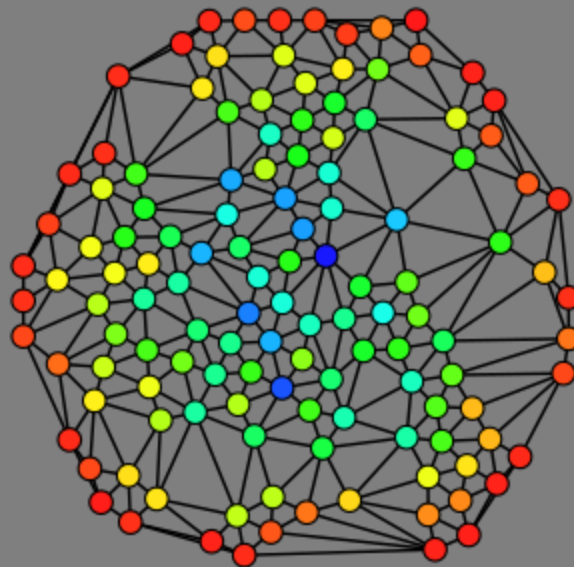


**ΟΙΚΟΝΟΜΙΚΟ
ΠΑΝΕΠΙΣΤΗΜΙΟ
ΑΘΗΝΩΝ**



**ATHENS UNIVERSITY
OF ECONOMICS
AND BUSINESS**



Social Network Analysis

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A card's game competitive deck network

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Introduction:

What is Yu-Gi-Oh! card game?

It's a card game between 2 players, there are a lot of rules in the game that makes it complicated, and every card has a different effect and type. Very briefly, you can win by make your opponent lose all his life points or wait for him not to run out of cards from his deck.

The rules and the card types are not important for the purpose of this document, so you don't have to know the game to understand the goal and the outcome of this network analysis.

What we need to know for our case?

The main thing we must understand is that the game contains a big pool of more than 11,000 different unique cards and each player must choose a deck of cards consisted of 40-60 and 0-15 for his extra deck. So, in total he should have 40-75 cards in his deck from the pool of cards the game offers.

Finding a good deck that maximizes your chances of winning is very important part in every card game. In our case, due to the game's cards pool expanding in addition with a banning list (by KONAMI) at regular intervals, people are trying every day to find the best deck to win in tournaments and the game is trying control the balance between decks by editing the banning lists or adding new cards.

We also need to know the idea of a "meta" deck. Meta decks are usually popular decks that tend to be powerful in between updates of the game (pool or banning list). People tend to play mostly meta-decks competitively due to a lot of reasons; they probably can't think of a better deck or by default the deck is very powerful, so everyone is playing the same small number of decks with small changes or choosing a deck that is very good on countering those decks (an anti-meta deck).

The game itself got more popular recently with the release of a video-game "Yu-Gi-Oh! Master Duel" at 18-Jan-2022. I used the last 1 month's (release date to 18-Feb-2022) meta decks to create a network of cards.



What is our Network consisted of?:

Our Nodes are the cards, we only use the Name and the ID of the card.

Our Edges are the relationship between the cards, if a card is in the same deck on a popular meta deck then they are related, this relationship isn't weighted with multiple relationships on various decks and it's an undirected relationship.

Dataset description:

Nodes.csv (Two columns)

ID: The ID of the card, each card with the same name has the same unique number.

Can be found in the bottom left of the card, is a number.

(Of course, there are multiple copies of the same card but the id between these cards is the same)

Name: The name of the Yu-Gi-Oh! card. Can be seen in the top of the example card "Time Wizard"

Edges.csv (Two columns)

Source: The source card node

Target: The target card node

The relationship is explained above.

Purpose of the analysis:

This can be used for various purposes.

- 1) We can find out which cards are important for the network. Some cards tend to be used in a lot of decks since they are more generally purposed. KONAMI can see if affecting a card's effect or adding it to the banning list/ limiting list, how will this affect the network of meta decks. Will it ruin the system of meta-decks and affect a lot of players? Maybe we want to find a small number of cards that will dismantle all the meta decks.
- 2) We can find which cards are close to each other, in the game some cards are from the same "family" of cards, usually they are released together, and they even have a similar name and can only be used with each other as combos. This could be a useful to deck suggestions to players on a deck builder application.
- 3) We can expand the analysis by containing more information on the Nodes, cards also include two types and an attribute. We can find patterns on the connection between the cards with the same attribute (Homophily) or see how the network structure looks like with colored communities.

How I collected the data?

I made some Python scripts.

Fetching the Nodes:

getNodes.py

```
import json
import pandas as pd

#File data is found on a GET request in the below link
#Provided by API of db.ygoprodeck.com (Fetched @February 2022)
#Simply download the data using a browser and the link (data must be placed in same directory)
#https://db.ygoprodeck.com/api/v7/cardinfo.php

#Read File of all yugioh cards data
f = open("cardinfo.php", "r")
stringfile = f.read()
f.close()

#String to JSON
jsonfile = json.loads(stringfile)

data = []

#Appending each card's data into data list
for carddata in jsonfile['data']:
    cardId = carddata['id']
    cardName = carddata['name']
    data.append([cardId, cardName])

#Making a pandas dataframe using the data
df = pd.DataFrame(data, columns = ['ID', 'Name'])

#Save file into csv
df.to_csv('Nodes.csv', index = False)
```

Getting the Nodes was quite simple after small research, it turns out there is an API that provides all the card's information. I made a GET request and filtered the id and the name into a csv file.

#<https://db.ygoprodeck.com/api/v7/cardinfo.php>

Following the above link, we can GET the cardinfo.php which is a json formatted file with all the game's information.

Fetching the edges:

I made a complicated script using automated libraries (Selenium and Chrome webdriver). I couldn't use traditional data scraping since the page didn't have the information on GET request, the information is added dynamically probably from a hidden API into the pages, so the HTML page isn't fully loaded on GET, I had to use Selenium to make the page load the decks dynamically.

```
#https://www.masterduelmeta.com/top-  
decks#dateRange=Last%204%20weeks&tournamentsOnly&page=1
```

Following the above link, you can find the master duel meta decks between 18-Jan and 18-Feb. Each deck can be clicked and there is a .ydk file inside which is basically a .txt file with the ids of the cards in the deck.

After downloading all the deck files from every page, I ended up with around 284 meta decks.

Now we create the edges by iterating between the decks. For every deck we add the corresponding edges, for every card in the deck we add the edge with the other cards of the deck if we haven't added that edge already. (getEdges.py)

```
import os  
import pandas as pd  
  
#Creating edges by checking meta deck files  
  
decks = []  
path = "decks/"  
#Reading the deck files  
for file_name in os.listdir(path):  
    file_extension = file_name.split(".",1)[1]  
    if file_extension == ".ydk":  
        try:  
            with open(path + file_name, encoding="utf8") as file:  
                filelines = file.readlines()  
                file.close()  
  
                current_deck = []  
                for line in filelines:  
                    line = line.strip()  
                    if line.isnumeric():  
                        current_deck.append(line)  
  
                decks.append(current_deck)  
  
        except:  
            print("There was an error on ydk file: {}".format(file_name))  
  
print("Reading files ended..")  
  
#Adding all edges between cards  
#If a card is in the same deck with other card there should be connected  
data = []  
count = 0  
  
for deck in decks:  
    count += 1  
    for card1 in deck:  
        for card2 in deck:  
            #Cards should not connect with itself  
            #We also don't have to add same edges multiple times  
            if card1 != card2:  
                if [card1, card2] not in data and [card2, card1] not in data:  
                    #Checking if the edge is already part of the data is increasing the algorithm's complexity  
                    data.append([card1, card2])  
        print("Finished: Deck {}".format(count))  
  
print("Edges:", len(data))  
  
#Making a pandas dataframe using the data  
df = pd.DataFrame(data, columns = ['Source', 'Target'])
```

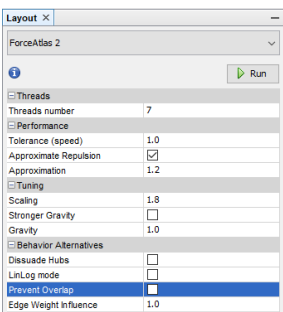
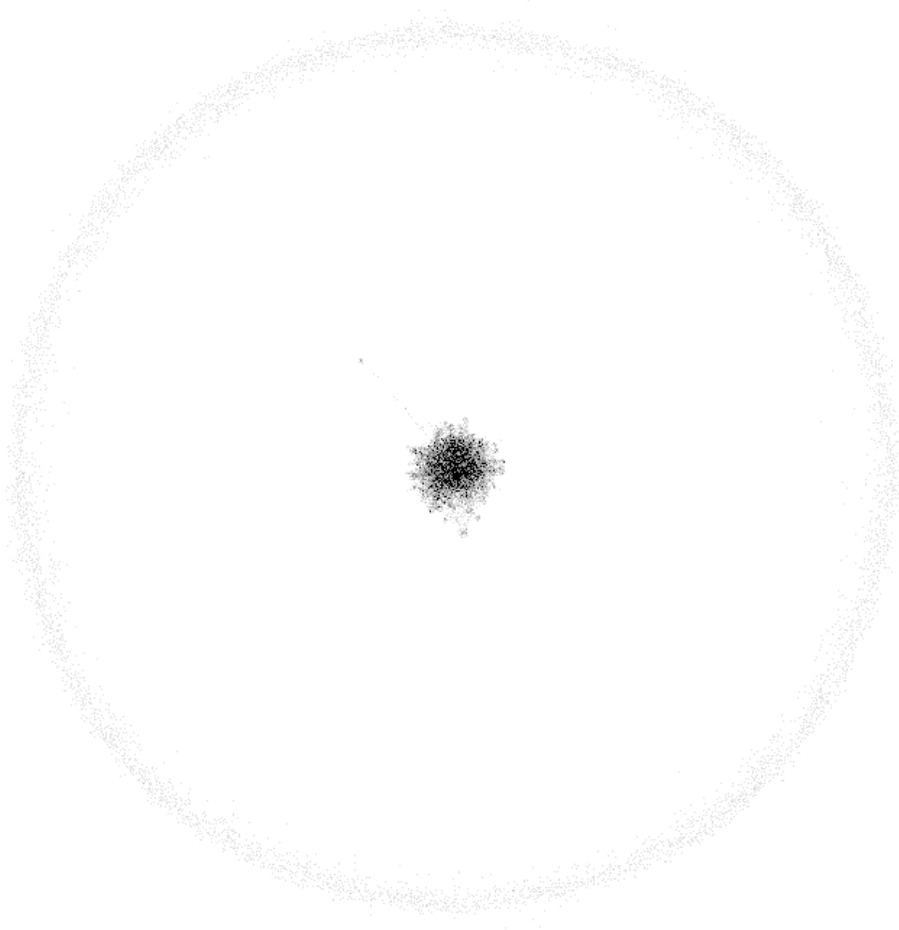
```
#Save file into csv  
df.to_csv('Edges2.csv', index = False)
```

Gephi:

Gephi is a very strong tool for Network Analysis, and it is used through all the representations, measures of this document. Now that the data is ready, we can import them in Gephi and analyze the network.

