Communities and sentiments in the Game of Thrones TV series

Anne Kjerstine Desler[a,4,6,7,8] **and Moamal Fadhil Abdul-Mahdi**[a,1,2,3,5,8]

December 5, 2023

Social networks often exhibit intriguing interactions and community formations. These communities, whether close to each other or not, may share attributes or be polar opposites. An example of such a network can be found in the fictional world of Game of Thrones. In this network, there can be a lot of ways communities form. Communities within this network can form on the basis of houses, cultures, or shared religion, or the network might not develop communities at all. Each character can experience or produce horrible things as the show, in many ways, is cruel, and how much can be quantified as a sentiment score. Using the Fandom.com website we can create a network of the characters and calculate the sentiment scores from wiki pages about the characters. We aim to study the best partitions and determine if characters share similar sentiment scores with the other characters in their communities and if neighboring communities have similar sentiment scores. We show that the Game of Thrones TV show is too interconnected to partition into houses, however, the characters do to some extent have similar sentiment scores to other characters within the same houses. The sentiment scores do not seem to influence the proximity of houses. Larger communities are better partitions these are especially obtained by the religions as there are very few religions compared to the number of houses and cultures in the series. The Louvain algorithm forms the best partitions with only six partitions. Overall, this reflects how the show takes place in its entire world with interaction between many different societies in the show. This perhaps mirrors how real-world communities might get more diffuse as societies globalize evermore.

Significance Statement

We study how well the Game of Thrones TV show characters can be partitioned into houses, cultures, and religions and investigate if these communities are more connected to other communities that are similar concerning the average sentiment scores of the characters within the communities. To answer these questions we use network science and natural language processing to construct a network and analyze their wiki pages on Fandom.com. Studying this might contribute to understanding Game of Thrones interactions better and serve as a prestudy to more in-depth studies.

Game of Thrones | Network science | Natural language processing | Sentiments | Communities

Game of Thrones is a fictional world taking place on two different continents, with rich history and stories. The TV show mainly revolves around different communities, divided into houses and individuals playing their part in the struggle for power. A secondary part of the show is more locally oriented, like the Great Wall in the northern part of their world and with one of the main characters and her travels in a neighboring continent.

We analyze this universe through a network science and natural language processing perspective. We study how to best partition the characters in the Game of Thrones network, whether it is through their houses, religions, or cultures. We also analyze the average sentiment of the houses, religions, and cultures and investigate if their average sentiment is similar to the houses/religions/cultures that they are most connected to.

The sentiment analysis is conducted on the wiki page for each character from the TV show. The wiki pages were obtained from the Game of Thrones site on the Fandom.com website*. Fandom.com is a wiki website where fans can contribute to their favorite lore. The pages contain valuable information about each character and are used to construct a directed graph where each character is a node, and there is an edge from one node to another if the character links to the other character on their wiki page, resulting in a graph consisting of one giant component with 221 nodes and 3719 edges. The sentiment analysis will be based on a list of words that were assigned a happiness score. The list was provided by Mechanical Turk's study about language (1). Our research question can therefore be boiled down to:
Are characters generally more connected to their house, religion, culture, or external characters and is there a similarity between the average sentiment of a house/religion/culture and the average sentiment of the houses/religions/cultures that they are most connected to?

* https://gameofthrones.fandom.com/wiki/Game_of_Thrones

Author affiliations: [a]DTU Compute

[1]Abstract
[2]Significant Statement
[3]Introduction
[4]Results
[5]Discussion
[6]Methods
[7]Explainer Notebook

[8]A.K.D (Anne Kjerstine Delser) and M.F.A-M (Moamal Fadhil Abdul-Mahdi) contributed equally to this work. Both contributed to all sections. The affiliations simply state the main author of each section

Results

Splitting the network up into communities corresponding to houses is an obvious choice. After all, people seem to be highly connected to their own family members as opposed to other families. However, the characters in the network belong to a total of 55 different houses and 107 characters do not belong to a house at all. This weakens our analysis as we do not expect the characters that do not belong to a house, to be one big community and we do not expect them to share similar sentiments. These characters will be held out of the for some parts of the analysis. We also have several houses with only one member. These cannot be expected to hold enough information to give an accurate assessment of the average sentiment of the houses and will thus also be held out of parts of the analysis, ending up with a graph consisting of only 85 characters and 23 houses. The same goes for cultures where we end up with 178 characters and 24 cultures, and for religions where we end up with 137 characters and 8 religions.

