes and links by these p-values; elements with a shared p-value are subjected to a secondary sort based on the ratio $b_G(c)/\langle b_{G'}(c)\rangle_{G'\in G'}$ (which we will henceforth denote as $b/\langle b\rangle$)[15].

Figure 1. Computation of *p*-values: Histograms of null model ensemble centrality values (insets) and bootstrapped cumulative probability functions used to compute p-values for **(A)** Gatotkaca and **(B)** Banowati from a rewired null model based on the *adegan* co-occurrence network.



2.3 Social factions and centrality

To investigate how characters of different types are embedded among one another throughout the network, nodes are endowed with metadata describing a character's affiliations with various social factions. We consider four partitions of the set of character nodes into f disjoint sets of interest $\boldsymbol{F}_i$, with $\bigcup_{i=1}^{f} F_i = C$ and $\boldsymbol{F}_i \cap \boldsymbol{F}_j = \emptyset$ for $i \neq j$. Each character is labelled by its *Tribe* affiliation[16] (*Korawa*, *Pandawa*, *Punokawan*, or Unaffiliated), by the *Mahabharata* tradition of its historical *Origin* (India or Java), by *Species* (Animal, Demon, Human, God, or *Raksasa*), and by *Gender* (Female or Male). More detailed information on these

15 Stefan Hennemann and Ben Derudder, "An alternative approach to the calculation and analysis of connectivity in the world city network," Environment and Planning B: Planning and Design 41, no. 3 (2014): 392–412.

16 Given the complexity and ambiguity of some allegiances, here we assign a tribe label only where a character's primary affiliation is unambiguously clear.

characters and the choices of metadata labels assigned can be consulted at our Digital Wayang Enyclopedia[17].

In order to quantify how various characters and social factions are situated between one another amid the network's co-occurrence patterns, we quantify the extent to which a node or link falls between members of two factions by restricting the shortest path counts used to compute betweenness such that they consider only shortest paths that join members of each of these two specific factions. The betweenness centrality of a node c in the network $G = (\boldsymbol{C}, L_E, w)$ is given by

$$b_G(c) = \frac{2}{(\|\boldsymbol{C}\| - 1)(\|\boldsymbol{C}\| - 2)} \sum_{s,t \in \boldsymbol{C}} \frac{\sigma_G(s,t|c)}{\sigma_G(s,t)}, \tag{5}$$

where $\sigma_G(s,t)$ counts the number of distinct shortest paths between nodes s and t in the network G, and $\sigma_G(s,t|c)$ counts the number of those shortest paths which pass through the character node c[18]. These shortest paths are identified by computing the length D of a path described by node sequence $\{c_i\}$ as the sum of the inverse weights of the links traversed[19]:

$$D(\{c_i\}) = \sum_{j=1}^{\|\boldsymbol{C}\|-1} \frac{1}{w\left((c_j, c_{j+1})\right)}. \tag{6}$$

For two factions F_1 and F_2, we define the F_1-F_2 *inter-faction betweenness centrality* in which we restrict shortest path counting to only consider paths connecting pairs having one member each from the two factions of interest:

$$b_{(F_1,F_2),G}(c) = \frac{2}{(\|\boldsymbol{C}\| - 1)(\|\boldsymbol{C}\| - 2)} \sum_{s \in F_1, t \in F_2} \frac{\sigma_G(s,t|c)}{\sigma_G(s,t)}. \tag{7}$$

17 Miguel Escobar Varela, Digital Wayang Encyclopedia, https://villaorlado.github.io/wayangnetworks/html/.

18 Linton C. Freeman, "A set of measures of centrality based on betweenness," Sociometry, 1977, 35–41.

19 Mark E. J. Newman, "Scientific collaboration networks. II. Shortest paths, weighted networks, and centrality," Physical Review E 64, no. 1 (2001): 016132.

We also define the *faction-world betweenness centrality* with respect to a faction F by restricting shortest path counting to paths connecting nodes of a given faction to target nodes outside the faction:

$$b_{(F,\overline{F}),G}(c) = \frac{2}{(\|\boldsymbol{C}\|-1)(\|\boldsymbol{C}\|-2)} \sum_{s\in F\,,t\in\overline{F}} \frac{\sigma_G(s,t|c)}{\sigma_G(s,t)}. \tag{7}$$

where $\overline{F}$ is the set of character nodes from C not in F.

3 Results

3.1 Global network metrics and metadata modularity reveal community structure along tribal lines

In order to understand the macroscopic differences between the empirical network and the null model, we first compare several global network metrics from the empirical network to the corresponding null model ensemble mean values (Table 1). The empirical network is less topologically dense[20], larger in diameter, and exhibits higher clustering[21] than most of its null model counterparts, as might be expected based on experience with real social networks. Modularity[22,23] values corresponding to each of the metadata-based partitions of the epic's characters (*Tribe* affiliations, Indian or Javanese historical *Origin*, *Species*, and *Gender*) suggest that this clustering is indeed related to preferential co-occurrence based on shared metadata characteristics. The highest of these values is observed for partition of nodes based on tribal affiliation; this tribe-based clustering is indeed confirmed in mean allocations of node strength for each tribe (Figure 2A) and is readily visible in a force-directed network visualization (Figure 3A), particularly for the *Korawa* and *Punokawan* factions.