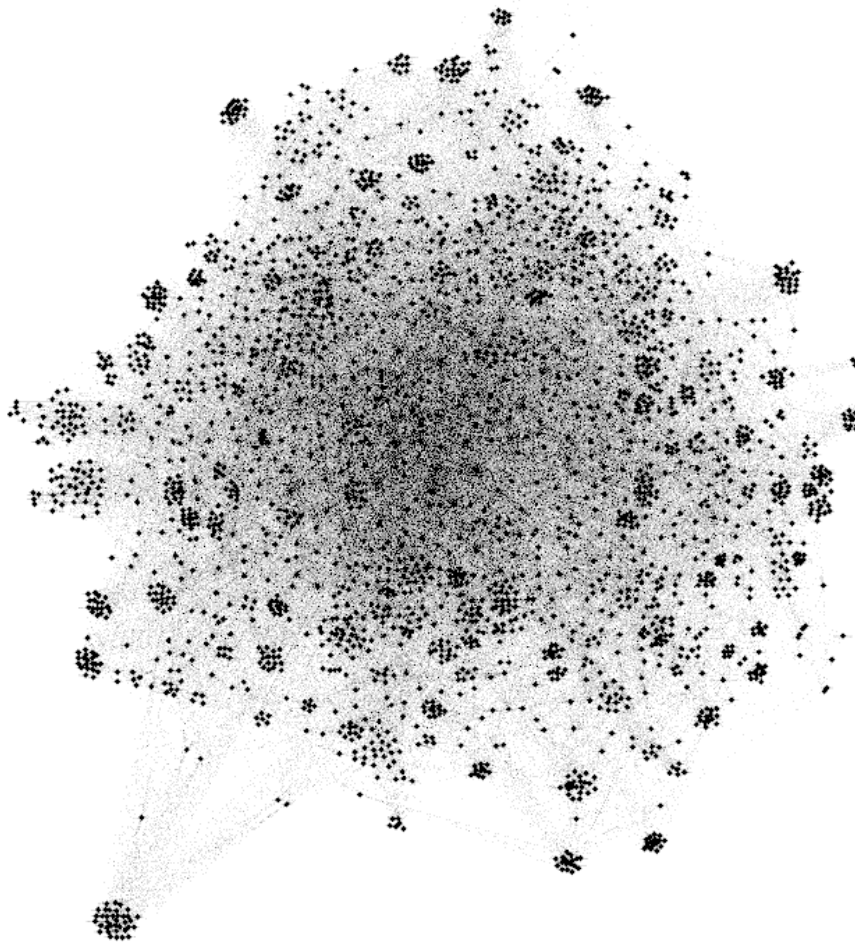
Network Analysis:

Graphical Representation (a first glance):



By running a layout algorithm (ForceAtlas2) with default settings, we can see there are a lot of “useless” cards in the pool. These cards are usually old and simply worse that have a very rare use on decks. Competitive decks tend to include newer cards in general. Also, these decks cannot be in a large number on any moment so even with ~280 decks we still cannot include every unique card on the pool.

We can filter out the 0-degree nodes and focus on the inner graph, which seems quite dense compared to other social traditional networks. From now we will ignore these nodes on every statistic on our analysis like they were not part of the data.



This is the actual network (excluding the 0-degree nodes), we will improve the visualization based on more metrics later.

Basic topological properties:

Nodes: 11804 (2438 with 1 or greater degree)
Edges: 90702

Network diameter: 4
Radius: 2
Average path length: 2.0777
Density: 0,031

Context ×	Context ×
Nodes: 11804	Nodes: 2438 (20,65% visible)
Edges: 90702	Edges: 90702 (100% visible)
Undirected Graph	Undirected Graph

Results:

Diameter: 4
Radius: 2
Average Path length: 2.0777297494902722

Network's diameter is 4 nodes which is a small size comparing to number of Nodes we have (2438). There are a lot of edges in the graph and that makes the longest shortest path between two connected nodes quite small. There are also nodes with a very high degree in the graph which helps a lot on making most of paths smaller.

The graph is very dense (small number of nodes compared to edges), this is due to the nature of the relationship I defined.

Every card/node must have in theory at least 12 connected cards since it's a part of a deck.

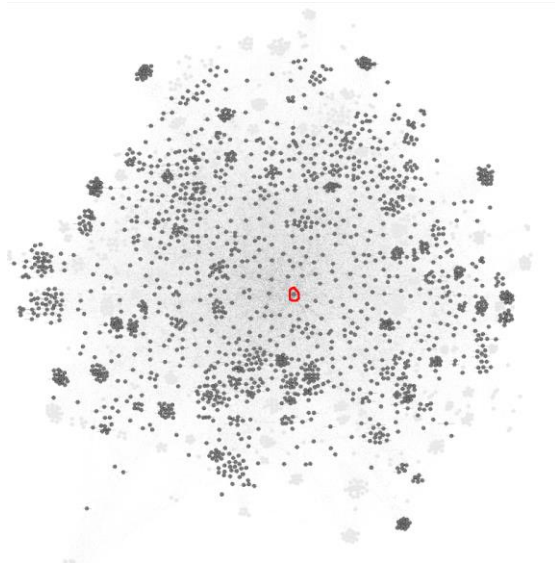
Decks can only have the same copy of a card 3 times so the minimum unique number of cards we can meet on a deck is $\left\lceil \frac{\text{minimum cards on a deck} - 2 \text{ extra copies of the card}}{3 \text{ copies for each other card}} \right\rceil = \left\lceil \frac{40-2}{3} \right\rceil = 12$

In practice, we have some very popular cards that are very powerful for various reasons and can be used in many decks.

They often have a powerful general-purpose effect in the game or have a new mechanic introduced which is more powerful like hand trap cards like Ash Blossom and Maxx "C". You can think of these cards like wild cards on a traditional game of cards.

The average path length is quite smaller than the diameter for the above reasons.

name	Degree
Ash Blossom & Joyous Spring	1690
Maxx "C"	1540
Called by the Grave	1365
Monster Reborn	1273
Accesscode Talker	1124
Lightning Storm	1082
Infinite Impenmanence	952
Knightmare Phoenix	938
Divine Arsenal AA-ZEUS - Sky Thu...	934
Raigeki	924
Cryston Halqibrax	897
Nibiru, the Primal Being	897
Knightmare Unicorn	883
Harpie's Feather Duster	760
Forbidden Droplet	708



Gray nodes relate to Ash Blossom, the most degree card in the game, compared to transparent nodes that the card is not related to. More than half of useful cards have been seen in the same deck with this card.

Component measures:

Number of connected components: 1

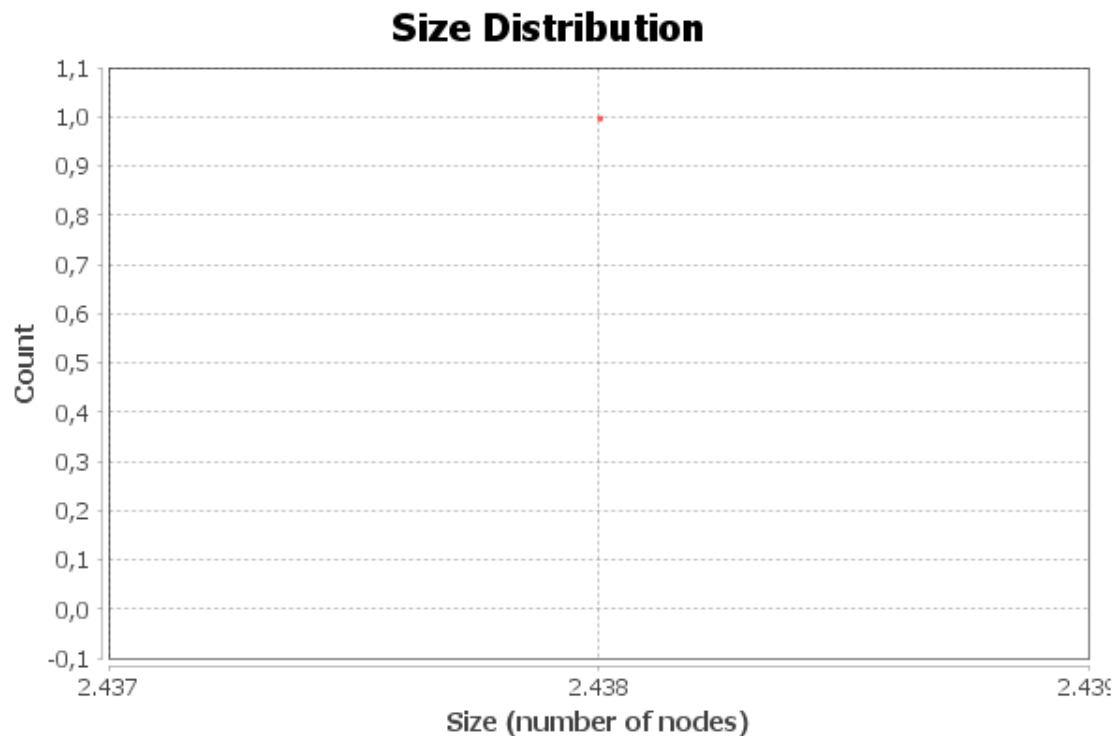
Connected Components Report

Parameters:

Network Interpretation: undirected

Results:

Number of Weakly Connected Components: 1



As expected we only have one connected component consisted of all the nodes on our undirected graph. Our graph is quite dense considering the nodes-edges ratio that makes every node connected with at least one path.

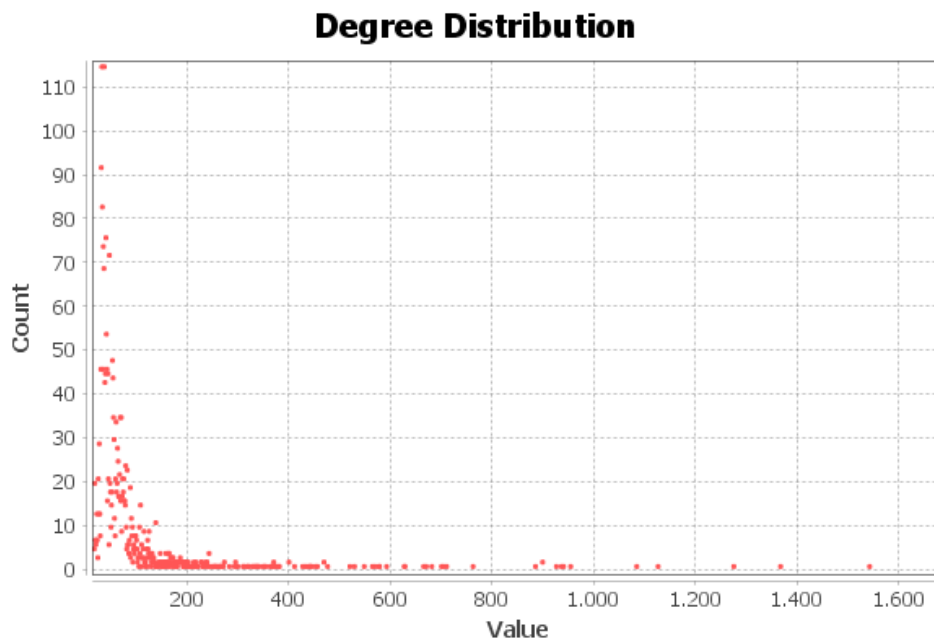
Degree measures:

Every node has a degree, which is the number of nodes he is connected to. Since we have an undirected graph, we do not have indegree or outdegrees since there is no direction on edges. We also do not have weights on edges, so the average degree is simply the sum of all the nodes' degrees divided by the number of nodes (remember we filtered out the 0 degrees nodes).