Communities. Two ways of measuring how well communities describe character interactions are assortativity and modularity. Both are explained in the section **Materials and Methods**. Despite, the fact that one would expect the characters to be very connected to their family members, splitting 85 characters into 23 communities does not yield high modularity nor assortativity coefficient as seen in Table 2. Since the modularity and assortativity are both positive, this indicates that the split is reasonable, however, they are very small, indicating that the characters do not in general link to other characters in the same house. Due to the low number of characters per community and to the nature of the universe being highly inter-house connected in the TV show, where there is a central power struggle, the network is probably better partitioned in other communities than houses.

Splitting the characters into their cultures yields a little higher modularity and assortativity, although still very small. Splitting the characters into their religions, however, yields a much higher modularity and assortativity. Comparing the results to the best community split found by the Louvain algorithm (2), we see that this split results in much higher modularity and assortativity than any of our proposed community splits. The characters per community ratio is also much higher especially than the house and culture splits. The religion split has a more similar characters per community ratio, which is most likely the reason why this split has the highest modularity out of the three.

Since Game of Thrones is a show comprised of a large part of its fictional world but centers around the ruling thrones of that part of the world, the interplay between the characters happens across culture, religion, and the house. It can be concluded that house communities only play a minor role and the religious communities play the largest of the three community splits.

Sentiments. We carry out a sentiment analysis for each character which contributes to the average sentiment of the communities they are a part of. First, we calculate the assortativity coefficient of the graph with respect to the sentiments. This is found to be -0.0081, which is slightly negative, indicating that the characters generally link to other characters with different sentiments, however, it is very close to zero, thus indicating that the graph is non-assortative with respect to the sentiments.

Split	Number of nodes	Number of communities	Node per community
Main house	85	23	3.7
Culture	178	24	7.4
Religion	137	8	17.1
Louvain Algorithm	221	6	36.8

Table 1. Overview of the community splits. After removing all characters without houses/religions/cultures and all characters that belong to a house/religion/culture with only that one member, the splitting of the characters into their houses results in the lowest character per community ratio. Out of our three proposed partitionings, the splitting of the characters into their religions results in the highest character per community ratio.

Split	Assortativity coefficient	Modularity
Main house	0.0845	0.0531
Culture	0.0982	0.0729
Religion	0.325	0.196
Louvain Algorithm	0.451	0.336

Table 2. Assortativity and Modularity. The splitting of the characters into their houses results in the lowest assortativity coefficient and modularity. Out of our three proposed partitionings, the splitting of the characters into their religions results in the highest assortativity coefficient and modularity. This is also the community split with the most similar character per community ratio, to the best community split obtained by the Louvain algorithm.

Continuing, we again only look at the houses/religions/cultures with more than one member, because a community consisting of only one member does not give a general idea of the average sentiment of the community.

We calculate both the average sentiment and the standard deviation of all the houses, religions, and cultures. To determine which community split best explains the sentiments of the characters in the communities we calculate the standard deviation of the average sentiments of all the communities as well as the mean of the standard deviation of the characters' sentiments within each community, these can be seen in Table 3

The standard deviation of the average sentiments tells us something about how spread out the average sentiments of the communities are. The higher the standard deviation of the average sentiments the more distinguishable the communities are from each other.

The mean of the standard deviation of the characters' sentiment within each community tells us something about how similar the sentiments of the characters in each community are. The lower the mean of the standard deviation the more similar the characters within the communities are.

