Networks of Twin Peaks: the Dale Cooper Effect

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1 The shape of stories

When Kurt Vonnegut speaks of the shape of stories [1], he is in the realm of calculus, continuous functions describing dynamics of the plot, the highs and lows of the protagonist’s emotions, the speed at which the story unravels. In a way, it corresponds to the historical development of calculus as a way to interpret motion as a function of time. The abscissa is the time, and the ordinate axis is something important for the hero—emotional state, for example. Figure 1 provides a detailed illustration from contemporary fantasy fiction.

There is another shape of a story we are interested in: one of its people, the world it lives in. That shape does not focus on the actions, but on the structures. It describes the contents of the carrier bag, like in Ursula K. Le Guin’s Carrier Bag Theory of Fiction [3], and they are neatly arranged in graphs, maps, and trees (as the eponymous work by Franco Moretti suggests [4]). The tools from it come from graph theory and algebra—and once put in context of arbitrary large networks, the field of research is usually dubbed network theory [5]. Are there only so many community types, networks of interactions in life and in literature? What can mathematics tell us about it? Are networks of characters in fiction anything like our social networks? A growing body of literature has been dealing with this application of network theory; investigating epic stories from the past, superhero universes from the modern era, etc. The more characters exist in a work of fiction, the more interesting and relevant network theoretic results become: patterns emerge, clusters and communities, and unexpected characters reveal themselves as keystone elements of networks: once removed, everything falls apart.

“I would go so far as to say that the natural, proper, fitting shape of the novel might be that of a sack, a bag. A book holds words. Words hold things. They bear meanings. A novel is a medicine bundle, holding things in a particular, powerful relation to one another and to us.” [4] Here, in this quote from Le Guin lies our motivation to explore the networks, rather than forward-driving, sharp-edged plots of Vonnegut. She proceeds: “If it’s clear that the Hero does not look well in this bag. (...) That is why I like novels: instead of heroes they have people in them.”

We are curious what the hero effect is in a network: are they just like anyone else, do they fit in the bag? Finally, we erase the linear time of Vonnegut’s plots by observing networks instead of actions, algebra instead of calculus. The community in the network exists independently of the passage of time, and it needs to feel real. Again, Le Guin writes “If, however, one avoids the linear, progressive, Time’s-(killing)-arrow (...) one pleasant side effect is that science fiction can be seen as (...) in fact less a mythological genre than a realistic one.”

In this work, we scratch the surface of character networks in the cult TV show Twin Peaks. For the readers who have not seen it, the first season of Twin Peaks revolves around a murder investigation in the town of Twin Peaks. FBI agent Dale Cooper comes to town to investigate alongside the local police department, and the viewers get to see networks of crime, romantic relationships, and law enforcement entangle and blur the lines between. Compared to other network theoretic treatises, this network is small scale, with sixty characters introduced over the course of eight episodes. The community is not even expected to behave as a social network; the crime-investigation-driven plot of Twin Peaks was expected to merely shine the light on those relationships relevant to the murder of Laura Palmer, hyperfocusing on a network built by the law enforcement officers conducting the investigation. Not only did the network analysis confirm that the community is more than just a set of photos pinned to a plywood board at the Sheriff’s office: we also discovered a new storytelling network phenomenon we called the Dale Cooper Effect, a phase transition in network structure.

2 Graphs and associated tools

A graph is a mathematical object made of vertices and edges (Fig. 2 left), which in the context of networks are often called nodes and links, respectively. A pair of vertices can be connected by a single edge or no edges—e.g. B and E have no edge connecting them, while A and B do. For large graphs and for algebraic manipulation of them, a commonly used representation is that of the adjacency matrix (Fig. 2 right). It is a square matrix whose
Figure 1: Annotated emotional arc of Harry Potter and the Deathly Hallows, by JK Rowling (from [2])

Figure 2: A graph and its adjacency matrix

|     | A  | B  | C  | D  | E  |
|-----|----|----|----|----|----|
| A   | 0  | 1  | 1  | 1  | 0  |
| B   | 1  | 0  | 0  | 0  | 0  |
| C   | 1  | 0  | 0  | 1  | 0  |
| D   | 1  | 0  | 1  | 0  | 1  |
| E   | 0  | 0  | 0  | 1  | 0  |

dimension corresponds to the number of vertices in the graph. As Fig. [2] shows, if there is an edge between the vertex corresponding to the row, and the one corresponding to the column, we place a “1” at their intersection in the matrix. Otherwise, that element is a “0” (no edge). If the graphs have no loops (i.e. if connecting vertex A to itself via an edge is not an option), the diagonal elements of the adjacency matrix are all zero. Furthermore, if the graph is undirected (i.e. if an edge between A and B is interpreted both as a connection of A with B and B with A), the matrix is symmetric.