Degree Report

Results:

Average Degree: 74,407



name	Degree
Ash Blossom & Joyous Spring	1690
Maxx "C"	1540
Called by the Grave	1365
Monster Reborn	1273
Accesscode Talker	1124
Lightning Storm	1082
Infinite Impenmanence	952
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Raigeki	924
Crystron Halqifbrax	897
Nibiru, the Primal Being	897
Knightmare Unicorn	883
Harpie's Feather Duster	760
Forbidden Droplet	708
Terraforming	702
Solemn Judgment	698
I:P Masquerena	679
Foolish Burial	668
Apollousa, Bow of the Goddess	663
Reinforcement of the Army	626
Effect Veler	625
One for One	590
Borrelsword Dragon	576
Linkuriboh	575
Crossout Designator	567
Borreload Savage Dragon	562
Twin Twisters	546
Pot of Desires	527
Predaplant Verte Anaconda	518
Forbidden Chalice	474
PSY-Frame Driver	467
PSY-Framegear Gamma	467
PSY-Framelord Omega	454
Abyss Dweller	450
Mekk-Knight Crusadia Avramax	442
	440
Allure of Darkness	439
Imperial Order	435
Pot of Prosperity	430
Evenly Matched	425

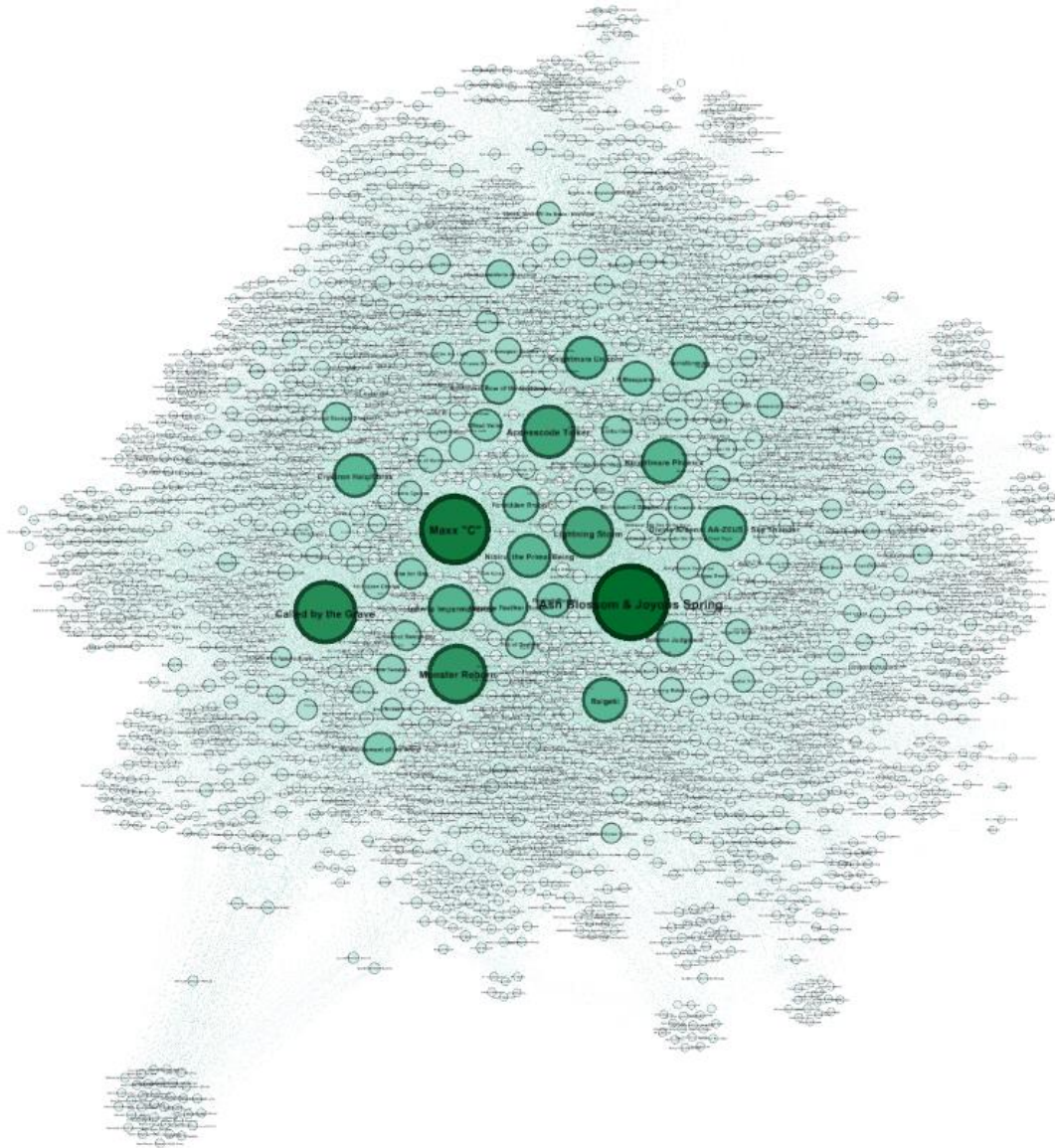
Average degree is ~74. Maximum degree is 1690.

There are a lot of nodes with a degree around 35. (Top left red dot)

There are also a lot of nodes with a degree more than 200.

We can see some popular cards on the graph like Ash-Blossom with 1690 at the bottom right side of the graph.

The degree of a card is a good metric of the synergy the card has between all the cards of the game.



A visualization of degree analysis, node size and label size has been adjusted to degree. Also, color of node has been adjusted to its degree, small degree nodes are whiter, higher degree nodes are greener. ForceAtlas2 was readjusted to prevent overlaps between nodes. We can see the most important nodes of the graph.

Centrality measures:

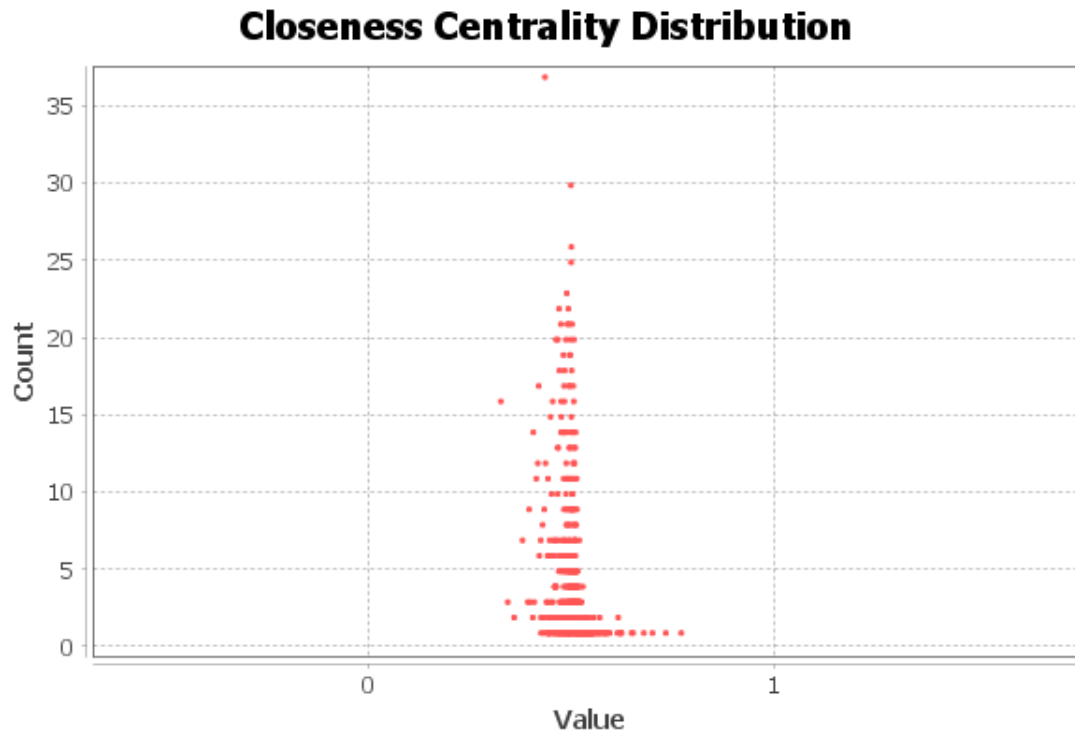
Degree centrality:

Degree centrality is based on the degree of its node.

The above graph shows the centrality ratios of each node with the color, white nodes are not that centered and green nodes are well centered.

Closeness centrality:

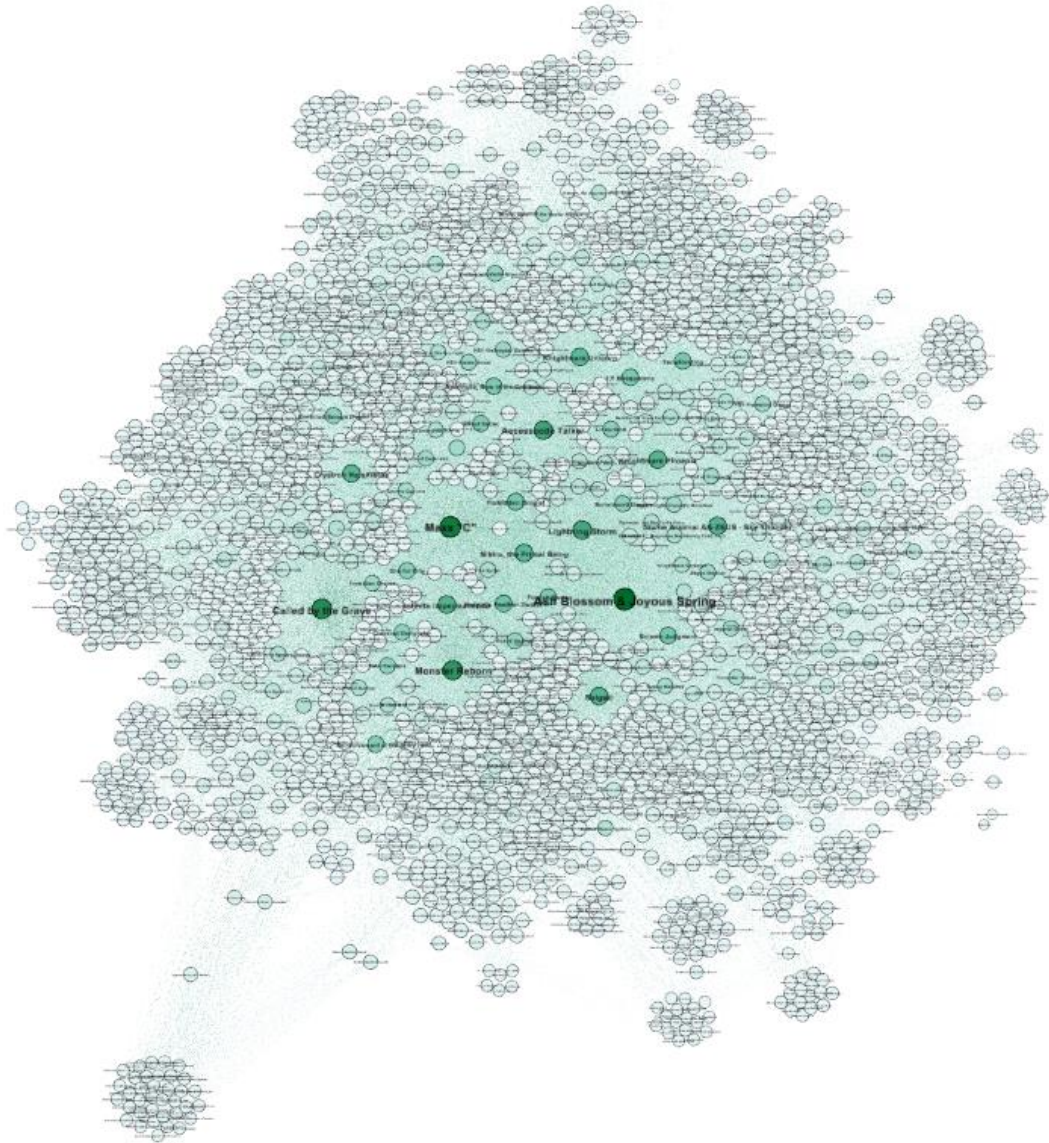
This is a metric for each node, it indicates how much the node is part of the center of the network. It is calculated via the sum of the length of the shortest path of the node for each other node in the graph.