Table 4 shows the community with the highest and the lowest average sentiment in each community split.

We find that the greatest difference between the highest and the lowest average sentiment is found in the community split generated by the houses, whereas the lowest difference is found in the community split generated by the Louvain Algorithm.

To get a better understanding of why the two houses *House Florent* and *House Glegane* are so different in average

(a) House Clegane

(b) House Florent

Fig. 1. Word clouds The word clouds are based on weighted TFTR scores for the house with the lowest average sentiment and the house with the highest average sentiment. Only the words that are in the wordlist are included. **(a)** The word cloud for the house with the lowest average sentiment score. **(b)** the word cloud for the house with the highest average sentiment

	Standard deviation of average sentiments	Mean standard deviation of character sentiments
Houses	0.0555	0.0334
Religions	0.0325	0.0394
Cultures	0.0189	0.0469
Louvain	0.0240	0.0585

Table 3. Average sentiment statistics The standard deviation of the average sentiment and mean standard deviation of character sentiments within the communities. The highest standard deviation of the average sentiments is obtained by the community split generated by the houses and the lowest is obtained by the community split generated by the cultures, indicating that the average sentiments of the houses are the most spread out and the average sentiments of the cultures are the least spread out. The highest mean standard deviation of the character's sentiments is obtained by the Louvain algorithm and the lowest is obtained by the houses, indicating that the sentiments of the characters within the houses are similar to other characters within the same house, whereas the sentiments of the characters within the Louvain communities are less similar to other characters within the same community.

	Highest Average Sentiment		Lowest Average Sentiment	
Houses	House Florent:	5.47	House Clegane:	5.23
Religions	Reach:	5.39	Giants:	5.24
Cultures	R'hllor:	5.35	Ghiscari religion:	5.29
Louvain	0:	5.35	3:	5.27

Table 4. Highest and lowest average sentiments The greatest difference in the average sentiment is found in the community split generated by the houses, whereas the lowest difference is found in the community split generated by the Louvain Algorithm.

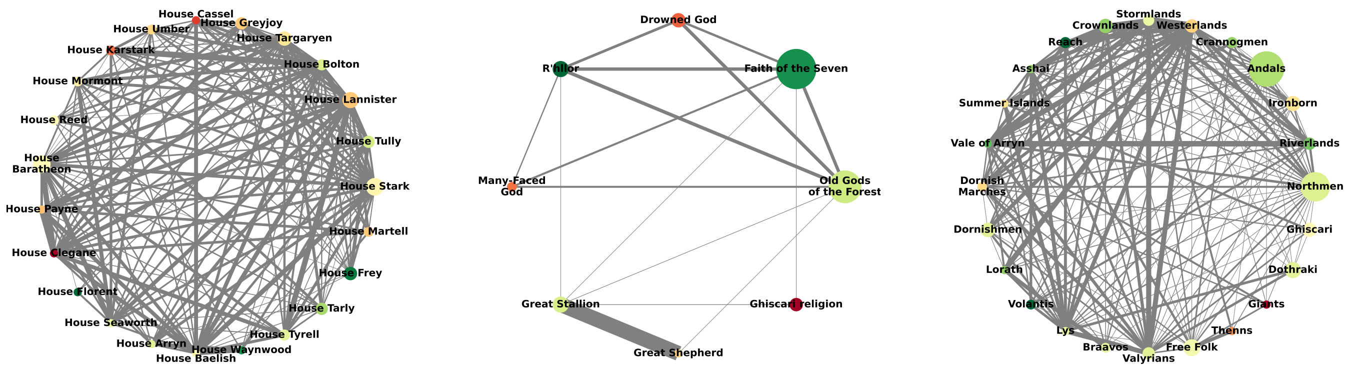
sentiments we calculate the weighted TFTR scores for words on the wiki pages of the characters within these two houses. The weighted TFTR score is described in the section **Materials and Methods**. We only include the words that are in the wordlist and the TFTR scores. Figure 1 shows the word clouds with the words that have the highest TFTR scores in the two houses.