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20 Density is equal to $2\|\mathbf{L_E}\|/[\|\mathbf{C}\|(\|\mathbf{C}\|-1)]$, the fraction of potential links that have non-zero weight in the character co-occurrence network.

21 Duncan J Watts and Steven H Strogatz, "Collective dynamics of 'small-world' networks," Nature 393, no. 6684 (1998): 440; Jukka-Pekka Onnela et al., "Intensity and coherence of motifs in weighted complex networks," Physical Review E 71, no. 6 (2005): 065103.

22 Mark E. J. Newman and Michelle Girvan, "Finding and evaluating community structure in networks," Physical Review E 69, no. 2 (2004): 026113; M. E. J. Newman, Networks: An Introduction (Oxford University Press, 2010).

23 These modularity values are computed with reference to an assumed unipartite network configuration model as the null model, rather than with reference to the bipartite network null models generated here.

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3.2 Null models identify centrality outliers at all levels of overall prominence

As illustrated by the visible lack of simple monotonic trend between raw centrality values and the corresponding p-values for both betweenness (Figure 4B) and closeness (Figure 4D), null model p-values indeed provide information that is qualitatively distinct from that provided by the corresponding raw centrality values. While in some sense the null model is intended to rescale the raw values in a way that accounts for node degrees, the null model's manner of accounting for degrees is also distinct from discarding link weights outright, as is confirmed in similar plots of the unweighted-network counterparts of these centrality measures which treat all co-occurrence weights as identically equal to 1 (Figures 4A and 4C). Over the entire range of node degrees, then, the approach distinguishes both high- and low-centrality outliers from characters whose centrality values more closely conform with null model expectations. Viewing the empirical network's betweenness centrality values within the context of the null model's predicted dependence of betweenness on degree clearly reveals number of high-betweenness outliers of both low and high degree (Figure 5A). High-betweenness outliers (ranked in Table 2) include many less-prominent characters whose appearances, though few, nonetheless serve to bridge other characters via chains of co-occurrence interactions.

Table 1. **Global metrics for the adegan co-occurrence network:** Empirical network values compared to results from *rewired* and *configuration* null model ensembles.

Network metric	Empirical network	*Rewired* mean	*Rewired* p-value	*Configuration* mean	*Configuration* p-value
Number of links $\|\|\boldsymbol{L}\|\|$	1032	1032	.5369	1030.05	.4947
Largest component	146	146	.5369	128.12	.0000
Diameter	5	3.78	.0000	3.44	.0000
Mean shortest path	1.34	1.28	.1122	1.11	.0000
Density (topological)	.10	.14	.9999	.15	.9999
Mean clustering coeff.	.72	.38	.1227	.05	.0000
Species modularity	.08	-.006	.0000	-.007	.0000
Origin modularity	.06	-.006	.0000	-.007	.0000
Tribe modularity	.17	-.017	.0000	-.018	.0000
Gender modularity	.01	-.001	.0020	-.002	.0007

Figure 2. (A) Allocations of node strength among tribes, averaged over each tribe for the *adegan* co-occurrence network, and similarly for **(B)** an alternative partition of the nodes by historical origin, but with *Korawa* and *Punokawan* communities considered separately.

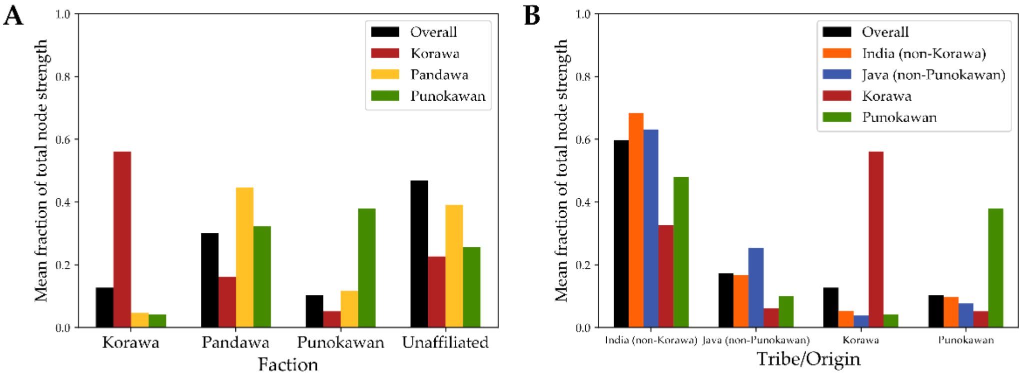
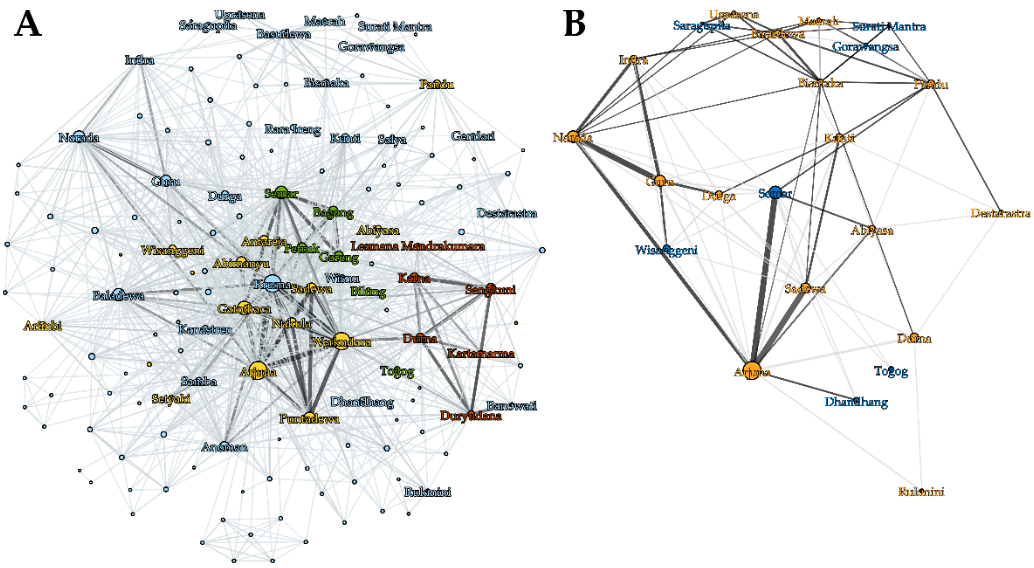