An extension of the concept of the graph is a multigraph, where multiple edges connecting same two vertices are allowed. An example of this is shown in Fig. [3] where vertices A and B now have two common edges. This maps directly into the adjacency matrix, and the entries AB and BA are now equal to two. This multigraph can also be interpreted in terms of weighted graphs: all edges would again be single, but the one between A and B would have the weight of 2, while others would have the weight of 1. Sometimes, for example in collaboration networks where the goal is to assess the distance between entities represented by nodes (e.g. co-authors in mathematics or co-stars in movies, c.f. Erdős number, Bacon number), n multiple links between two nodes can be taken to correspond to the weight of $1/n$.

At this point, it is useful to define the degree of a vertex in a graph: for undirected graphs it is simply the number of edges connected with it (i.e. the sum of the corresponding row/column in the adjacency matrix). In the example in Fig. [2] the degree of nodes A and D is 3, the degree of the node C is 2, and the degree of nodes B and E is 1.

When drawing conclusions from networks appearing in the world around us, it is often useful to compare their structure to that of basic network models; common features stand out and cross over in different contexts, suggesting general patterns. Two common random network models are the Erdős-Renyi (random network) and the Barabasi-Albert (preferential attachment) model.

In the Erdős-Renyi model, the adjacency matrix is filled by tossing a biased coin. Let it be a $200 \times 200$ matrix,
and let the probability of two vertices being connected by an edge be $0.1$. The upper triangle of the adjacency matrix is then populated entry by entry with the result of tossing a coin which has $10\%$ chance of heads ($1$), and $90\%$ tails ($0$). After the upper triangle is filled, it is symmetrically copied into the lower triangle, finalising the undirected Erdős-Renyi graph generation.

The Barabasi-Albert model recognises the observation that many networks in the real world are built with the mechanism of preferential attachment. When a new node is added to such a network, the links it forms are not drawn with equal probability from the set of all nodes already in the network. The nodes that are already well-connected with other nodes will have more chance in attracting the new node. Let our network once again have $200$ nodes; in the process of preferential attachment we will be adding one node at a time, assign $4$ links connecting it to existing nodes in the network, and end the process once all $200$ nodes are added. The probability that the newly added node will establish a link with a particular existing node is proportional to the existing node’s degree.

In Figure 4 we depict the complementary cumulative distribution function of the degrees in two network model examples we described. The plot represents the probability that a node in the network has degree $X$ greater than some value $x$. For an $n$-node random network, the degree of a node is a function of $n - 1$ coin tosses and hence is a function of scale: $50\%$ of the nodes will be expected to have, in our numerical example, degree lower than $200 \cdot 0.1 = 20$, and $50\%$ will be expected to be over it. However, for the preferential attachment network, no such scale exists as the network generative process could have continued beyond $n$ nodes (this is why we often refer to these networks as scale-free). The complementary cumulative distribution function for such a network is theoretically a straight line in a log-log scale plot (here we present the actual plot from $200$-node network to show the deviations seen at small scales for a single instance of a network). While the “preferential attachment results in power law” maxime often holds, interesting exceptions have been observed—a famous one is the citation distribution of Physical Review papers demonstrated by Sid Redner to follow a log-normal distribution [6].

Another measure of interest for us in this note is that of assortativity. Are nodes with large/small degrees more likely to be connected to other vertices with large/small degrees in a network? In real-world social network, it is expected to see more popular nodes of the network to cluster together, while in networks such as the internet, webpages with few links to other webpages are more likely to be connected to well-linked hubs. The former is the case of a positive assortativity coefficient, and the latter of a negative one. Random networks, such as ones created by processes introduced earlier in this section, are expected to have a neutral (zero) assortativity.