All the nodes have a value of closeness centrality, the smaller node is 0.32 and highest 0.84.

Most nodes have a value of 0.5 which is an indication of the density of the network.

All the nodes are referring to the non-0-degree nodes.



Node colors are “Ranking” of their degree.

Node sizes are based on the closeness centrality.

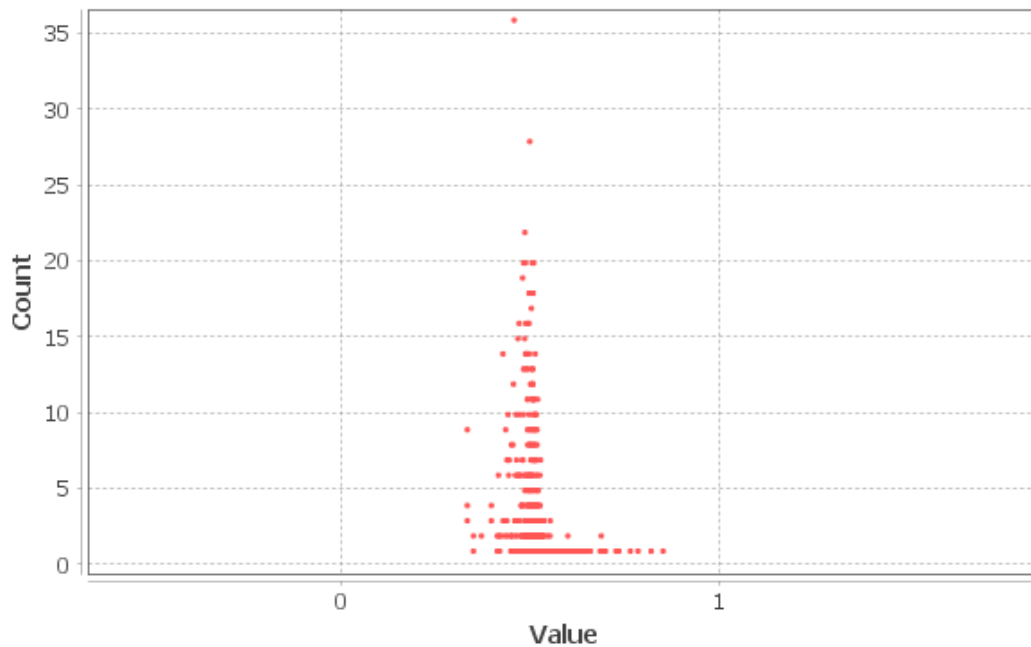
We can see that all the nodes have a quite large size. The network is quite dense, the average path is quite small, and all the nodes are well centered.

This is reasonable because every card in the game can affect all the other decks and gameplay. So, in a sense even if two decks do not use a card, if the game makes a change on a card then the players will not use the same deck on a tournament.

Harmonic Closeness centrality:

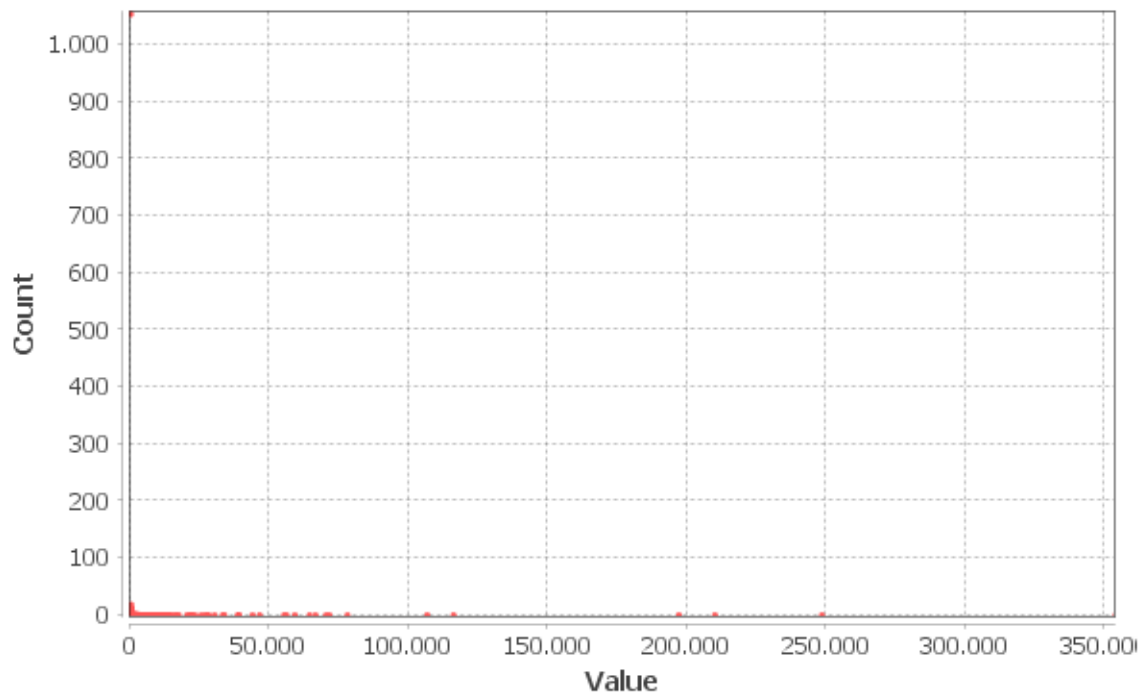
HCC is a variation of Closeness centrality; the metric distribution of each node is quite like the closeness centrality with the exception that the mean is a little higher (each node has a higher harmonic than closeness value). Our graph is connected so there is not much value in this metric.

Harmonic Closeness Centrality Distribution



Betweenness centrality:

Betweenness Centrality Distribution



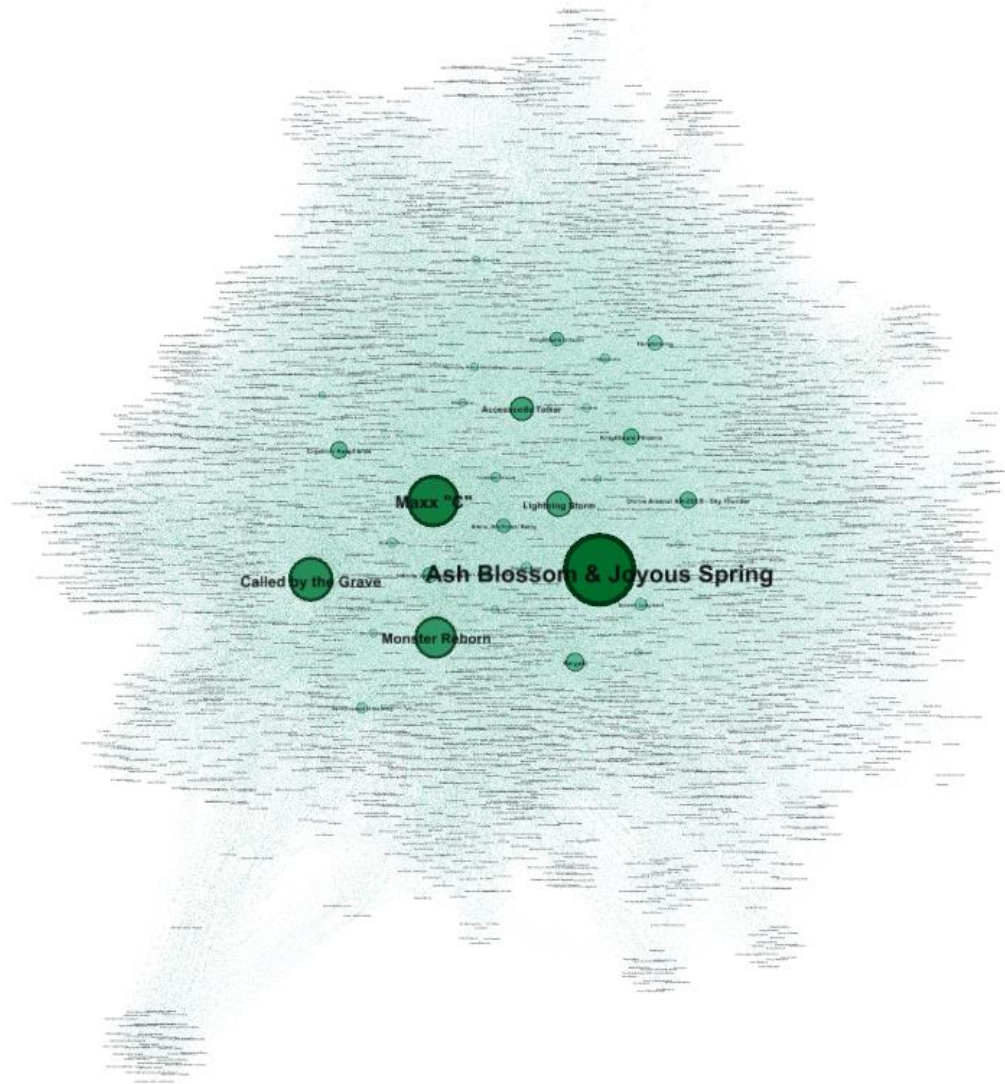
Metrics of the most centered nodes by betweenness centrality