Figure 3. ***Adegan* co-occurrence network: (A)** Force-directed network visualization showing tribal affiliations (Korawa (red), Pandawa (yellow), Punokawan (green), and Unaffiliated (light blue)). **(B)** Detail of high-betweenness outliers showing characters' historical origins (India (orange) and Java (blue)). Darker link color indicates a lower link betweenness *p*-value.



However, even for higher-profile characters whose importance is already readily apparent through their high degrees and raw centrality values, these *p*-values offer a more complete account of their structural roles than do the raw values alone. Characters like Arjuna, Werkudara, and Durna not only have high betweenness centrality values, but these values are also significantly higher than expected; not only do they appear often, but the contexts of their appearances

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situate them on paths between other characters to an even greater extent than can be explained by such high frequencies of appearances alone. This distinguishes them from other high-profile characters such as Kresna, Gatotkaca, or Sengkuni, who are highly central but are not situated between other characters significantly more than their frequent appearances would, in themselves, lead one to expect. Viewing closeness centrality values in the context of the null model's predicted dependence of closeness on degree (Figure 5B) reveals a number of low-closeness outliers as ranked in Table 3. Higher-degree characters tend to conform more closely with null model expectations, with the most salient exception of three extreme low-closeness outliers, who are all members of the antagonist *Korawa* tribe.

Figure 4. Character ($1 - p$)-values versus raw centrality values for the *adegan* co-occurrence network from a *rewired* null model, distinguishing Indian characters (orange), *Punokawan* (green), and non-*Punokawan* Javanese characters (blue): **(A)** Unweighted betweenness centrality, **(B)** Weighted betweenness centrality, **(C)** Weighted closeness centrality, and **(D)** Unweighted closeness centrality.

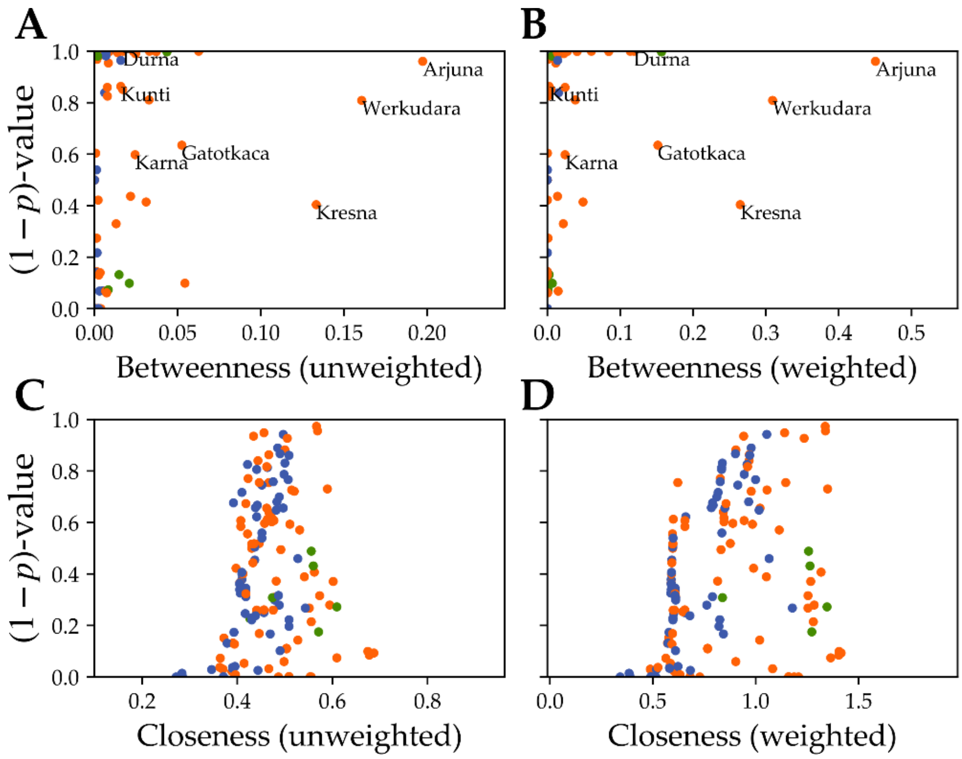


Table 2. High betweenness centrality outliers as ranked by p-value (ascending) and then by the ratio $b/\langle b\rangle$ (descending) for the *adegan* co-occurrence network.