The common reason to investigate networks in works of fiction is to compare their statistical properties to those of real networks. For example, in [7] the authors apply the network theory tools to study networks of characters in the epic narratives of The Beowulf, The Táin Bó Cúailnge and The Iliad. The network of the Iliad was found to have features of realistic networks such as positive assortativity, scale-free behaviour. For Beowulf, these properties are achieved once the protagonist, Beowulf, is removed from the story—Beowulf’s disproportionate degree of interaction with the world otherwise skews it. For The Táin Bó Cúailnge, the key to reaching realistic network properties has been removing one-off interactions between the six protagonists of the epic and the remainder of the world. There is always a component of “historicity evaluation” when discussing the studies of epics—assessing the realness of social networks in them is a factor in thinking about their genesis. For Twin Peaks, we have no such concerns; it is a fantasy world for which we do not expect to be a snapshot of the society. However, we are curious to see what the storytelling structure reveals.
To investigate the networks of interaction in *Twin Peaks*, we analysed the transcripts from season 1 of the show (total of 8 episodes)[8]. The choice to restrict the dataset to season 1 was motivated by the evolution of the script and cast in season 2, followed by the constraints passage of time put on season 3 (filmed two decades after the first two). Season 1 was hypothesised to be the smallest homogeneous unit appropriate for analysis. The adjacency matrix was formed chronologically: every time a new character appears, a new node is added to the graph. For every scene two characters share screentime in, a new edge is added to the graph, allowing multiple edges between the same pair of nodes. If three characters appear in the scene, all pairs get a new edge.

The resulting matrix is graphically presented in Fig. 5, our visualisation is similar to that of the Les Miserables Co-occurrence [9]—the difference is in ordering, as we preserve the order of appearance in the matrix. The left representation corresponds to the binary interpretation of the graph seen in Fig. 2: characters either share screentime, or they don’t, the quantity of time is irrelevant. Red squares correspond to edges of the graph, i.e. characters that...
Figure 6: The graphical representation of the Twin Peaks network: the black nodes are BC, the red are AD

| The most connected characters | #   | The most repeated links      | #   |
|------------------------------|-----|------------------------------|-----|
| 1   Dale Cooper              | 35  | Cooper & Truman              | 47  |
| 2   Sheriff Truman           | 35  | Truman & Lucy                | 16  |
| 3   Deputy Andy              | 20  | Cooper & Hawk                | 15  |
| 4   Donna                    | 19  | Truman & Hawk                | 14  |
| 5   Bobby                    | 18  | Donna & James                | 13  |

Table 1: Popular links and nodes in the network: all of them are in the BC part. The most connected AD character appears as the 18th in the list; the top repeated link which includes an AD character appears as the 13th in the list.

are connected. On the right, the shade of red changes with respect to the number of scenes characters have in common (i.e. interpretation akin to Fig. 3)–brighter means more interactions.

We recognise that the characteristic “cross” in the middle of the matrix, dividing it into four quadrants is the protagonist of the show, Special Agent Dale Cooper. Cooper appears 36 minutes into the pilot (first episode of the show), and he is the median character: ≈ 30 characters are introduced before him, and ≈ 30 after him (as we stated already, the adjacency matrix is filled chronologically, so nth row/column of it correspond to the nth character to appear in the show). If we now divide the characters into two categories–those appearing before Cooper (denoted BC in the remainder of this paper) and those after Dale (AD). The brightest points in the right adjacency matrix are usually either couples, or the Twin Peaks Police Department combined with Cooper. Graphically, this is shown in Fig. 6, while the most popular nodes and links are tabulated in Table 3.

In Fig. 7 we discuss the relationship between networks of BC characters and AD characters, what we call The Dale Cooper Effect. This cartoon version of the adjacency matrix aims to show how BC is a closely knit community–the part of the adjacency matrix corresponding to it (top left quadrant) is densely filled with connections. On the other end, the AD characters interact among themselves very little, the bottom right quadrant is very sparse in connections. It is by virtue of interacting with BC characters that AD characters are a part of the network (bottom left and top right quadrants).

This suggests a mechanism by which the two networks are spliced together. After the nodes of BC network are set up, and Dale Cooper is introduced, new AD nodes are added with a preferential attachment to BC: a newly
added node has a much higher probability of being connected to the BC core than fellow AD periphery. Also, the density of connections is indicative: the full graph has 236 edges, while the BC graph (in this treatise, we include Cooper in BC) has 128. Doubling the number of characters (i.e. adding AD to BC) hence results in doubling the number of edges (linear scaling).

