# Temporal Multilayer Network Analysis for Marvel Superheroes

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**Network analysis is a systematic way of studying movie (1) or comic character relationships. Applying network techniques enables researchers to discover hidden community structures that can be surprising to fans. We construct a temporal multilayer network to study how relationships among Marvel superheroes change across different eras since the 1950s. Preliminary numerical experiments show initial success of our method, but a more sophisticated edge weighting scheme is needed.**

Temporal Network | Multilayer Network | Social Network Analysis | Comic Character Analysis

## Introduction

In recent years, using network analysis to study community structures of movie (1) or comic characters has gained popularity. The main characters can be obvious sometimes, but it is harder to draw a conclusion for a franchise with multiple episodes and storylines (2). Therefore, applying network techniques such as centrality measures enables researchers to discover hidden community structures. Comic character analysis derives many of its techniques from movie character analysis, pioneered by computer scientists who led the early developments of facial recognition algorithms (1). One can think about comics as simplified versions of movies in our context because movie dialogues and visuals are harder to parse. The richer display of emotions also involve careful sentiment analysis to thoroughly study a movie character network. Both comic and movie character network are part of the broader study of Social Network Analysis (SNA), and they exhibit properties similar to real-world social networks like a Facebook friendship network.

In our paper, we study the community structure of Marvel superheroes over time, namely, the different periods of comic book development. We use a temporal multilayer network to divide heroes into different layers: each layer contains all heroes that appear in comics released in an era. Within a layer, each node represents each character, and an edge exists between two nodes if the two characters have interacted. Across different layers, we use the convention that an inter-layer edge joins the character itself if it appeared in different periods.

Comic books have significantly different common themes across eras due to social changes. For example, the Bronze Age that lasted from 1970 to 1985 focused on reflecting issues like racism in its storylines (3). Temporal multilayer network is still a new approach in analyzing comic characters, and we want to see if it helps us to understand whether character relationships were affected by stylistic changes.

## Relevant Work

Temporal multilayer network is a new approach of studying comic character relationships, and past works have been limited. Existing works revolve around movie character analysis, which is very similar to comic analysis, so we used it as the basis of our exploration. They use a traditional, one-dimensional node-edge structure to construct networks, where a node represents a character, and an edge exists if the two characters have interacted. Basic degree centralities (2) were used to assign communities, which is not always reliable for complex networks.

To collect character co-appearance data, these studies organize researchers and volunteers to watch the movies or read the comics, and take an "average" of their responses to decide if an interaction exists (2). In addition, they use sophisticated facial recognition or computer vision algorithms (1) to detect a change in scenes so that researchers can assign sentiment score of each interaction to weigh the edges. As we can see, this approach is very labor-intensive and is impossible for large networks. Although their results correctly predict character relationships most of the time (1), this approach is error-prone since it relies on human judgement to assign sentiment scores. Despite having a cross-validation step to normalize across all responses, the interpretation can still be biased if there are only a few researchers available.



### Significance Statement

Past papers on movie (1) or character network analysis have been one-dimensional, ignoring the time component when evaluating how network structures change. They use degree centralities as thresholds to cluster characters into major, minor, or extra roles(2). This is computationally efficient, but doesn't work well for large, complex networks. In addition, they rely on the assumption that the characters can usually be clustered into two or three communities each led by a leading character(1). This motivates the goal of our project: we want to consider temporal component of a network and use more sophisticated, eigenvector-based centrality methods and Louvain algorithms for community detection.

Allen did research on prior works in comic and movie network analysis and worked on community detection with Ruiyao. He compared and contrasted our result with past works. He wrote the Abstract, Introduction, Significance Statement, and Conclusions and Discussion.Amy pre-processed the data and worked on visualization of multilayer network. She wrote the the centrality and temporal network definitions and data pre-processing sections of the report. Hercy helped determine and layers of the temporal network, researched supracentrality analysis of temporal networks, and ran experiments on them. She also wrote the definitions of supracentrality matrix construction, joint and conditional centralities, and all the other supracentrality methods section on the final report and the presentation. Owen did research on visualization of temporal networks. He summarized the output of community detection, intercepted them, and wrote about real-life explanations of these results. Jim researched the available datasets, and cleaned and processed the original dataset. He also created visualizations for the general dataset and visualizations for the centrality measures. He wrote the Data Visualization and the Temporal Network Centrality Visualization sections on the final report and the presentation. Ruiyao did research on multilayer community detection and worked on community detection with Allen. She also worked on the visualization of the partition result. She wrote the background, methods, some parts of results, and limitations section of community detection.

## Background

### A. Brief overview of centrality measures.

***Degree Centrality.*** The degree centrality of a node $i$ is simply its degree, often denoted $k_i$:

$$k_i = \sum_{j=1}^{n} A_{ij} \qquad [1]$$

where $A_{ij}$ is the $ij$th entry of the adjacency matrix of the network, and $n$ is the number of nodes(4).