Adj. rank	Raw rank	Character	Species	Origin	Tribe	Gender	Degree	Node strength	Betweenness centrality	p-value (B.C.)	$b/\langle b\rangle$ (B.C)
1	6	Pandu	Human	India	Pandawa	M	8	36	.060	.0000	40.62
2	7	Narada	God	India	Unaffiliated	M	25	105	.114	.0000	4.6
3	6	Durna	Human	India	Korawa	M	26	110	.119	.0000	4.4
4	13	Rukmini	Human	India	Unaffiliated	F	4	16	.027	.0005	89
5	11	Durga	God	India	Unaffiliated	F	10	42	.041	.0010	14.99
6	8	Guru	God	India	Unaffiliated	M	22	107	.084	.0010	4.87
7	16	Bismaka	Human	India	Unaffiliated	M	7	26	.024	.0015	20.11
8	4	Semar	God	Java	Punokawan	M	34	192	.157	.0025	2.54
9	23	Saragupita	Human	Java	Unaffiliated	M	4	9	.014	.0034	50.22
10	26	Surati Mantra	Raksasa	Java	Unaffiliated	M	2	8	.001	.0059	10.78
11	24	Ugrasena	Human	India	Unaffiliated	M	5	12	.014	.0061	27.1
12	25	Dhandhang	Demon	Java	Unaffiliated	M	4	22	.014	.0069	42.61
13	17	Basudewa	Human	India	Unaffiliated	M	9	36	.023	.0094	11.08
14	26	Gorawangsa	Raksasa	Java	Unaffiliated	M	3	10	.013	.0182	41.25
15	30	Destarastra	Human	India	Unaffiliated	M	4	13	.005	.0189	17.79
16	29	Togog	God	Java	Punokawan	M	4	22	.006	.0190	18.07
17	38	Maerah	Human	India	Unaffiliated	F	4	15	.001	.0320	2.45
18	21	Wisanggeni	Human	Java	Pandawa	M	9	39	.014	.0359	5.98
19	1	Arjuna	Human	India	Pandawa	M	62	310	.451	.0379	1.27
20	18	Abiyasa	Human	India	Pandawa	M	6	33	.012	.0458	12.65

3.3 Null model p-values eludicate bridging features within the network's core-periphery structure

Considering these p-values now within the context of a network visualization by highlighting high-betweenness outliers as in Figure 3B, we observe some intricate finer features embedded within the network's basic coreperiphery structure. These include an aggregate of bridge-like features anchored to the core of the network on one side by high-betweenness outliers such as Durga, Guru, and Narada, and bypassing the network core to approach Pandu – father of the protagonist *Pandawa* tribe and the #1-ranked high-betweenness outlier – and the *Korawa* on the other end. Having identified these characters as high-betweenness outliers, we can look at their allocations of betweenness centrality among specific inter-faction components, and so clarify their positions as bridges between certain factions. Durga, for example, acts mostly as a bridge between gods and other characters (Figure 6A).

Figure 5. (A) Betweenness and (B) Closeness centrality versus node degree for the *adegan* co-occurrence network plotted atop density plots based on histogram data from the *rewired* null model.

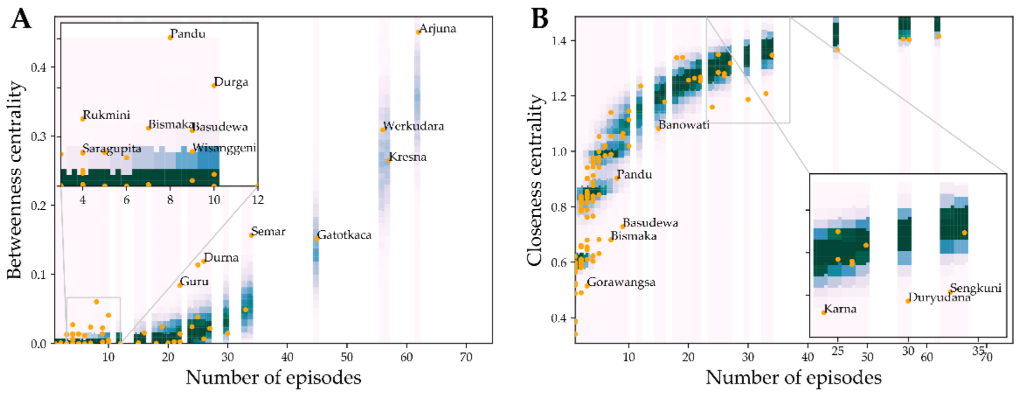


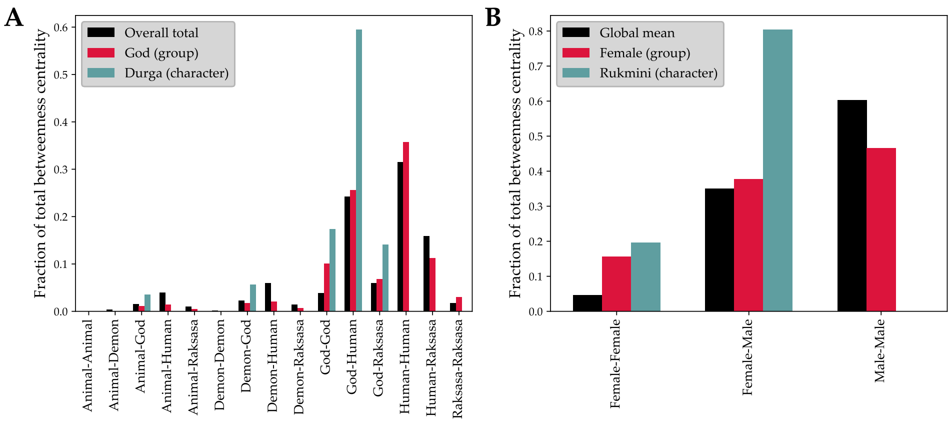
Table 3. Low closeness centrality outliers as ranked by *p*-value (descending) and then by the ratio $b/\langle b\rangle$ (ascending) for the *adegan* co-occurrence network.