We see that some of the most prominent words for House Clegane are the words *Mountain* and *Hound*. These are the nicknames of the two characters belonging to this house. The word Mountain does not have a particularly low happiness score, Hound on the other hand does have a low happiness score. The same goes for the words *without*, *kill*, *killed*, *ser*, *sword*, and many more of the words with high TFTR scores. For House Florent, we see the words *light*, *lord*, *house*, *wife*, *daughter*, and many more, which are all words with high happiness scores in the wordlist.

To analyze whether the communities are in general more connected to other communities with similar sentiments we create three weighted graphs, one where all the nodes are the houses, one where the nodes are the religions, and one where the nodes are the cultures. There is an edge between two nodes if any of the characters within the two houses/religions/cultures link to one another. The weights on the edges are the total number of connections between the two weighted by the maximum number of possible connections between the two.

The three graphs are visualized in Figure 2. The thicknesses of the edges are based on the weights, the sizes of the nodes are based on the sizes of the houses/religions/cultures and the color of the nodes indicates the average sentiment of the house/religion/culture (green means high sentiment, red means low sentiment). It is difficult to tell from the graph if there is any correlation between the sentiment of a house and the sentiment of the houses it is connected to. Most of the houses interconnect and there does not seem to be any two houses that with a significantly higher weight than others. The same goes for the cultures. For the religions, however, we see a strong connection between *Great Stallion* and *Great Shepherd*. These two religions do have similar average sentiment scores and in general, the religions with high average sentiment do tend to connect to each other. The three religions with the lowest average sentiment scores do however not connect to each other at all.

We define a measure for how much the houses/religions/cultures tend to connect to other



(a) Houses **(b)** Religions **(c)** Cultures

Fig. 2. Weighted Community graphs. There is an edge between two houses/religions/cultures if any of the characters within the two houses/religions/cultures link to one another. The weights on the edges are the total number of connections between the two weighted by the maximum number of possible connections between the two, this is illustrated by the thicknesses of the edges. The sizes of the nodes are based on the sizes of the houses/religions/cultures and the color of the nodes indicates the average sentiment of the house (green means high sentiment, red means low sentiment). **(a)** is the graph showing the connections between houses. **(b)** is the graph showing connections between religions. **(c)** is the graph showing the connections between cultures.

houses/religions/cultures with similar sentiments, by averaging the absolute difference in sentiment scores multiplied by their edge weight.

We find the difference between the average sentiment of the houses to be 0.0136, for the cultures it is 0.00683, and for the religions, it is 0.00173. Thus in general the characters are more connected to other characters that practice a religion that has a similar average sentiment to their own religion.

Discussion

Sentiment Analysis: The sentiment analysis is an overall quantitative method and its only purpose is to show how positive/negative a text is. This leaves room for further studying why the average sentiment of a house/religion/culture scores high or low. For instance, a house in Game of Thrones might be affected by cruelty and hardship while another might be affected by the overall malicious nature of the house.

Furthermore, the wiki pages are written by different users and the sentiment of the text can be influenced by the user's style of writing, which might lead to biases that this study has not addressed.

However, if one is familiar with the house with the lowest average sentiment scores, one would know that the two characters belonging to House Clegane are both known to be malicious of nature, which the average sentiment score does seem to capture.

Scope of Character Analysis: As this analysis centers around the Game of Thrones TV show the scope of the analysis is limited to characters who were part of the show. Therefore, it makes sense to only include characters who were portrayed by the casting crew. Getting all the characters from the books would require a different dataset.

Community splits: The modularity of the communities obtained by the Louvain algorithm is naturally higher than the modularity obtained by communities constructed by the houses, cultures, or religions since the aim of the Louvain algorithm is to obtain the community split with the highest modularity. Besides the community split obtained by the Louvain algorithm, we found the community split obtained by the religions led to the highest modularity, followed by the community split obtained by the cultures, and lastly, the community split obtained by the houses had the lowest modularity. However, the characters per community ratio is much higher for the religions than for the houses. What we most likely observed is that the higher the number of communities the lower the modularity which is also confirmed by the results obtained by the Louvain algorithm as this only contained six communities and a higher number of communities would naturally lead to a lower modularity.