Id	Label	Interval	name	Degree	Weighted Deg...	Eccentricity	Closeness Centr...	Harmonic Closeness Centr...	Betweenness Centra...	Authority	Hub	Modularity Class	PageRank	Component ID	Clustering Coeff...	Number of triangles	Eigenvector Centr...
14538127	Ash Blossom & Joyous Spring		Ash Blossom ...	1690	1690.0	2.0	0.763389	0.846738	383798.547297	0.163499	0.163497	0	0.008442	0	0.048946	63575	1.0
22404538	Peaks "C"		Peaks "C"	1540	1540.0	3.0	0.727463	0.814868	248246.893499	0.155243	0.155241	4	0.007596	0	0.050799	60151	0.945551
24214830	Called by the...		Called by the...	1365	1365.0	2.0	0.6945	0.780057	329765.94466	0.144695	0.144693	2	0.006647	0	0.059073	54993	0.876887
83764719	Monster Reborn		Monster Reborn	1273	1273.0	3.0	0.673204	0.759882	286846.820406	0.131506	0.131504	1	0.006325	0	0.058747	47963	0.802247
8606372	Accesscode Taker		Accesscode Taker	1124	1124.0	3.0	0.647306	0.729517	356447.37711	0.120374	0.120373	8	0.005429	0	0.072534	45778	0.776878
14532163	Lightning Storm		Lightning Storm	1082	1082.0	2.0	0.642669	0.721994	115896.028732	0.120535	0.120534	11	0.003334	0	0.072488	42389	0.762885
10045474	Infinite Impermanence		Infinite Impo...	952	952.0	3.0	0.618842	0.694228	64255.283034	0.117555	0.117554	5	0.004519	0	0.08588	38876	0.763365
2857636	Knightmare Phoenix		Knightmare P...	938	938.0	3.0	0.61665	0.691355	86352.876546	0.117136	0.117135	9	0.00448	0	0.087365	38393	0.698267
89448279	Divine Arsenal AA-08US - Sky Thunder		Divine Arsen...	924	924.0	3.0	0.616626	0.690535	70131.091154	0.115374	0.115373	7	0.004464	0	0.08661	37737	0.679678
12588477	Rageful		Rageful	924	924.0	3.0	0.614472	0.688483	77810.775567	0.107608	0.107607	13	0.004518	0	0.082059	34892	0.631077
50588353	Cytron Hologram		Cytron Hologram	897	897.0	3.0	0.610318	0.682944	71305.839367	0.105535	0.105534	4	0.004356	0	0.086817	34888	0.638435
27204511	Nibiru, the Primal Being		Nibiru, the Primal Being	897	897.0	3.0	0.610318	0.682944	35910.523696	0.112262	0.112261	2	0.004352	0	0.089698	35644	0.669891
30342355	Knightmare Unicorn		Knightmare ...	883	883.0	3.0	0.60836	0.68071	55059.21099	0.115799	0.115798	11	0.004147	0	0.097264	37875	0.688217
18144507	Harpe's Feather Duster		Harpe's Feat...	760	760.0	3.0	0.588644	0.65463	45737.204977	0.098924	0.098923	9	0.00363	0	0.102361	29523	0.590763
24299458	Forbidden Droplet		Forbidden Dr...	708	708.0	2.0	0.584874	0.645261	33637.734892	0.097869	0.097868	7	0.003304	0	0.115763	28973	0.580586
7368305	Terrafarming		Terrafarming	702	702.0	3.0	0.581891	0.642035	36921.09193	0.088645	0.088643	0	0.003486	0	0.106344	26186	0.532058
41420227	Solemn Judgment		Solemn Judg...	698	698.0	3.0	0.58053	0.642009	46327.250348	0.08976	0.08976	0	0.003459	0	0.10892	26495	0.536072

Notice that a card with only 38 degree is in the top of the metrics. Each metric can change the order of the "who is most centered node" by a lot of positions, so we need to understand what each metric counts and how this is related to each network.

Betweenness centrality is a metric that is based on how many time the node acts like a bridge to a shortest path between two other nodes. It's a centrality metric.

Below we see a graph that the size of the nodes and labels is corresponding to the betweenness centrality metric.

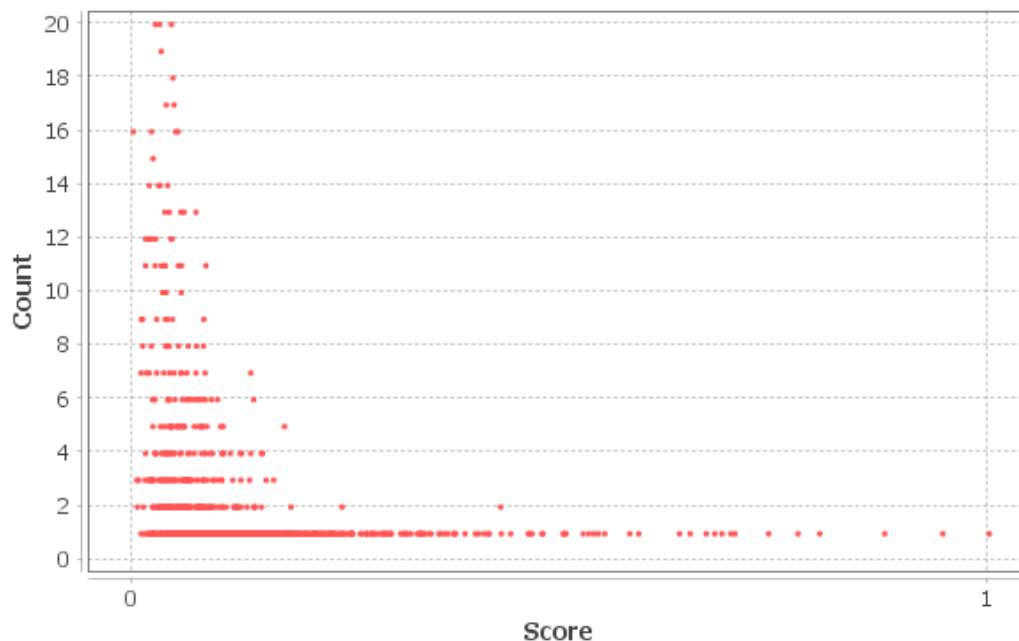


Eigenvector centrality:

Network Interpretation: undirected
Number of iterations: 100
Sum change: 0.0590935462135583

Results:

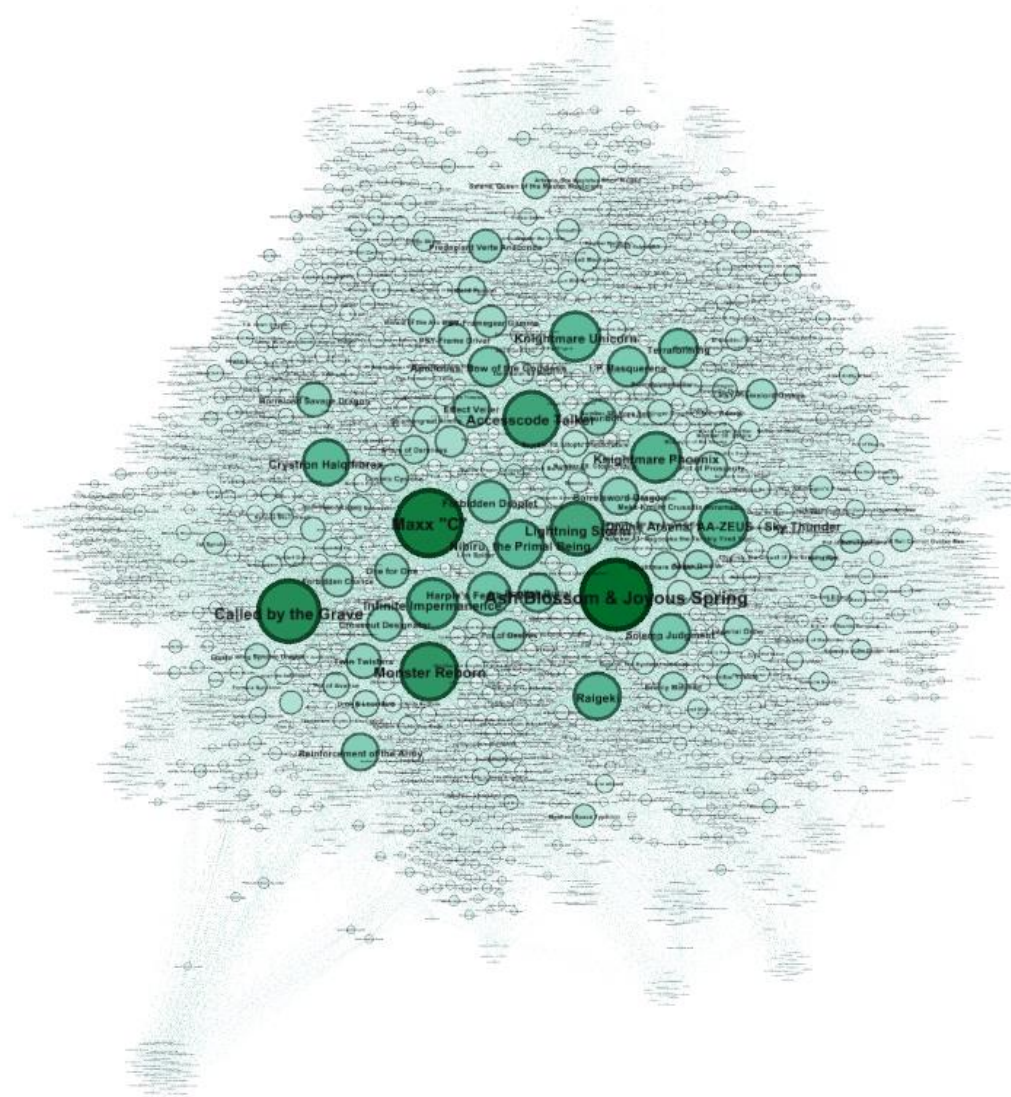
Eigenvector Centrality Distribution



Distribution: very little cards are above 0.6-1, most cards are around 0.13.