Adj. rank	Raw rank	Character	Species	Origin	Tribe	Gender	Degree	Node strength	Closeness centrality	*p*-value (C.C.)	$b/\langle b\rangle$ (C.C.)
1	1	Jaya Bajra	Raksasa	Java	Unaffiliated	M	1	2	.341	.9999	.57
2	6	Gorawangsa	Raksasa	Java	Unaffiliated	M	3	10	.515	.9999	.65
3	67	Basudewa	Human	India	Unaffiliated	M	9	36	.728	.9999	.68
4	127	Duryudana	Human	India	Korawa	M	30	93	1.187	.9999	.88
5	128	Sengkuni	Human	India	Korawa	M	33	121	1.208	.9999	.88
6	125	Karna	Human	India	Korawa	M	24	88	1.160	.9990	.89
7	5	Surati Mantra	Raksasa	Java	Unaffiliated	M	2	8	.490	.9990	.71
8	65	Bismaka	Human	India	Unaffiliated	M	7	26	.681	.9984	.68
9	3	Ngembat Landeyan	Human	Java	Unaffiliated	M	1	1	.388	.9953	.65
10	57	Ugrasena	Human	India	Unaffiliated	M	5	12	.632	.9922	.69

3.4 Structural distinctions between the protagonist *Pandawa* tribe, their *Punokawan* allies, and their *Korawa* rivals

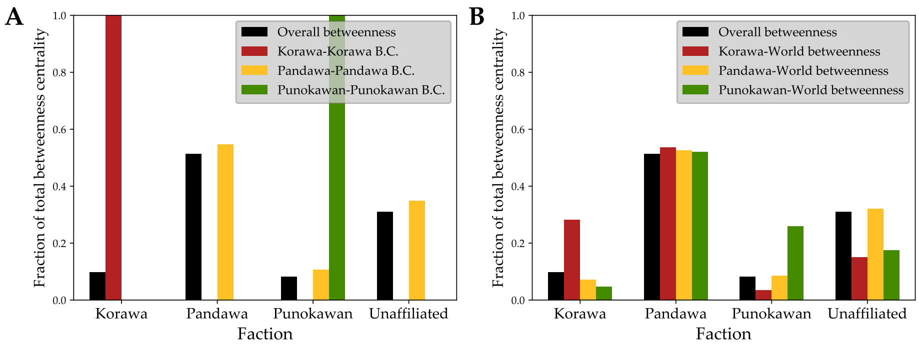
As indicated previously by modularity values (Table 1) and mean node strength allocations for the partition of the network by Tribe (Figure 2), most members of the *Korawa* and *Punokawan* are depicted primarily through interactions with members of their own tribes. Applying the faction-specific betweenness centralities discussed above, we examine the relative contributions made by each tribe to the network-wide sum of intra-faction betweenness for each tribe (that is, *Korawa-Korawa*, *Pandawa-Pandawa*, and *Punokawan-Punokawan* inter-faction betweenness centrality as defined in Equation 7) in order to observe which (if any) factions are embedded internally between members of each group (Figure 7A). The *Korawa* and *Punokawan* communities are each internally bridged only by members of their own faction; meanwhile, some *Pandawa* are internally connected via non-*Pandawa* characters: the god Kresna and the *Punokawan* leader Semar.

Figure 6. Female high-betweenness outliers: Allocations of overall betweenness centrality among its interfaction components for **(A)** Durga with respect to *Species*, and for **(B)** Rukmini with respect to the *Gender* partition.



Examining how these groups are bridged to the outside universe in terms of the overall allocations of faction-world betweenness among tribes for each group (Figure 7B), we find clues that the *Korawa* and *Punokawan* communities are each bridged to the wider universe via a primary in-group representative. Indeed, rankings of the top high-betweenness outliers (Table 2) include a primary character representing each of these tribes: Durna of the *Korawa* and Semar of the *Punokawan*. Decomposing these characters' betweenness centrality values into their inter-faction components with respect to the *Tribe* partition, we confirm their roles as representatives who specifically bridge their own factions with the outside universe (Figure 8). Durna's co-occurrences with his mentor Werkudara of the *Pandawa* give their link the third highest raw link betweenness centrality value in the network, and the highest of any *Korawa-Pandawa* link. While the role of Semar as the representative that bridges the other *Punokawan* to the world is obvious, adjusted rankings also identify the unique role of a much lower-profile *Punokawan* character, Togog. Togog appears in just 4 scenes, but is ranked at #15 in adjusted betweenness rankings, and at #1 in adjusted rankings of high *Punokawan*-world and *Korawa-Punokawan* betweenness outliers.