***Eigenvector Centrality.*** The eigenvector centrality of a node $i$ is its corresponding entry in the leading eigenvector of the adjacency matrix:

$$x_i = \kappa^{-1} \sum_{j=1}^{n} A_{ij} x_j \qquad [2]$$

or in matrix form:

$$\mathbf{A}\mathbf{x} = \kappa \mathbf{x} \qquad [3]$$

where $\mathbf{A}$ is the adjacency matrix of the network and $\kappa$ is the corresponding eigenvalue for the leading eigenvector $\mathbf{x}$(4). This centrality measure rewards a node for the importance of the nodes that it connects to.

***PageRank Centrality.*** The PageRank centrality of a node $i$ is:

$$x_i = \alpha \sum_{j=1}^{n} A_{ij} \frac{x_j}{k_j^{out}} + 1 \qquad [4]$$

or in matrix form:

$$\mathbf{x} = (\mathbf{I} - \alpha \mathbf{A}\mathbf{D}^{-1})^{-1}\mathbf{1} \qquad [5]$$

where $\alpha$ is a predetermined parameter with $\alpha < \frac{1}{\lambda_1(\mathbf{AD}^{-1})}$ ($\lambda_1(\mathbf{AD}^{-1})$ is the largest eigenvalue of $\mathbf{AD}^{-1}$), and $k_j^{out}$ is the out-degree of node $j$(4). This centrality measure rewards a node for the importance of the nodes that it connects to, but for an amount inversely proportional to their out-degrees, and it gives each node a "free" centrality value of 1.

***Closeness Centrality.*** The closeness centrality is the inverse of the mean distance from a node to other nodes:

$$C_i = \frac{1}{l_i} = \frac{n}{\sum_j d_{ij}} \qquad [6]$$

where $d_{ij}$ is the shortest distance from node $i$ to node $j$(4).

***Betweenness Centrality.*** The betweenness centrality measure the extent to which a node lies on the paths between other nodes, and it is defined to be:

$$x_i = \sum_{st} \frac{n_{st}^i}{g_{st}} \qquad [7]$$

where $n_{st}^i$ is the number of shortest paths from node $s$ to node $t$ that pass through $i$, $g_{st}$ is the total number of shortest paths from node $s$ to node $t$, and we let $n_{st}^i / g_{st} = 0$ if both $n_{st}^i = g_{st} = 0$(4).

### B. Temporal networks.

A temporal network is a special type of multilayer network (which is a set of individual networks, each with its own nodes and edges, plus some edges between different layers), in which each layer represents the network at a different point or interval of time(4).

### C. Single-layer modularity maximization.

Consider an $\mathbf{N}$-node network $\mathbf{G}$ and let the edge weights between pairs of nodes be $\{\mathbf{A}_{ij} \mid i,j \in \{1,\dots,N\}\}$, so that $\mathbf{A}$ is the adjacency matrix of $\mathbf{G}$. Suppose that there is a partition $\mathbf{C}$ of a network into $\mathbf{K}$ disjoint sets of nodes $\{\mathbf{C}_1,\dots,\mathbf{C}_K\}$. We can define $\mathbf{c(i)} = \mathbf{c(j)} = \mathbf{k}$ if and only if $\mathbf{i}$ and $\mathbf{k}$ lie in the same $\mathbf{C}_k$. The value of modularity for a given partition $\mathbf{C}$ is then

$$\mathbf{Q}(\mathbf{C} \mid \mathbf{A};\mathbf{P}) := \sum_{\mathbf{i,j=1}}^{\mathbf{N}} (\mathbf{A}_{ij} - \mathbf{P}_{ij})\delta(\mathbf{c}_i, \mathbf{c}_j) \qquad [8]$$

where $\mathbf{P}$ is the adjacency matrix of the null network and $\delta(\mathbf{c}_i, \mathbf{c}_j)$ is the Kronecker delta function. Then, we can state the modularity-maximization problem as follows:

$$\max_{\mathbf{c}\in\mathbf{C}} \sum_{\mathbf{i,j=1}}^{\mathbf{N}} (\mathbf{A}_{ij} - \mathbf{P}_{ij})\delta(\mathbf{c}_i, \mathbf{c}_j) \qquad [9]$$

where modularity matrix $\mathbf{B}$ can be defined as $\mathbf{A} - \mathbf{P}$ (5).

### D. Multilayer modularity maximization.

Consider an $\mathbf{N}|\mathcal{T}|$-node multilayer network, where $\mathcal{T} = \{\mathbf{A}_1,\dots,\mathbf{A}_{|\mathcal{T}|}\}$ represents adjacency matrix for a layer $\mathbf{A_s}$. we can state the multilayer modularity-maximization problem

$$\max_{\mathbf{c}\in\mathbf{C}} \sum_{\mathbf{i,j=1}}^{\mathbf{N}|\mathcal{T}|} \mathbf{B}_{ij}\delta(\mathbf{c}_i, \mathbf{c}_j) \qquad [10]$$

where $\mathbf{B}$ is the multilayer modularity matrix

$$\mathbf{B} = \begin{bmatrix} B_1 & \omega\mathbf{I} & 0 & \dots & 0 \\ \omega\mathbf{I} & \ddots & \ddots & \ddots & \vdots \\ 0 & \ddots & \ddots & \ddots & 0 \\ \vdots & \ddots & \ddots & \ddots & \omega\mathbf{I} \\ 0 & \dots & 0 & \omega\mathbf{I} & B_{|\mathcal{T}|} \end{bmatrix} \qquad [11]$$