Further research. A similar analysis could be conducted using other datasets. It could be interesting to analyze the entire manuscript of the series and analyze the sentiments of each character's lines.

A potential area for further exploration in this study could be to investigate the underlying factors that contribute to the sentiment score assigned to a house/religion/culture. This might give a clearer image of how the sentiment of communities relates to the communities they are connected to.

Materials and Methods

Data and building the network. To conduct this study, we needed a lot of consistent data from Game of Thrones. The data retrieval process involved a systematic three-step approach: downloading, analyzing, and processing the data. This was done in Python using requests and regular expressions.

To download the data, we used the Fandom API. Fandom.com provides an API that makes it possible to get the text from each page.

The front page, of the Game of Thrones wiki, includes a list of the cast and a wiki link to the character they played. This list was extracted using regular expressions to obtain a list of all the characters' wiki pages.

We saved the wiki page for each character and extracted the houses they belong to, the culture they belong to, and the religion they practice. For each character, we also calculated the text length as well as the sentiment score and extracted the links to all other character wiki pages. We constructed a directed graph where each character is a node, and there is an edge from one node to another if the character links to the other character on their wiki page. Each node also holds the following attributes

- houses - The houses they belong to (one character can belong to multiple houses, e.g. their birth house and the house they married into).
- main house - The main house of the character e.i. if the character belongs to multiple houses the main house is the house they connect the most to.
- culture - The culture they belong to.
- religion - The religion they practice.
- sentiment - The sentiment scores
- text length - The length of the text on their wiki page.

Assortativity and Modularity. Assortativity measures how much nodes prefer to link with nodes with a specific attribute. The assortativity coefficient ranges between -1 and 1. 1 means that nodes that share a specific property always connect to each other whereas -1 means they never connect. 0 is the neutral case. Assortativity is calculated as (3):

$$r = \sum_{jk} \frac{jk(e_{jk} - q_j q_k)}{\sigma^2} \quad [1]$$

where e_{jk} is the probability of finding a node with attribute values j and k at the two ends of a randomly selected link. q_j is the probability of finding a node with attribute value j and σ^2 is the variance of the attribute distribution.

Modularity measures the quality of a split in a network into communities. It quantifies the degree to which the number of edges within communities is greater than the expected number in an equivalent random network. This measure helps in identifying the community structure of the network and can be useful in understanding the organization and function of complex systems. Modularity for a partition is calculated as (3):

$$M = \sum_{c=1}^{n_c} \left(\frac{L_c}{L} - \left(\frac{k_c}{2L} \right)^2 \right) \quad [2]$$

where n_c is the number of communities, k_c is the total degree of the nodes in the community, L is the total number of links in the network and L_c is the total number of links within a community.

Weighted TFTR scores. The TFTR scores for two texts are defined as

$$w_t^{(1)} = \frac{TF_t^{(1)}}{TF_t^{(2)} + c} \quad [3]$$

and

$$w_t^{(2)} = \frac{TF_t^{(2)}}{TF_t^{(1)} + c} \quad [4]$$

where $w_t^{(i)}$ is the TFTR score for a specific token t in text i. $TF_t^{(i)}$ is the term frequency of token t in text i and c is a parameter ensuring a non-zero denominator. Since the two texts can be very different in length we define a weighted TFTR score

$$w_t^{(1)} = \frac{r \cdot TF_t^{(1)}}{TF_t^{(2)} + c} \quad [5]$$

and

$$w_t^{(2)} = \frac{TF_t^{(2)}}{r \cdot TF_t^{(1)} + c} \quad [6]$$

where $r = \frac{\text{text 2 length}}{\text{text 1 length}}$.

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