Figure 7. Internal and external betweenness by tribe: Fractions of total global **(A)** Intra-faction betweenness and **(B)** Faction-world betweenness contributed by each tribe.



Togog is a member of the clown-servant *Punokawan* who differs from other *Punokawan* in that he associates with the *Korawa* rather than the *Pandawa*. Null model rankings uncover the otherwise-obscured structural manifestations of this character's unique role in the narrative: Togog is isolated from the other *Punokawan*, with the shortest paths that bridge Togog himself to other nodes often passing directly through non-*Punokawan* characters such as Sengkuni (*Korawa*) rather than through the *Punokawan* leader Semar (Figure 8B).

Both the *Korawa* and *Punokawan* communities are of similar size and interact preferentially with members of their own tribes to a similar extent. Their overall degrees are similar, on average, and they even show similar raw average closeness centrality values (Table 4). However, the *Korawa* have smaller mean node strength, and comparisons with the null model demonstrate that the co-occurrence patterns of the highest-profile *Korawa* (excluding the bridge-like Durna) leave them significantly more distant from the rest of the network than is expected despite their frequent appearances, as seen in Table 3 and Figure 5B for a rewired null model. Under a configuration null model, which de-emphasizes peripheral characters when counting shortest paths, the low-closeness outlier rankings of Duryudana, Sengkuni, and Karna rise even further to #1, #2, and #4, respectively. Meanwhile, the *Punokawan* are embedded more closely to the core of the network in accord with their frequent appearances, as reflected in their smaller mean closeness p-value (Table 4).

Figure 8. Inter-tribal bridges: Allocations of overall betweenness centrality among its inter-faction components for **(A)** Durna of the *Korawa* and **(B)** Togog of the *Punokawan* with respect to the *Tribe* partition.

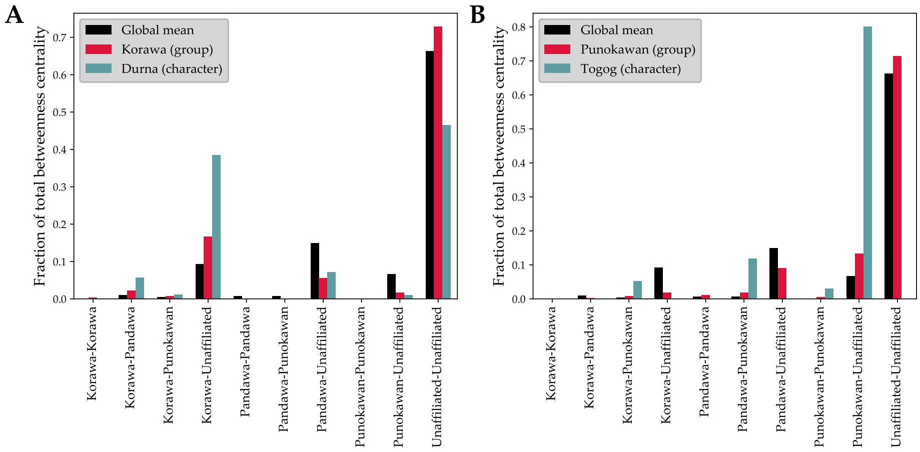


Table 4. Mean centrality values and p-values by faction for the *adegan* co-occurrence network with a rewired null model ensemble.

Faction	Mean degree	Mean node strength	Mean betweenness	Mean *p*-value (B.C.)	Mean closeness	Mean *p*-value (C.C.)
Female	3.77	15.35	.002	.7281	.779	.5406
Male	7.96	38.5	.018	.6627	.833	.6061
Korawa	18.71	69.29	.030	.6314	1.081	.7211
Pandawa	19.38	105.68	.069	.4030	1.127	.5005
Punokawan	17.83	101.83	.029	.6194	1.096	.6826
Unaffiliated	4.14	18.09	.006	.7197	.750	.5924
India	9.96	46.64	.025	.6050	.893	.5918
Java	4.01	19.8	.003	.7523	.746	.5926