and $\omega \in \mathbf{R}$ is the value of the inter-layer edge weight. We can rewrite the multilayer modularity-maximization problem in 10 as:

$$\max_{\mathbf{c}\in\mathbf{C}} [\sum_{\mathbf{s=1}}^{|\mathcal{T}|} \sum_{\mathbf{i,j=1}}^{\mathbf{N}|\mathcal{T}|} \mathbf{B}_{ijs}\delta(\mathbf{c}_{\mathbf{i}_s}, \mathbf{c}_{\mathbf{j}_s}) + 2\omega \sum_{\mathbf{s=1}}^{|\mathcal{T}|\mathbf{-1}} \sum_{\mathbf{i=1}}^{\mathbf{N}} \delta(\mathbf{c}_{\mathbf{i}_s}, \mathbf{c}_{\mathbf{i}_{s+1}})] \qquad [12]$$

where $\mathbf{B}_{ijs}$ denotes the $(i,j)^{\text{th}}$ entry of $\mathbf{B_s}$ (5).

### E. Supracentrality Matrix Construction.

A supracentrality matrix $\mathbb{C}(\omega) \in \mathbb{R}^{NT \times NT}$ is the matrix from which eigenvectors will be calculated, where $\mathbf{N}$ represents the number of nodes in the network, and $\mathbf{T}$ denotes the number of time layers for temporal networks. Given a sequence of adjacency matrices $\mathbf{A}^{(t)} \in \mathbb{R}^{N\times N}$ for $t \in \{1, 2, ..., T\}$, we will turn them into corresponding centrality matrices $\mathbf{C}$ (the function is related to the desired centrality measure, for example, eigenvector centrality uses $\mathbf{C}(\mathbf{A}) = \mathbf{A}$). Then, these centrality matrices

$\mathbf{C}^{(t)}$ are coupled together. We define an interlayer-adjacency matrix $\tilde{A} \in \mathbb{R}^{T\times T}$, where each entry $\tilde{A}_{tt'}$ encodes the interlayer coupling from layer $t$ to layer $t'$, $\tilde{A}$ can be either directed or undirected. The parameter $\omega \geq 0$ then controls the strength of connections between the layers. We will formally define the supracentrality matrix

$$\mathbb{C}(\omega) = \begin{bmatrix} \mathbf{C_1} & \mathbf{0} & \mathbf{0} & \dots \\ \mathbf{0} & \mathbf{C_2} & \mathbf{0} & \dots \\ \mathbf{0} & \mathbf{0} & \mathbf{C_3} & \ddots \\ \vdots & \vdots & \ddots & \ddots \end{bmatrix} + \omega \begin{bmatrix} \tilde{\mathbf{A}}_{11}\mathbf{I} & \tilde{\mathbf{A}}_{12}\mathbf{I} & \tilde{\mathbf{A}}_{13}\mathbf{I} & \dots \\ \tilde{\mathbf{A}}_{21}\mathbf{I} & \tilde{\mathbf{A}}_{22}\mathbf{I} & \tilde{\mathbf{A}}_{23}\mathbf{I} & \dots \\ \tilde{\mathbf{A}}_{31}\mathbf{I} & \tilde{\mathbf{A}}_{32}\mathbf{I} & \tilde{\mathbf{A}}_{33}\mathbf{I} & \dots \\ \vdots & \vdots & \vdots & \ddots \end{bmatrix}, \quad [13]$$

where the second part is the Kronecker product of $\tilde{A}$ and $\mathbf{I}$ (6).

**F. Joint and Conditional Centralities.** Let $\mathbf{v}(\omega)$ be the calculated right dominant eigenvector that represents the centrality scores. The joint centrality of a node $i$ in time layer $t$, denoted $W_{it}(\omega)$, is defined as

$$W_{it}(\omega) = \mathbf{v}_{N(t-1)+i}(\omega), \quad [14]$$

this joint centrality score emphasizes the importance of both the node $i$ and the time layer $t$.

Given the joint centralities $\{W_{it}(\omega)\}$, we can thus define the conditional centralities of nodes as follows

$$Z_{it} = W_{it}(\omega) \ / \sum_i W_{it}(\omega), \quad [15]$$

this conditional centrality of nodes is conditioned on layer $t$, so it can reflect the relative importance of nodes within a layer(6).

## Methods and Models

**Data Pre-processing.** The raw data we obtained contains all Marvel comics before 2002 (7). This dataset works for our initial attempts to find the most popular heroes, but we need a smaller subset of it for our detailed analysis, due to restriction in time and our resources.

We decided to analyze only the Avengers series, which includes volumes 1, 2, and 3, and the annuals of the years before 2002. In order to do so, we use the bipartite graph between heroes and comics and first filter out all comics that we will not use. Then we check the publication dates of the comics to divide them into the four eras - silver age, bronze age, modern age, and heroes relaunched (8). We project each network onto the hero-nodes to create a weighted hero-hero network, in which the weight is the number of issues the heroes occur together.

**Data Visualizations.** We begin our Exploratory Data Analysis (EDA) process with a visualization of our network. In our first visualization of the general dataset, each node represents a hero, and each edge represents the interaction between two heroes when they appear in the same issue. This is a weighted undirected network, with the weight of the edge representing the number of common issues. In figure 1, we visualize the network dataset with only the top 25 nodes with the highest degree.