Id	Label	Degree	Closeness Centra...	Harmonic Closeness Cent...	Betweenness Centra...	Eigenvector Centr...
14558127	Ash Blossom & Joyous Spring	1690	0.765389	0.846738	353750.547297	1.0
23434538	Maxx "C"	1540	0.727463	0.814868	248246.893499	0.945951
24224830	Called by the Grave	1365	0.6945	0.780057	209795.94466	0.878087
83764719	Monster Reborn	1273	0.673204	0.759882	196840.920406	0.802247
86066372	Accesscode Talker	1124	0.647106	0.729517	106447.37711	0.776878
14532163	Lightning Storm	1082	0.642669	0.721994	115899.007672	0.742685
10045474	Infinite Impermanence	952	0.618842	0.694228	64255.283034	0.703365
2857636	Knightmare Phoenix	938	0.61665	0.691355	66352.976546	0.698267
38342335	Knightmare Unicorn	883	0.608186	0.680071	55059.210999	0.688027
90448279	Divine Arsenal AA-ZEUS - Sky Thunder	934	0.616026	0.690535	70131.093154	0.679678
27204311	Nibiru, the Primal Being	897	0.610318	0.682944	55910.523696	0.669891
12580477	Raigeki	924	0.614473	0.688483	77810.775567	0.651077
50588353	Crystron Halqifbrax	897	0.610318	0.682944	71305.839367	0.638435
18144507	Harpie's Feather Duster	760	0.589644	0.65463	43737.204977	0.590763
24299458	Forbidden Droplet	708	0.584974	0.645261	33637.734892	0.580586
65741786	I:P Masquerena	679	0.578722	0.638216	30067.398061	0.551163
4280258	Apollousa, Bow of the Goddess	663	0.576532	0.634934	27899.63278	0.544149
41420027	Solemn Judgment	698	0.58093	0.641909	46257.256348	0.539072
73628505	Terraforming	702	0.581901	0.642935	58921.109193	0.532958
81439173	Foolish Burial	668	0.577215	0.63596	38511.841682	0.526041
85289965	Borrelsword Dragon	576	0.564512	0.616879	21893.632365	0.506207
32807846	Reinforcement of the Army	626	0.571127	0.627137	38796.907662	0.503916

Top nodes based on Eigenvector metric.



Node size is adjusted on Eigenvector metric.

Eigenvector counts the influence of a node in the network, if a node is connected to an important node it gets more score on their influence of the network. It calculates how important is the node you are connected to not only to how many nodes you are.

There is not much difference between centrality measures in our network, there are some exceptions but in general we know which nodes are well centered in our graph.

Clustering effects:

Average clustering coefficient: 0.8

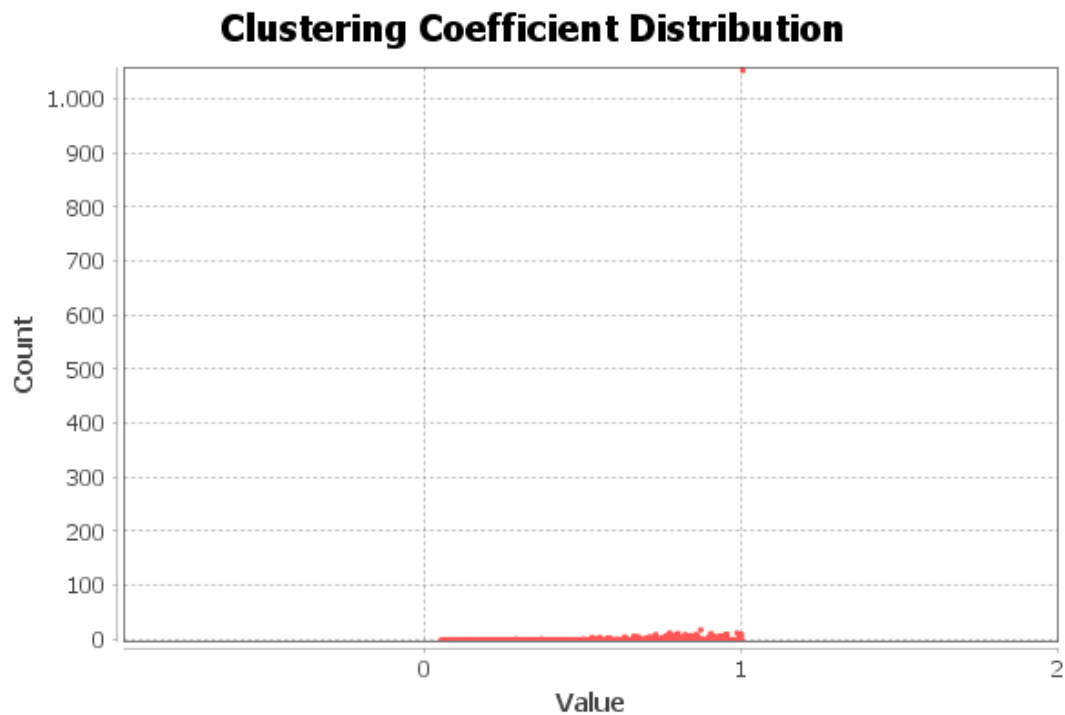
Number of triangles: 1,595,904

Results:

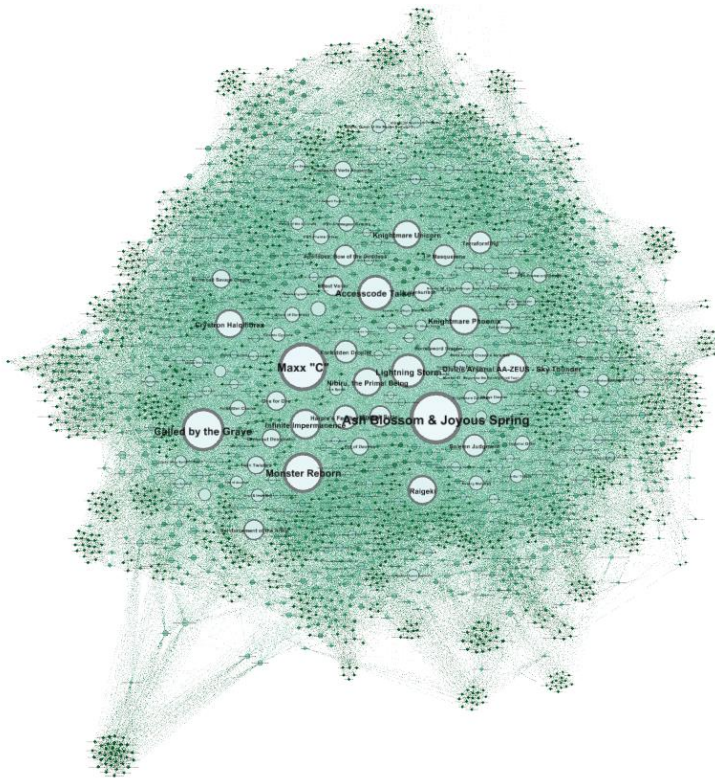
Average Clustering Coefficient: 0,800

Total triangles: 1595904

The Average Clustering Coefficient is the mean value of individual coefficients.



Nodes with big degree tend to have low clustering coefficient, and nodes with lower degree have a high coefficient.



We can see that green nodes have high coefficient, it's more likely for them to form new edges (triadic closure).

If there are 3 nodes connected with $A - B$, $B - C$, then its more likely to form a new edge $A - C$ in our next version of a graph.

In practice, we can think for 3 cards where $A - B$, $B - C$, have a lot of synergy and let's say $A - C$ do not have, then in a next month's version of meta decks is more possible to see those 3 cards on the same deck, $A - C$ combination will still not be a good thing but these cards would not end up on the same deck without an undirect reason (B).

The average of the coefficient indicates our network is well connected which is confirmed by previous statistics such as number of edges and density.

Bridges and local bridges:

A bridge is an edge that unifies two parts of the graph, if the bridge would be deleted then we would have two separated components. Since our network is dense we do not have any edge that is a global bridge, all our nodes are connected.

Local bridges are edges that when deleted they increase the shortest path between two nodes.

I am going to use another python code to check for bridges, although it seems unlikely we have one, it's a great chance to get my hand into another library. So, in order for a local bridge to exist we need to find two connected nodes that do not have a common friend, which is fairly difficult in our dense network with average path of 2.

bridges.py

```
import pandas as pd
import networkx as nx

#Read edges file
df = pd.read_csv("Edges.csv")

#Turn it into a graph
G = nx.from_pandas_edgelist(df, source='Source', target='Target',
create_using=nx.DiGraph())

#We need to transform our graph into an undirected graph
G2 = G.to_undirected()

#Prints the list of bridges
print(G2)
print(list(nx.bridges(G2)))
print(list(nx.local_bridges(G2)))

===== RESTART: C:\Users\Alexis\Desktop\yugioh\network.py
=====
Graph with 2429 nodes and 90433 edges
[]
[]
>>>
```

Turns out there are neither bridges nor local bridges on our network.

Homophily:

With our data we do not have any node attributes that we can make a hypothesis that nodes with the same attribute are more likely to be connected.

Although we can check with networkX if the nodes with similar degree have the same connections.

homophily.py

```
print(nx.degree_assortativity_coefficient(G2))
-0.15649205292940063
>>>
```

The assortativity_coefficient is negative which means there is no indication that this would happen.

It would be interesting if we checked if there is Homophily in other card/node attributes imported by the API in a less succinct analysis.

Each card has a card type: Monster Card/ Trap Card/ Spell Card and more

Each Monster card has a type: Aqua/Beast/Dinosaur and much more..

Each card has an attribute: DARK,DIVINE,EARTH,FIRE and more



We can also get a price attribute, the price that a card costs to buy online, categorize them by price range and see if expensive cards tend to connect with each other.

We can also add the set name the card was released, since cards that are released on the same set tend to work together (high synergy).

There are plenty of node attributes we could check the homophily of the network other than the degree which would make more sense.

```
{
  "id": 6983839,
  "name": "Tornado Dragon",
  "type": "XYZ Monster",
  "desc": "2 Level 4 monsters\nOnce per turn (Quick Effect): You can detach 1 material from this card, then target 1 Spell/Trap on the field; destroy it.",
  "atk": 2100,
  "def": 2000,
  "level": 4,
  "race": "Wyrm",
  "attribute": "WIND",
  "card_sets": [
    {
      "set_name": "Battles of Legend: Relentless Revenge",
      "set_code": "BLRR-EN084",
      "set_rarity": "Secret Rare",
      "set_rarity_code": "(SCR)",
      "set_price": "4.08"
    },
    {
      "set_name": "Duel Devastator",
      "set_code": "DUDE-EN019",
      "set_rarity": "Ultra Rare",
      "set_rarity_code": "(UR)",
      "set_price": "1.4"
    },
    {
      "set_name": "Maximum Crisis",
      "set_code": "MACR-EN081",
      "set_rarity": "Secret Rare",
      "set_rarity_code": "(SCR)",
      "set_price": "4.32"
    }
  ],
  "card_images": [
    {
      "id": 6983839,
      "image_url": "https://storage.googleapis.com/ygoprodeck.com/pics/6983839.jpg",
      "image_url_small": "https://storage.googleapis.com/ygoprodeck.com/pics_small/6983839.jpg"
    }
  ],
  "card_prices": [
    {
      "cardmarket_price": "0.42",
      "tcgplayer_price": "0.48",
      "ebay_price": "2.99",
      "amazon_price": "0.77",
      "coolstuffinc_price": "0.99"
    }
  ]
}
```

Graph density:

Graph density is a simple metric that shows how well connected the nodes are. We simply calculate the maximum possible number of edges the graph can have in a ratio with how many edges we have.

Density is 0.031 in our network which is very high compared to other common networks like a social network. So, we can say our graph is dense. The reason why we have a lot of edges on our graph is explained in the topology section.