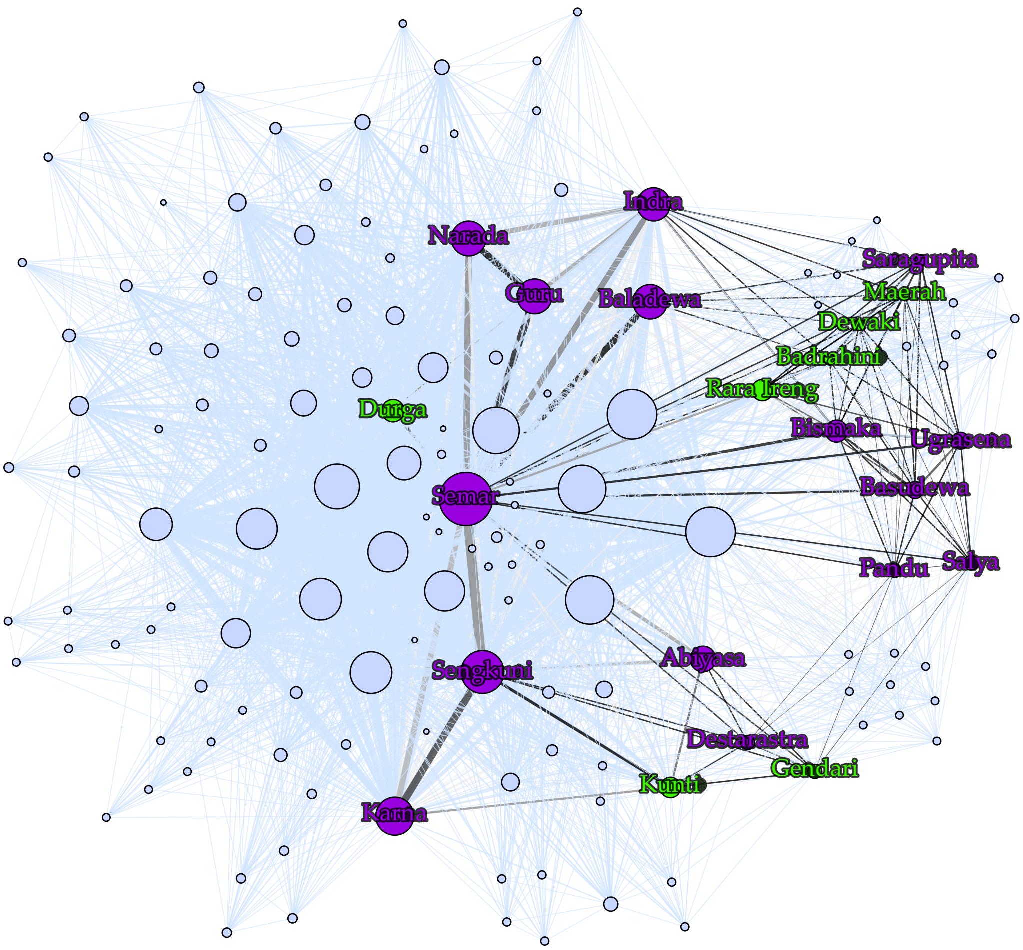
3.5 Female characters often top adjusted betweenness rankings

A cursory inspection of the outliers with high adjusted rankings of betweenness (Table 2) or its faction-specific variants also appears to reveal an unforeseen structural pattern related to another type of social faction: female characters often appear at or near the top of rankings. Rukmini (who ranks at #4 among overall high-betweenness outliers, #1 in Human-world betweenness, #1 in Male-Female betweenness, #1 in India-India betweenness, and #2 in *Pandawa*-world betweenness) and Durga (#5 among overall betweenness outliers, #1 in God-world betweenness, #1 in God-Human betweenness) are identified among the most bridge-like characters. A configuration null model, which tends to exclude low-strength characters in its shortest path counting, further elevates these rankings, placing Rukmini at #2 and Durga at #4 overall. These characters' bridge-like positions are readily apparent in the network visualization of Figure 3.

Although this trend does not generalize to all female characters, who on average show less extreme p-values than do male characters (Table 4), inspection of the shortest paths that explain these characters' betweenness centrality values reveals this to be a structural manifestation of the epic's depiction of these female characters' particular social roles. Rukmini is seen to act as a bridge between male and female characters (Figure 6B); the women she bridges to the predominately-male outside universe are those with whom she shares a domestic role within the kedhaton (palace). As a wife of the god Kresna, one of the most central characters in the *Mahabharata*, Rukmini's co-occurrences with her husband place her closely adjacent to his central position; meanwhile, the fact that she appears more frequently with Kresna's other wives than does Kresna himself places her on all of shortest paths joining those wives and all other characters via Kresna. Durga's high ranking similarly results from her adjacency to her high-profile husband, Guru, combined with her interactions with other characters who do not appear so frequently with Guru.

Under the coarser co-occurrence window of the lakon co-occurrence network, female characters Rara Ireng (#1 overall in a rewired null model), Kunti (#5 overall, and #1 in *Korawa*-world betweenness), and Gendari (#9 overall, #2 in *Korawa*-world betweenness) play bridge-like roles that are readily visible in force-directed network visualizations (Figure 9). Female characters like Arimbi (#1 in *Korawa-Pandawa* betweenness) and Banowati (#1 in *Korawa-Punokawan* betweenness) also top many of the faction-specific adjusted betweenness rankings. However, as the broader co-occurrence window results in more links for high-profile characters like Semar who tend to appear in many lakon, regardless of whether or not they actually encounter other characters directly within the story's scenes, shortest paths between lower-profile characters who may interact more directly with one another are effectively short-circuited through these higher-profile characters.

Figure 9. ***Lakon*** **co-occurrence network:** Force-directed network visualization highlighting the highest-ranking betweenness centrality outliers according to a *configuration* null model, distinguishing Female (green) and Male (purple) outliers.



The high-betweenness outliers identified here thus cannot be explained in terms of their close adjacency to higher-profile characters, but instead tend to form bridges which do not traverse the core of the network. For example, Rara Ireng is the wife of the *Pandawa* hero Arjuna, but the shortest paths which explain her unexpectedly high betweenness do not involve Arjuna, but rather bridge characters who appear in a story depicting her own birth with other peripheral characters. Similarly, Kunti appears more often than any of her male consorts. Her highest-ranked link – which in fact has the second-highest raw betweenness centrality of all links in the lakon co-occurrence network – does not correspond to a domestic relationship with a protagonist, but rather to an adversarial one with her enemy (and would-be suitor) Sengkuni of the *Korawa*. These examples emphasize the qualitative differences in perspective offered by different levels of co-occurrence resolution.