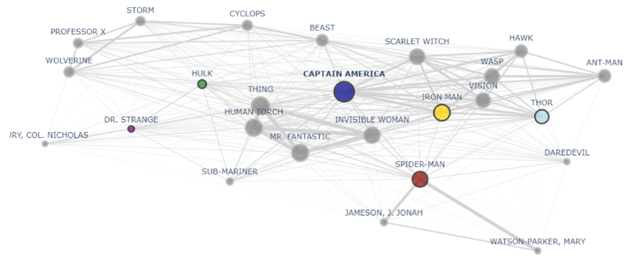



**Fig. 1.** The visualization of top 25 heroes network. Each node represents a hero, and each edge represents the interaction between two heroes when they appear in the same issue. The size of the node represents the degree centrality

We further visualized PageRank, eigenvector, degree, and closeness centralities as a part of our exploratory process. Figure 2 is an example of our visualizations for the centrality measures.

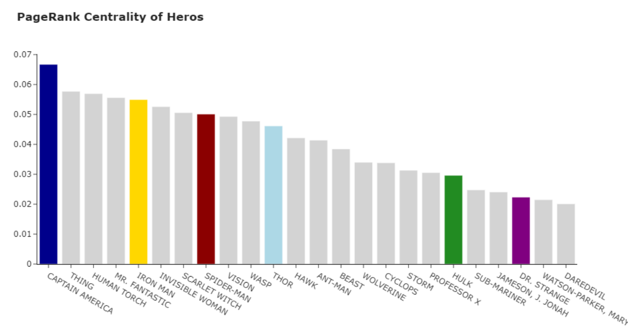



**Fig. 2.** Top 20 heroes PageRank Centrality. We see that Captain America has the highest PageRank Centrality follow by the Thing

However, because each centrality measure represents different information, we need to find a way to show a summary of the 4 centralities we used. As a result, we decided to use a measure called average centrality rank. The average centrality rank is equal to the mean of the ranks of PageRank, eigenvector, degree, and closeness centralities. For example, Captain America is ranked 1st in PageRank, ranked 4th in Eigenvector centrality, ranked 1st in degree centrality, and ranked 1st in closeness centrality. So Captain America's average centrality rank is 1.75. The measures is also demonstrated in table 1 below.

**Table 1. Demonstration of Centrality Measures we used**

| | Captain America | Thing |
|---|---|---|
| PageRank Centrality | 0.066699 | 0.057688 |
| Eigenvector Centrality | 0.312066 | 0.318561 |
| Degree Centrality | 4409.0 | 3828.0 |
| Closeness Centrality | 141.338880 | 104.086414 |
| PageRank Ranking | 1 | 2 |
| Eigenvector Ranking | 4 | 1 |
| Degree Ranking | 1 | 8 |
| Closeness Ranking | 1 | 2 |
| Average Centrality Rank | 1.75 | 3.25 |

We compute the 20 lowest average centrality rank to obtain the list of heroes with the highest centralities overall, as shown in figure 3 below.

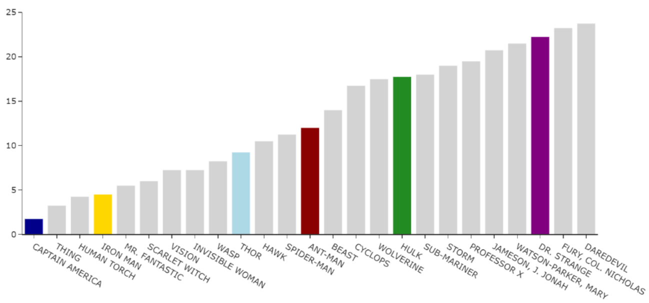



**Fig. 3.** Top 20 Heroes with Lowest Average Centrality Rank. The lowest is Captain America followed by the Thing, this means that Captain America has the Highest centrality overall, followed by the Thing.

We double check on the heroes with top 10 centrality ranking and find out that all of them exist in all four layers, so we decide to further filter our network to include only the nodes that occur on all four layers. This can make later calculations that require all nodes to exist on all layers possible, and we will not end up with a lot of zero entries if we were to add all nodes in all layers to each layer.

**Temporal Network Centrality Visualizations.** Once we obtained our temporal network, we decided to apply the same algorithm to compute their Average Centrality Ranking, so that we could get an overall idea of how heroes' centrality changes over time. Figure 4 shows four visualizations of Average Centrality Ranking as we move from Silver Age to Heroes Age.

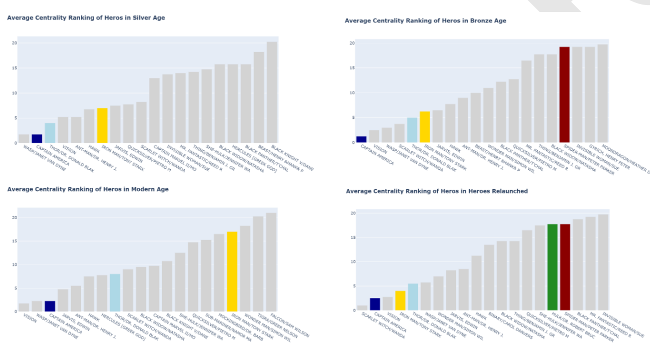


**Fig. 4.** Average Centrality Rank of each layer of the Temporal Network. We see that as we move from layers to layers, the average centrality ranking changes

**Community detection in multilayer networks.** We apply community detection by maximizing the modularity function in multilayer networks to our data with `Genlouvain` package for Matlab (9). To simplify our study, we choose the coupling parameter $\omega$ as 0.5.