The mechanism of network growth in the previous paragraph inspires a dive into the degree distribution of the network. Cooper and Sheriff Truman appear together in many scenes and share most of their contacts: their degree is the same, and rather high (35 in the entire network, i.e. more connected with more than 1/2 of other characters; 20 in the BC network, growing the fraction to 2/3 of other characters). Motivated by the findings from Beowulf and the Táin where adjustments are needed to make the protagonists more realistic, we were curious to see if such high degree nodes as Cooper and Truman are expected in networks like these.

Figure 8 presents our findings. First, we note that the BC degree distribution is similar to one of a random Erdos Renyi network seen in [4], and not too far off from a log-normal distribution (whose surprising appearance in some preferential attachment networks we already mentioned). For the BC+AD network, we examine significant deviation from the shape: the curve appears to be a superposition of three segments: one for low degrees ($x < 10$), one for moderately high degrees ($x < 20$) and one for very high degrees ($x > 30$). This is the effect of the mechanism by which AD characters are connected: they dominate the low degree segment of the distribution and shift it leftwards, while contributing to an increase in degree for Cooper and Truman (the very high degrees data point in the plot), pushing them rightwards. From here we deduce that Truman and Cooper are not abnormally well connected in the BC network, but in the BC+AD network, they are more popular than they would be in a random network.

This makes sense as Truman and Cooper drive the plot in the AD introduction period, and are often the first point of contact for new characters. This is mirrored in the assortivity measures for BC and BC+AD networks: BC assortativity is approximately zero (neutral), while for BC+AD the assortativity is negative: less connected characters in AD are connected to popular BC characters.

Following the ideas from [7], we proceed with studying the options of character removal. The first question is about the effect of removing characters that appear in a single scene (correction similar to that applied to the Táin Bó Cúailnge in [7]). This is the pruned network in Fig. 8: the removed nodes are predominantly in the AD group (20 removed from AD, and 4 from BC), so it is not surprising that the pruned network gets closer to the BC degree distribution. However, the anomaly of Cooper and Truman remains. As it turns out, the pruned network collapses onto BC if one of the two dominant nodes is removed: a case for “this town ain’t big enough for both of us”. In a way, removing Cooper could be justified as removing the outsider (or Beowulf, following on [7]) from the local network of Twin Peaks.

Finally, given the importance of the law enforcement characters in a show driven by crime investigation, an interesting test is whether the BC+AD network remains connected after the members of the FBI and the Twin Peaks Police Department are removed. The answer is yes—it still remains a single graph (with the exception of the few characters whose appearance in the show, if limited to Season 1, is tied exclusively to the police investigation) with Benjamin Horne as its central figure, tying together the young population of Twin Peaks through his daughter Audrey, and the criminal milieu through his business connections.

This process of “police removal” is interesting from the clustering point of view. Networks can often be split into meaningful clusters of nodes based on the connections between them. Sometimes this split is ambiguous and it is hard to deal with borderline cases, but they give a general idea of the communities existing in the network. Using
the Louvain algorithm \cite{10} we perform clustering of both the network before and after removal of police officers in Twin Peaks, with the results shown in Fig. \ref{fig:8}. The blue cluster on the left represents the cluster consisting of the police and people primarily interacting with the police, either as suspects or witnesses. Once the police officers are removed from the network, some nodes are left disconnected, and the rest of the nodes that had connections with other clusters join those clusters.

4 Final Remarks

It is hard to draw conclusions from small data and somewhat arbitrary conventions applied in its analysis. Given that we are in the realm of art, creation, and interactions, one alternative to the approach taken in this work would have been resorting to the actor network theory (despite the fact that Latour would object to observing the actor network as a mathematical network \cite{11}.) Is the dead body of Laura Palmer a character? Is the photo of Laura Palmer, and is it the same one? How about the Roadhouse?

Furthermore, this study largely ignored the multiplicity of common appearances of characters in scenes. For instance, in our count, Truman and Cooper share almost 50 common appearances, often in scenes that involve other characters as well. This makes them heavily correlated and they may appear as a single entity, a strongly connected pair. Studying correlations of this sort is a natural extension of the work presented here.

The one takeaway that stands out and presents a statistically robust result is The Dale Cooper Effect. The sharp demarcation between the two networks embodied by the protagonist introduced as a median character is the peculiar shape of story. Do similar structures emerge in other works of fiction? What is the fundamental relationship of The Dale Cooper Effect with storytelling? Those questions guide our future work.

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Figure 9: Clusters in the Twin Peaks network before (left) and after (right) removing the law enforcement

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