Community structure (modularity), cliques:

Modularity is a measure that shows how much diverse there is in the network, how much the network can be split in groups. Our network is quite dense so there is high modularity (0.379). The algorithm splits the network into 16 groups. (With resolution parameter = 1)

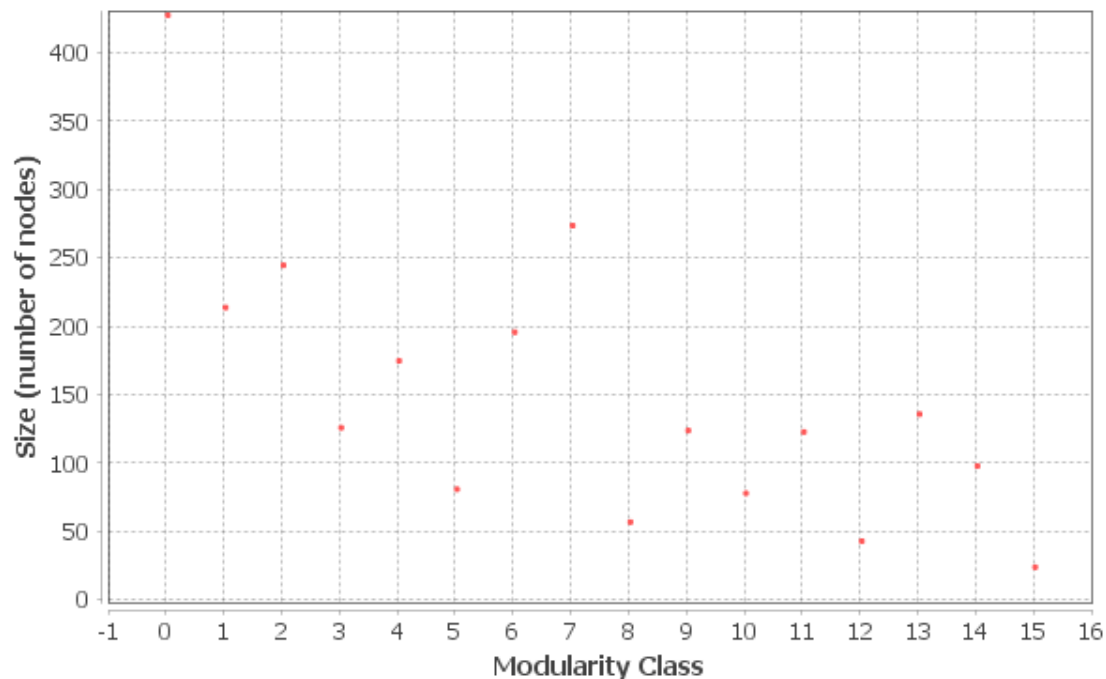
Results:

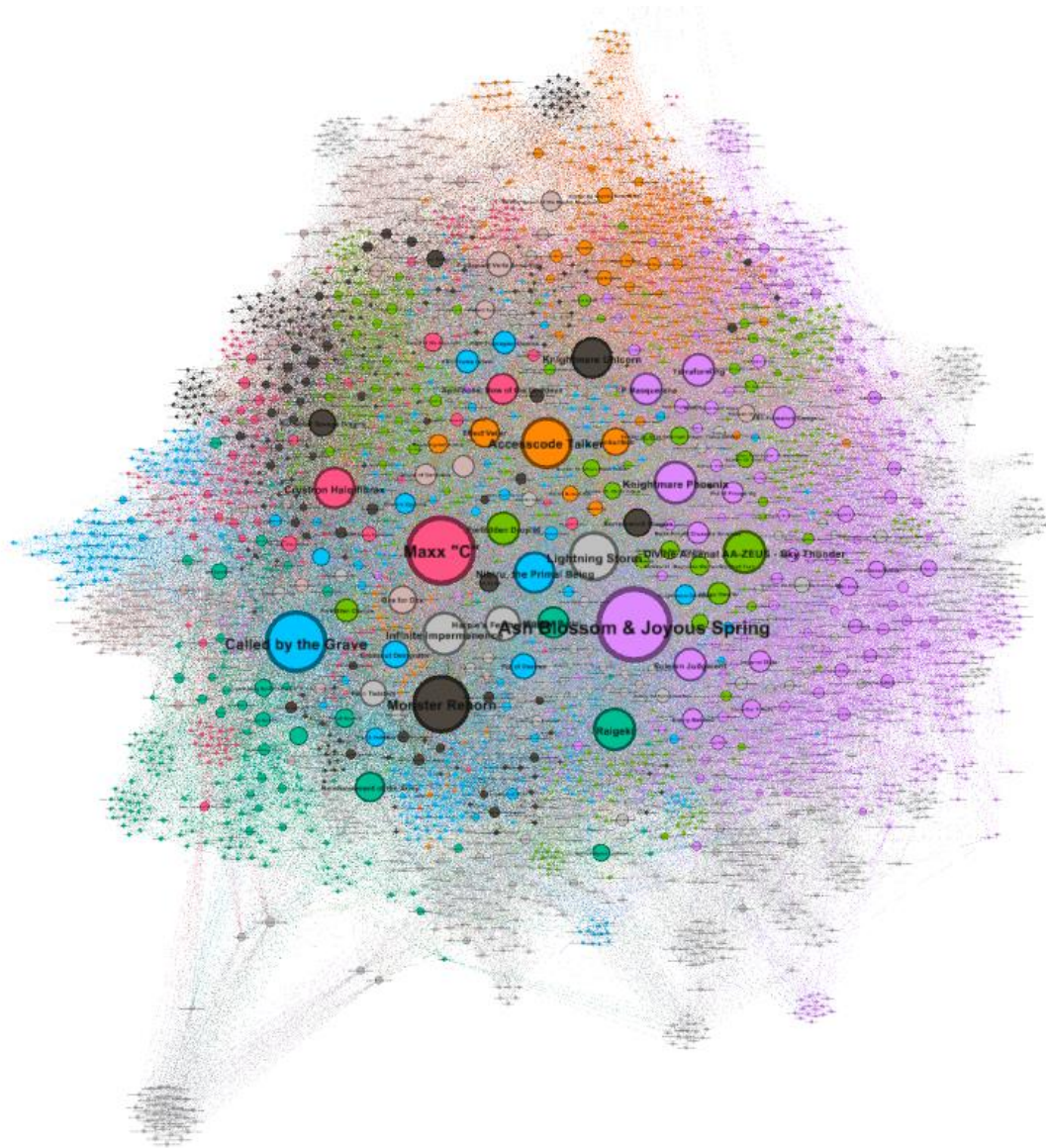
Modularity: 0,379

Modularity with resolution: 0,379

Number of Communities: 16

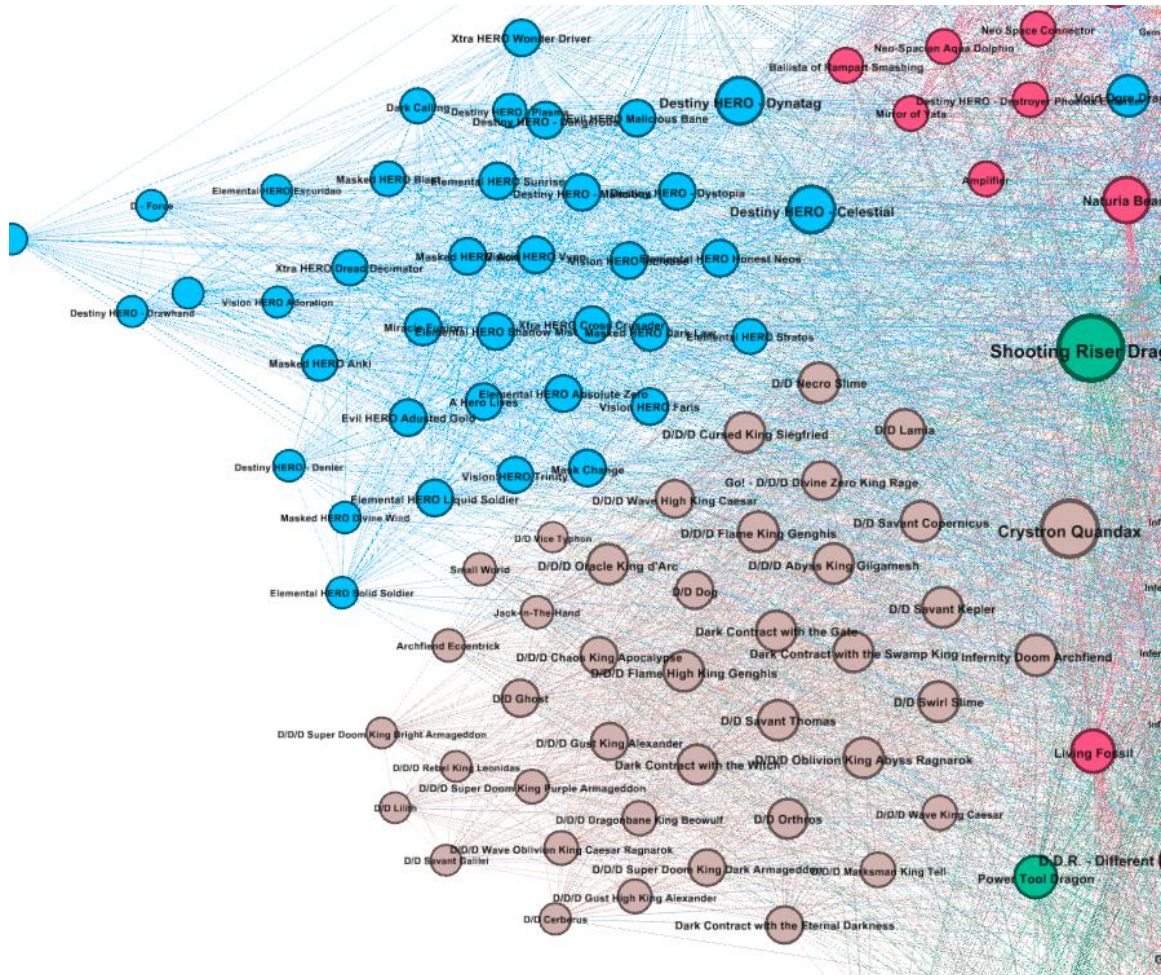
Size Distribution



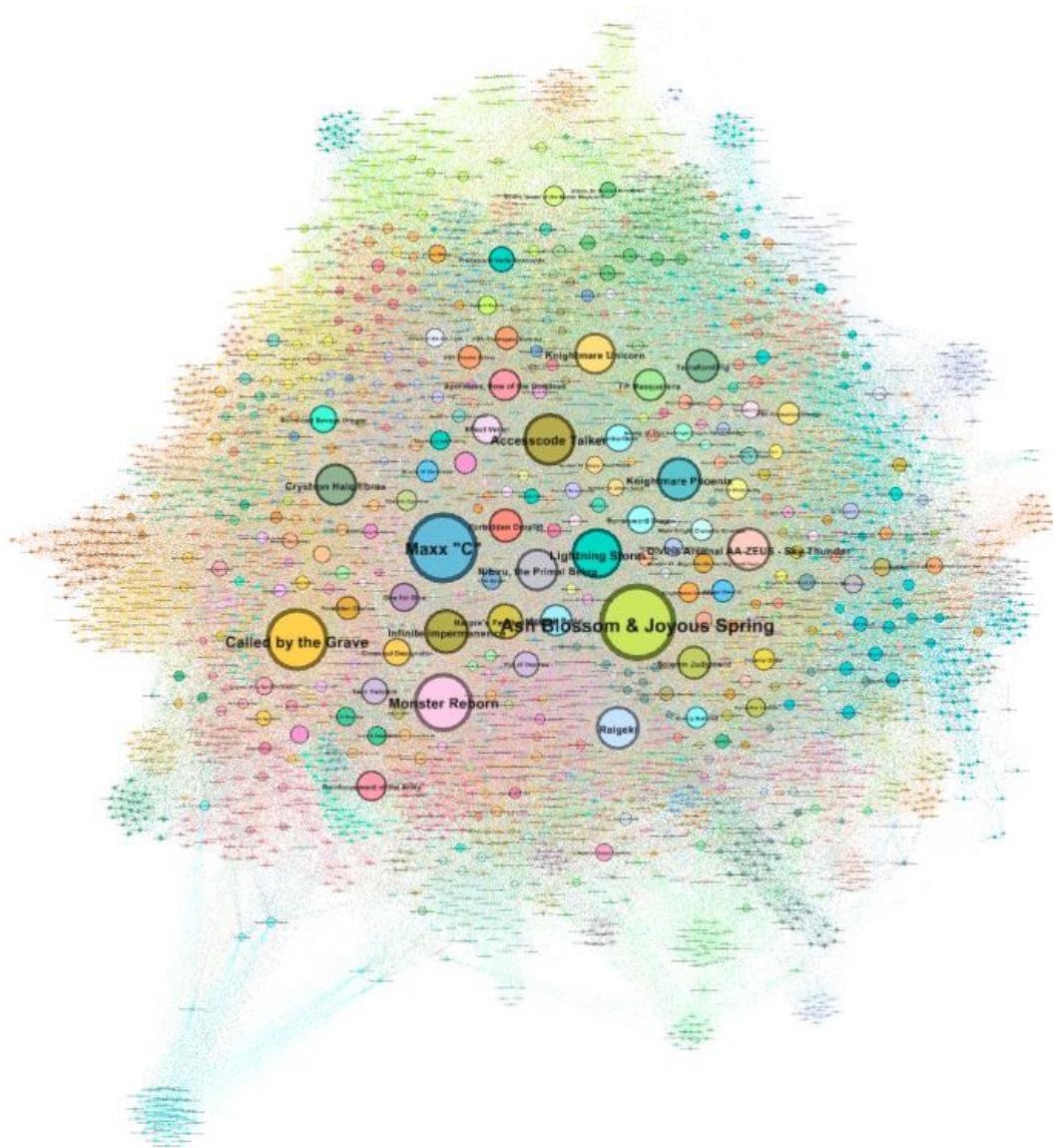


This is very interesting to see since there are a lot of communities in our network. Some cards are part of series, and they usually have similar names and can work with other cards of the same series.

For example, we can notice the left part of the graph below, the cards from HERO series are in different group than the D/D/D series.



The algorithm has split all the series like that in the network with different colors. In general, each group has cards from series including more general-purpose cards in the center.



Increasing number of groups (79) make the distinction clearer. (Resolution = 0.2)

We can find the maximal cliques on our graph. A clique is a complete graph that contains a node, a complete graph is a group of nodes that are all connected with each other, so for each node on the graph we can find the maximal clique he belongs to, meaning the clique that has the most nodes and he is included.

The maximum clique is the biggest clique from all the maximal cliques (the biggest clique from all the nodes' biggest cliques).

This is easy with networkX, we already have imported our data to make a network, now we can iterate in `nx.find_cliques(G2)`, and get all the maximal cliques in the graph. In the code below we try to find the longest maximal clique, aka the maximum clique.

cliques.py

```

count = 0
maximumlength = 0
for clique in nx.find_cliques(G2):
    if len(clique) > maximumlength:
        maximumlength = len(clique)
        print(maximumlength)
        print(clique)
    count +=1
print(count)
>>>
===== RESTART: C:\Users\Alexis\Desktop\yugioh\cliques.py
=====
34
[40392714, 58577036, 7614732, 31437713, 90448279, 20137754, 35058588, 48608796,
423585, 2857636, 1218214, 35726888, 23434538, 72664875, 2434862, 34325937,
30270176, 41114306, 43040603, 86066372, 3775068, 15610297, 70369116, 39317553,
72336818, 38342335, 41999284, 54366836, 84013237, 51735257, 4998619, 9659580,
12580477, 90590303]
36
[31893528, 94772232, 58577036, 48068378, 67598234, 51993760, 82732705, 2857636,
595626, 23434538, 67616300, 40771118, 66547759, 72336818, 41999284, 19665973,
49238328, 88000953, 31829185, 50588353, 86066372, 30170981, 1966438, 58616392,
48934760, 102380, 67287533, 14386013, 52615248, 87988305, 14509651, 94212438,
77637979, 70369116, 1861629, 38342335]
46
[78876707, 59057152, 7452945, 95772051, 94730900, 58346901, 95953557, 81570454,
5361816, 51670553, 19680539, 74029853, 59934749, 43898403, 7811875, 32807846,
21351206, 23562407, 56824871, 51412776, 40251688, 75719089, 41359411, 88923963,
22091647, 24224830, 10613952, 14745409, 42472002, 37478723, 63789924, 24027078,
19748583, 55742055, 83438826, 83519853, 21223277, 15693423, 57690191, 90861137,
73359475, 42052439, 46008667, 77656797, 64867422, 42199039]
52
[71645242, 85840608, 34959756, 67922702, 2295440, 96363153, 9622164, 8487449,
44097050, 63362460, 59934749, 99674361, 32807846, 27548199, 48686504, 303660,
33420078, 33158448, 62706865, 35272499, 41999284, 79606837, 17955766, 50954680,
1118137, 2403771, 9742784, 65993085, 50588353, 67696066, 4280258, 81439174,
1200843, 61677004, 60071928, 94693857, 242146, 52947044, 60461804, 3113836,
83764718, 37780349, 7394770, 44935634, 28985331, 99645428, 75944053, 74997493,
51405049, 70369116, 39964797, 11066358]
217931
>>>

```

We iterated between 217k maximal cliques (cliques that are the biggest cliques for a node), this number is quite bigger than the nodes because a node can have multiple maximal cliques. We found out that the last printed clique is the biggest in the graph with 52 members. (The numbers are the IDs of the cards).

PageRank:

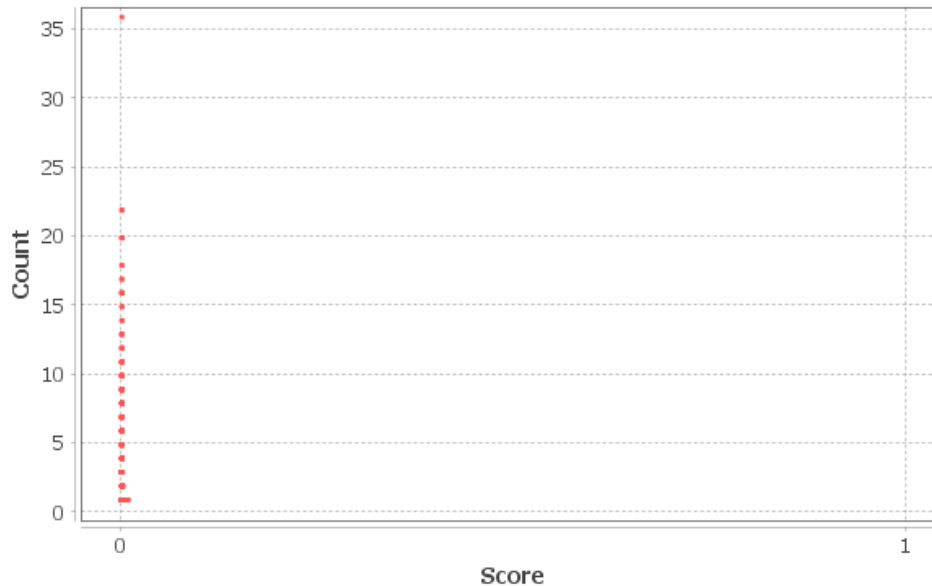
Parameters:

Epsilon = 0.001

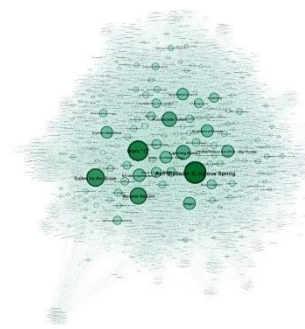
Probability = 0.85

Results:

PageRank Distribution



Label	PageRank
Ash Blossom & Joyous Spring	0.008442
Maxx "C"	0.007596
Called by the Grave	0.006647
Monster Reborn	0.006325
Accesscode Talker	0.005429
Lightning Storm	0.005304
Infinite Impermanence	0.004519
Ragefi	0.004518
Divine Arsenal AA-ZEUS - Sky Thunder	0.004494
Knightmare Phoenix	0.00448
Crystron HaloBrax	0.004356
Nibiru, the Primal Being	0.004302
Knightmare Unicorn	0.004147
Terraforming	0.003486
Solemn Judgment	0.003419
Foolish Bural	0.003202
Zip Masquerena	0.003185
Apollousa, Bow of the Goddess	0.003093
Reinforcement of the Army	0.002996
Effect Veller	0.002983
One for One	0.002906



Each node has a PageRank metric from almost 0 to 0.008.

The nodes order is like centrality measures which is a good thing for the network.

Similar graph with PageRank as color.

PageRank value is based on the number of edges each node has, and it works better with directed graphs. It's a repeating algorithm that calculates the PageRank metric based on the PageRank metrics of the nodes that are pointing the current node.

In our case it is showing the important of the nodes which returns the centrality of the node. It's used on web pages, that is why it works better with directed graphs (web pages have links pointing to other pages).

Sources (citations):

Yu-Gi-Oh! Cards information:

Provided by API of db.ygoprodeck.com

Link: <https://db.ygoprodeck.com/api/v7/cardinfo.php>

Yu-Gi-Oh! Decks information:

Fetches from <https://ygoprodeck.com/>

Link: [https://ygoprodeck.com/deck-](https://ygoprodeck.com/deck-search/?&_sf_s=master%20duel&sort_order=views&post_date=2022-01-18%202022-02-18&offset=0)

[search/?&_sf_s=master%20duel&sort_order=views&post_date=2022-01-18%202022-02-18&offset=0](https://ygoprodeck.com/deck-search/?&_sf_s=master%20duel&sort_order=views&post_date=2022-01-18%202022-02-18&offset=0)

Gephi:

All the visualizations and statistic graphs, as also the whole analysis of the network is being completed with the help of the Gephi tool.

Link: <https://gephi.org/>

Python:

Used to fetch and create the dataset, libraries that were used are pandas, os, BeautifulSoup, requests, json, time, Selenium, networkX and respective documentations

Lectures: Social Network Analysis

Link: <https://edu.dmst.aueb.gr/course/view.php?id=24>