**Supracentrality Analysis with Temporal Network.** Previously, we computed basic centrality measures over our datasets, and we could see some changes in the rankings, but it lacked a time component. In an attempt to dig deeper into the effects of time on character importance, we decided to proceed to perform a supracentrality analysis on this temporal character network.

After constructing the supracentrality matrix $\mathbb{C}(\omega)$, we then compute the dominant eigenvector $\mathbf{v}(\omega)$, and use its entries as scores for centrality measures. Thus, we solve the following equation

$$\mathbb{C}(\omega)\mathbf{v}(\omega) = \lambda_{max}(\omega)\mathbf{v}(\omega), \qquad [16]$$

and $\mathbf{v}(\omega)$ would contain all the centrality scores (6, 10, 11).

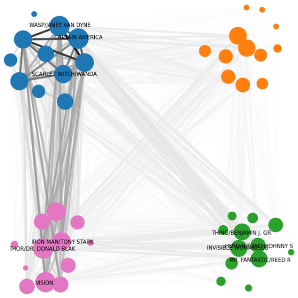
## Results

We present the results of our numerical experiments with different methods, respectively.

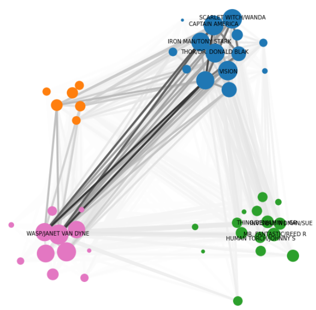
**Community detection result visualization.** Figure 5a and Figure 5b depict a partition into 4 communities that we found with $\omega = 0.5$, while Figure 5c and Figure 5d depict a partition into 3 communities. We also present the resulting communities of the top 10 heroes in Figure 6.

**Community detection result interpretation.** Here are the results from community detection 9. For each layer that represents a period, all forty-seven heroes are sorted into four or three communities. We now analyze the community formation of all four ages and the top ten centrality heroes. In the Silver era, which is the earliest ear in our dataset, we found four communities with relatively obvious traits. For instance, the heroes in group one all have learned martial arts. Captain America taught most of them, such as Wanda. Most of the heroes in group two have different states, and most heroes in group three have objects as their weapons, such as Thor's hammer and Ironman's armor. The heroes in the last group all experienced mutation, such as the Hulk, infected by gamma rays. What's more, looking at the heroes with the top ten centrality ranking, we notice that they are evenly distributed in three different communities. To sum up, at the very earliest age of the marvel comic era, which can be seen in figure 5a, most of the heroes appear in the same scene because they share commonalities in background or ability. However, such a trend started to change when we look at the following eras. In the bronze age, there is hardly any obvious traits for each community 10. The top ten heroes are mostly gathered into two communities as 5b shows. The connections between the most popular characters have a clear increase. Such a trend continues in the next two eras. In the Modern age 11, the number of communities has decreased from four to three 5c, and in the Heroes age 12, all ten top heroes have gathered into two out of the three communities 5d. Overall, as time goes by, marvel tends to create more interactions between the more popular heroes instead of following the more logical storyline base on the background, which is a widely used strategy for commercial works.

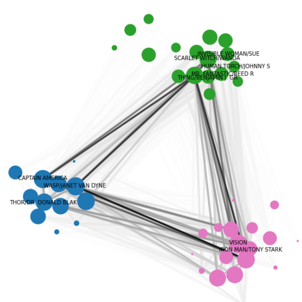
**Supracentrality Analysis with Temporal Network.** To better understand changes in the top 10 characters' importance over time, we performed PageRank Supracentrality with teleportation parameter $\sigma = 0.85$, and $\omega \in \{1, 10, 100, 1000\}$ in Figure 7a and Figure 7b. We then obtained the results from performing Eigenvector Supracentrality with $\omega \in \{1, 10, 100, 1000\}$ in Figure 8a and Figure 8a. All experiments were done with undirected interlayer coupling because we noticed that directed



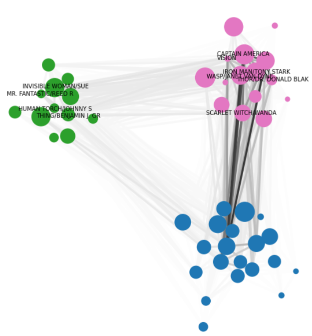
**(a)** Silver Age



**(b)** Bronze Age



**(c)** Modern Age



**(d)** Heroes Age

**Fig. 5.** The visualization of communities we found in four eras. The node color represents different communities and the node size is proportional to its centrality.