3.6 How deeply have Javanese characters been assimilated into the epic's co-occurrence structure?

Turning now to the relationship between characters' structural positions and historical origins, Figures 4C and 4D for the *adegan* network illustrate that characters with their historical origins in the Javanese wayang kulit incarnation of the *Mahabharata* tradition (plotted in blue, with *Punokawan* plotted in green) span a full range of closeness centrality p-values just as do characters of Indian origin (plotted in orange). This is echoed in faction mean node metrics (Table 4), which demonstrate that while characters from the Indian tradition have a much higher mean closeness value than do Javanese characters ($.89 > .75$), this appears to be almost entirely explained by their higher mean degrees and not by any higher-patterns of assortative co-occurrence by tribe, as both groups share almost identical mean closeness centrality p-values of $p \approx .59$. The same holds under the lakon co-occurrence window, where Indian-origin characters' higher mean closeness ($.96 > .74$) obscures the fact that both groups share almost-identical mean closeness p-values ($p \approx .51$). Although the *Punokawan* have the highest mean degrees and raw centrality values among Javanese characters by far, many non-*Punokawan* Javanese characters exceed null model expectations for closeness more than do the *Punokawan*, such that the overall mean p-value for Javanese characters is lower ($p = .59$) than that of the *Punokawan* alone ($p = .68$). That is, non-*Punokawan* Javanese tend to exceed the corresponding null model expectations to a greater extent than do the *Punokawan*, and overall, Javanese-origin characters conform to the null model expectations to a similar extent as do Indian-origin characters. Javanese characters, while not as ubiquitous throughout the stories as are characters from the original Indian canon, are not generally relegated to peripheral positions that would give them lower-than-expected closeness values any more than are Indian-origin characters, nor do they form detached co-occurrence "branches".

High-betweenness outliers, as ranked in Table 2 and highlighted in the network visualization of Figure 3B, include a number of Javanese-origin characters interspersed among bridge-like network features at the adegan level. Attempting to locate any hidden clusters of Indian- and Javanese-origin clusters by examining rankings of India-Java betweenness centrality outliers, we find that this faction-specific betweenness almost exactly reproduces the rankings of Table 2. However, in the adjusted Java-Java intra-faction betweenness rankings, which excludes India-Java paths, the *Korawa* bridge Durna drops in rank from

#3 to #24. The dependence of his betweenness on paths between characters of different historical origins reflects his role as a bridge between the *Korawa*, a community of homogenously Indian origin, to the rest of the universe. Observations such as these suggest that the observed higher-than-expected modularity along the lines of historical origin (Table 1) seems to be largely explained by the homogeneiety of historical origins within the epic's two most tight-knit tribal communities. While non-*Punokawan* Javanese characters are thoroughly interspersed throughout the network, the isolation of the *Korawa* in still preserved. Mean node allocation profiles for an alternative partition of the nodes, which distinguishes characters by origin but with *Korawa* and *Punokawan* communities considered separately, demonstrates that there is relatively little assortative co-occurrence based on historical origin, except insofar as it occurs along tribal community lines (Figure 2B). Javanese- and Indian-origin characters have apparently come to be thoroughly inter-mixed with one another throughout the network, but this has occurred in such a way that the *Korawa* remain structurally isolated.

4 Conclusion

By examining one representative version of the Javanese *wayang kulit Mahabharata* canon, we have presented an initial proof-of-concept demonstrating how several issues of interest in the cultural and historical study of this and other related art forms can be approached in network-theoretical terms. The many intangible aspects of *wayang*'s appeal certainly cannot be quantified. Still, without purporting to replace existing approaches towards understanding this tradition, a network-theoretical perspective can provide concrete, meaningful information about the mechanics of a particular work of fiction to complement traditional perspectives.

The results presented here are perhaps most interesting if considered as a first step towards comparative studies involving multiple tellings of the epic, or other works of fiction. For example, since network modularity can be used to quantify the extent to which the storylines are advanced through depictions of in-group interactions rather than inter-faction encounters, it could also allow us to quantitatively compare how distinct retellings – representing different regional traditions, or distinct performances by multiple *dhalang* – differ in their depictions. If null model analyses of betweenness centrality can indeed reveal some structural hallmarks of the gender roles depicted in *wayang kulit*, then the relative exaggeration or de-emphasis of these features in networks representing distinct retellings of the epic could help to inform discussions of the broader cultural differences which may have shaped their different structures. If network-theoretical tools like closeness centrality can quantify the extent to which Javanese characters have been assimilated into central roles within the epic, they could also potentially be used to quantitatively track the incorporation of those elements into the epic over time.

These types of comparative or dynamical network analyses would require the preparation of data sets of sufficient resolution and scope to represent mutiple incarnations of the epic. In most cases, this would not be a straightforward matter. For example, attempts to compare Indian and Javanese *Mahabharata* traditions using co-occurrence networks would be complicated by the fact that many incarnations of the epic are not organized into episodic subdivisions of comparable resolution. Our ability to compare co-occurrence networks representing multiple stages of the historical evolution of the *wayang kulit* tradition, throughout which various Javanese innovations were assimilated into the originally Indian canon over time, is highly contingent on the availability of suitable historical sources. But if these obstacles can be creatively overcome, co-occurrence networks may serve as a useful new tool with which to more fully understand the rich diversity and complexity which makes the *wayang kulit* tradition so fascinating, and the processes which have shaped it throughout its centuries-long history.

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