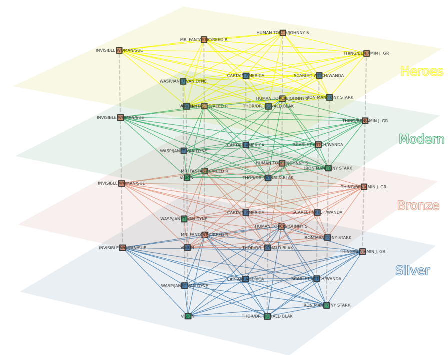



**Fig. 6.** The visualization of communities we found in four eras in a 3D view of all layers.The node color represents different communities (same color in different layers do not share similarities, color is only used to differentiate nodes in the same layer). Intralayer edges have different colors for different layers; this is not related to color of nodes either, but only used to differentiate different layers.



interlayer coupling gives the largest importance to the earlier time periods, and it is not easy to observe the temporal changes given we only have four time periods.

We vary the strength of coupling parameter $\omega$ to see how it affects the temporal changes in centrality measures. One interesting thing to note is when $\omega$ becomes very large, the conditional centralities become very smooth, almost straight lines as shown in Figure 7b when $\omega = 1000$.

Comparing the supracentrality analysis results with the basic centrality results, we found that Captain America remains the most important hero throughout the Avengers period. Although some heroes are more important in the Avengers Bronze period like Vision, they are not so prominent in the overall basic centrality analysis performed previously.

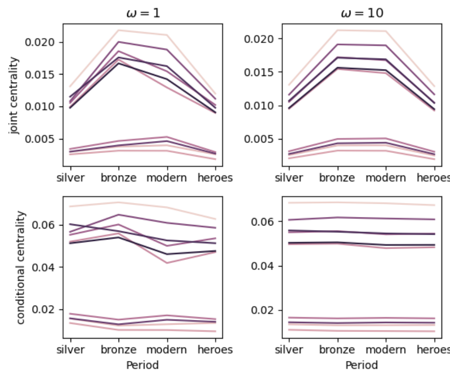
In both PageRank and Eigenvector centrality analysis, a trend we noticed is that there seems to be a large rise in hero importance during the Bronze Period. This could be explained by the large increase in the volumes of comics during the Bronze Period, leading to more character co-appearances, and potentially more complex character interactions.

## Limitations

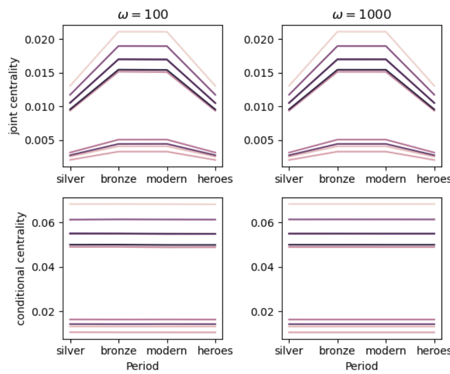
First, to simplify our study, when we construct the multilayer network for further study, we choose to consider characters who appear in all four ages and thus it is likely to lose important information due to this decision.
For our approach of community detection in multilayer network, we choose the inter-layer coupling $\omega$ to be 0.5 without rigorous numerical experiment. Normally, the highest achievable value of persistence for an optimal partition obtained with a given value of $\omega$ is a non-decreasing function in $\omega$(5). The choice of inter-layer coupling might affect the reasonability of partitions based on our data set.

## Conclusions and Discussion

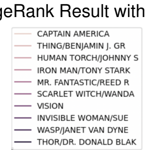
As we enter the Modern Age, we note a significant change in community structure: the four communities in previous eras condense into three communities, and interactions between




**(a)** PageRank Result with small $\omega$




**(b)** PageRank Result with large $\omega$



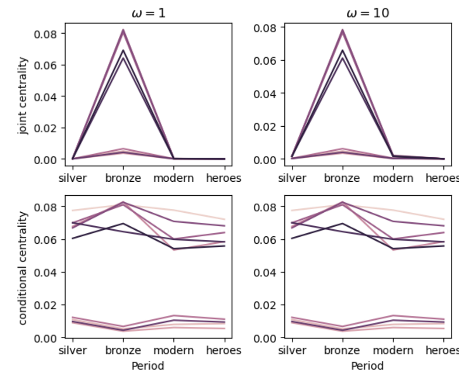

**(c)** Legend

**Fig. 7.** Results of performing supracentrality analysis using PageRank centrality, with teleportation parameter $\sigma = 0.85$, and varying the strength of coupling parameter $\omega \in \{1, 10, 100, 1000\}$.

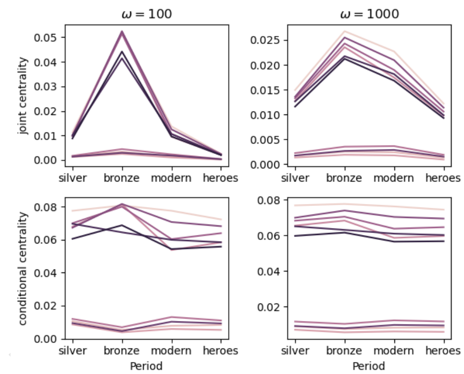
communities are more frequent. One possible explanation for this is that comics entered a "dark age" (8) in which a shift in fan preferences steered productions to focus on dark or anti-heroes such as Scarlet Witch or Wolverine. This stylistic shift also added vigilante elements to traditional characters. As a result of a more similar character design of this era, community structure changed accodingly.

One limitation of the Louvain algorithm is how it searches in the space of solutions. Although the modularity function is deterministic, a consistent solution is not guaranteed since the algorithm can completely miss it. This may have contributed to some of the random noises in our results which deviate from real-world Marvel hero relationships.

Contrary to our anticipation, some characters whom we believed to take minor roles in fact have higher centralities than some major characters. Due to limitations in time and resources, we weren't able to label weights according to character relationships in a careful manner. Ideally, characters who are for example, siblings, should be weighted higher than characters who are just friends. However, this involves carefully reading the comics and observing character interaction, which were carried out by many sophisticated studies we mentioned.




**(a)** Eigenvector Centrality Result with small $\omega$




**(b)** Eigenvector Centrality Result with large $\omega$

**Fig. 8.** Results of performing supracentrality analysis using Eigenvector centrality varying the strength of coupling parameter $\omega \in \{1, 10, 100, 1000\}$.

Therefore, despite being time-consuming, these studies were able to produce more accurate predictions.

## Code

Readers can find our code from our Github repository.


## Acknowledgement

We want to thank our Professor Mason Porter for the helpful advice he gives regarding our topic and method choice, and the papers that he recommends to us. We also thank the authors of our data sets.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# Appendix

| | Layer 1 | Silver | |
|---|---|---|---|
| ANT-MAN/DR. HENRY J. | ATTUMA | BEAST/HENRY &HANK& P | COUNT NEFARIA, LUCHI |
| BLACK WIDOW/NATASHA | CAPTAIN MARVEL II/MO | BINARY/CAROL DANVERS | CRYSTAL [INHUMAN] |
| CAPTAIN AMERICA | DR. DRUID/ANTHONY LU | BLACK KNIGHT V/DANE | DAREDEVIL/MATT MURDO |
| GRIM REAPER/ERIC WIL | FALCON/SAM WILSON | BLACK PANTHER/T'CHAL | HULK/DR. ROBERT BRUC |
| HAWK | HELLCAT/PATSY WALKER | GYRICH, HENRY PETER | HUMAN TORCH/JOHNNY S |
| HERCULES [GREEK GOD] | MOCKINGBIRD/DR. BARB | IRON MAN/TONY STARK | ICEMAN/ROBERT BOBBY |
| POWER MAN/ERIK JOSTE | MOONDRAGON/HEATHER D | JARVIS, EDWIN | INVISIBLE WOMAN/SUE |
| QUICKSILVER/PIETRO M | O'BRIEN, MICHAEL | PHARAOH RAMA-TUT | LUNA/LUNA MAXIMOFF |
| SCARLET WITCH/WANDA | SHE-HULK/JENNIFER WA | SPIDER-MAN/PETER PARKER | MR. FANTASTIC/REED R |
| SWORDSMAN/JACQUES DU | SUB-MARINER/NAMOR MA | STARFOX/EROS | THING/BENJAMIN J. GR |
| WASP/JANET VAN DYNE | TIGRA/GREER NELSON | THOR/DR. DONALD BLAK | |
| | WIZARD/BENTLEY WITTM | ULTRON | |
| | | VISION | |
| | | WONDER MAN/SIMON WIL | |
| **martial arts** | **different state** | **has special object** | **mutations** |

**Fig. 9.** This chart includes the four communities of the Silver era for the 47 heroes that this paper mainly focuses on. Each column represents a community. The order does not have any specific meanings. Heroes in four communities has some similar traits. Most of the heroes in group two have different states, and most heroes in group three have objects as their weapons. The heroes in the last group all have experienced mutation. The heroes that have the top ten average centrality are marked in green. They are evenly spread in three groups.

| | Layer 2 | Bronze | |
|---|---|---|---|
| BLACK KNIGHT V/DANE | BLACK WIDOW/NATASHA | ANT-MAN/DR. HENRY J. | CAPTAIN MARVEL II/MO |
| BLACK PANTHER/T'CHAL | HELLCAT/PATSY WALKER | ATTUMA | CRYSTAL [INHUMAN] |
| CAPTAIN AMERICA | HERCULES [GREEK GOD] | BEAST/HENRY &HANK& P | HUMAN TORCH/JOHNNY S |
| DR. DRUID/ANTHONY LU | ICEMAN/ROBERT BOBBY | BINARY/CAROL DANVERS | INVISIBLE WOMAN/SUE |
| GRIM REAPER/ERIC WIL | MOONDRAGON/HEATHER D | DAREDEVIL/MATT MURDO | LUNA/LUNA MAXIMOFF [ |
| HAWK | PHARAOH RAMA-TUT | FALCON/SAM WILSON | MOCKINGBIRD/DR. BARB |
| HULK/DR. ROBERT BRUC | | GYRICH, HENRY PETER | MR. FANTASTIC/REED R |
| IRON MAN/TONY STARK | | JARVIS, EDWIN | O'BRIEN, MICHAEL |
| MOCKINGBIRD/DR. BARB | | SUB-MARINER/NAMOR MA | SHE-HULK/JENNIFER WA |
| SCARLET WITCH/WANDA | | POWER MAN/ERIK JOSTE | SPIDER-MAN/PETER PARKER |
| STARFOX/EROS | | WONDER MAN/SIMON WIL | WIZARD/BENTLEY WITTM |
| QUICKSILVER/PIETRO M | | ULTRON | TIGRA/GREER NELSON |
| THOR/DR. DONALD BLAK | | VISION | THING/BENJAMIN J. GR |
| WASP/JANET VAN DYNE | | SWORDSMAN/JACQUES DU | |

**Fig. 10.** This chart includes the four communities of the Bronze era for the 47 heroes that this paper mainly focuses on. Each column represents a community. No obvious commonality was spotted among any of the groups. The order does not have any specific meanings. The heroes that have the top ten average centrality are marked in green. Nine out of ten of them are gathered in two of the groups.

| Layer 3 | Modern | |
|---|---|---|
| ATTUMA | ANT-MAN/DR. HENRY J. | DAREDEVIL/MATT MURDO |
| BLACK KNIGHT V/DANE | BEAST/HENRY &HANK& P | FALCON/SAM WILSON |
| CAPTAIN AMERICA | BINARY/CAROL DANVERS | HAWK |
| CAPTAIN MARVEL II/MO | BLACK PANTHER/T'CHAL | HELLCAT/PATSY WALKER |
| DR. DRUID/ANTHONY LU | BLACK WIDOW/NATASHA | HULK/DR. ROBERT BRUC |
| JARVIS, EDWIN | COUNT NEFARIA, LUCHI | HUMAN TORCH/JOHNNY S |
| POWER MAN/ERIK JOSTE | CRYSTAL [INHUMAN] | INVISIBLE WOMAN/SUE |
| SHE-HULK/JENNIFER WA | GRIM REAPER/ERIC WIL | MOCKINGBIRD/DR. BARB |
| STARFOX/EROS | GYRICH, HENRY PETER | MOONDRAGON/HEATHER D |
| SUB-MARINER/NAMOR MA | HERCULES [GREEK GOD] | MR. FANTASTIC/REED R |
| THOR/DR. DONALD BLAK | ICEMAN/ROBERT BOBBY | O'BRIEN, MICHAEL |
| WASP/JANET VAN DYNE | IRON MAN/TONY STARK | SCARLET WITCH/WANDA |
| | LUNA/LUNA MAXIMOFF [ | SPIDER-MAN/PETER PARKER |
| | PHARAOH RAMA-TUT | THING/BENJAMIN J. GR |
| | QUICKSILVER/PIETRO M | TIGRA/GREER NELSON |
| | SWORDSMAN/JACQUES DU | WIZARD/BENTLEY WITTM |
| | ULTRON | WONDER MAN/SIMON WIL |
| | VISION | |

**Fig. 11.** This chart includes the three communities of the Modern era for the 47 heroes that this paper mainly focuses on. Each column represents a community. No obvious commonality was spotted among any of the groups. The order does not have any specific meanings. The heroes that have the top ten average centrality are marked in green. They evenly spread among three communities.

| Layer 4 | Heroes | |
|---|---|---|
| ATTUMA | ANT-MAN/DR. HENRY J. | DAREDEVIL/MATT MURDO |
| BEAST/HENRY &HANK& P | BINARY/CAROL DANVERS | DR. DRUID/ANTHONY LU |
| BLACK KNIGHT V/DANE | CAPTAIN AMERICA | GRIM REAPER/ERIC WIL |
| BLACK PANTHER/T'CHAL | COUNT NEFARIA, LUCHI | HELLCAT/PATSY WALKER |
| BLACK WIDOW/NATASHA | GYRICH, HENRY PETER | HULK/DR. ROBERT BRUC |
| CAPTAIN MARVEL II/MO | IRON MAN/TONY STARK | HUMAN TORCH/JOHNNY S |
| CRYSTAL [INHUMAN] | JARVIS, EDWIN | INVISIBLE WOMAN/SUE |
| FALCON/SAM WILSON | PHARAOH RAMA-TUT | MOCKINGBIRD/DR. BARB |
| HAWK | POWER MAN/ERIK JOSTE | MR. FANTASTIC/REED R |
| HERCULES [GREEK GOD | SCARLET WITCH/WANDA | SPIDER-MAN/PETER PARKER |
| ICEMAN/ROBERT BOBBY | THOR/DR. DONALD BLAK | SWORDSMAN/JACQUES DU |
| LUNA/LUNA MAXIMOFF [ | ULTRON | THING/BENJAMIN J. GR |
| MOONDRAGON/HEATHER D | VISION | |
| O'BRIEN, MICHAEL | WASP/JANET VAN DYNE | |
| QUICKSILVER/PIETRO M | WONDER MAN/SIMON WIL | |
| SHE-HULK/JENNIFER W | | |
| STARFOX/EROS | | |
| SUB-MARINER/NAMOR MA | | |
| TIGRA/GREER NELSON | | |
| WIZARD/BENTLEY WITTM | | |

**Fig. 12.** This chart includes the three communities of the Hero era for the 47 heroes that this paper mainly focuses on. Each column represents a community. No obvious commonality was spotted among any of the groups. The order does not have any specific meanings. The heroes that have the top ten average centrality are marked in green. They all gathered in two of the communities.