

Social Networks in the Marvel Universe

ISSS606 Social Analytics and Applications

Group 8

Chen Jin Chuan Brian

Clara Chua Kiah Hwii

Jin Xi Yuan

Lee Kern Choong

Agenda

- Project Objective
- Data Collection & Preparation
- Analysis & Results
- Limitations and Further Work
- Q&A



Project Objectives

- 21 MCU movies grossed \$17.9B worldwide over the past 12 years
- To discover:
 - How importance of MCU characters have changed over time
 - If future characters in the MCU can be predicted
- Ideas:
 - Comics dataset size >> MCU dataset size
 - Comics serve as storyline for MCU movies



Data Collection

- **Primary Datasets**

- MCU Movie Cast (IMDB): spanning 2008 – 2019
- Marvel Universe Social Graph: spanning 1939 - 2018

- **Secondary Dataset**

- Marvel Superheroes Dataset (incomplete)

- **Assumptions**

- Character co-occurrence is equivalent to an edge



The Infinity Saga: 3 phases of MCU movies

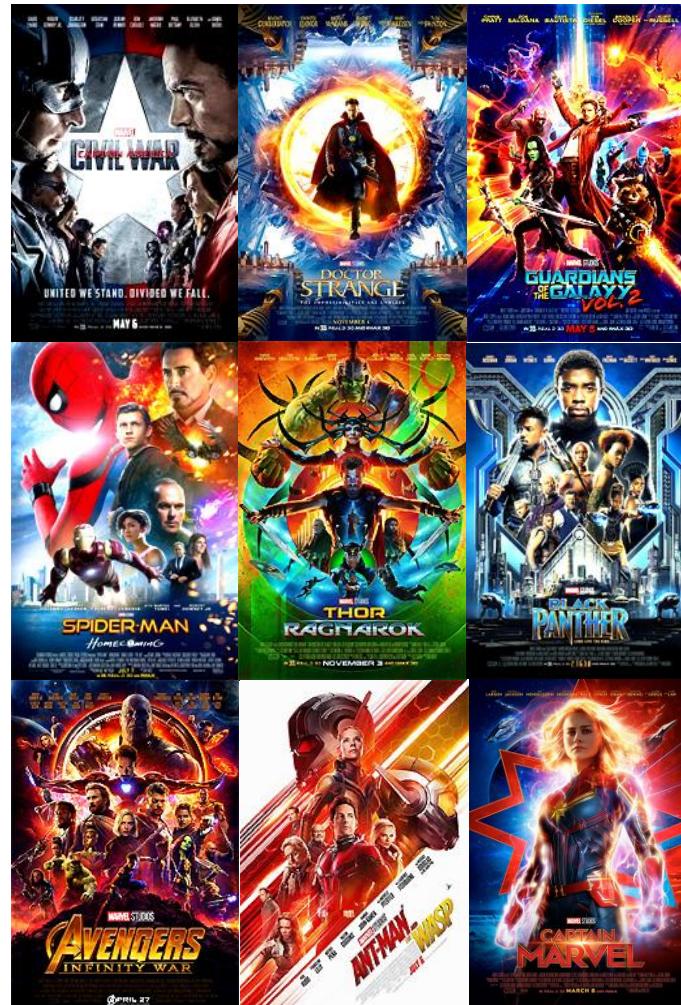
Phase 1 (2008 – 2012)



Phase 2 (2013 – 2015)



Phase 3 (2016 – 2019)



- Captain America: Civil War
- Doctor Strange
- Guardians of the Galaxy Vol 2
- Spiderman – Homecoming
- Thor: Ragnarok
- Black Panther
- Avengers: Infinity War
- Ant-Man & The Wasp
- Captain Marvel

- Iron Man
- The Incredible Hulk
- Iron Man 2
- Thor
- Captain America: The First Avenger
- The Avengers

- Iron Man 3
- Thor: The Dark World
- Captain America: The Winter Soldier
- Guardians of the Galaxy
- Avengers: Age of Ultron
- Ant-Man

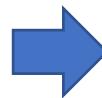
Movie Data Collection & Preparation



1. **Iron Man** (2008)
PG-13 | 126 min | Action, Adventure, Sci-Fi
★ 7.9 ⚰ Rate 79 Metascore
After being held captive in an Afghan cave, billionaire engineer Tony Stark creates a unique weaponized suit of armor to fight evil.
Director: Jon Favreau | Stars: Robert Downey Jr., Gwyneth Paltrow, Terrence Howard, Jeff Bridges
Votes: 844,264 | Gross: \$318.41M

Tony Stark / Iron Man <77:15>
Pepper Potts <23:15>
Obadiah Stane / Iron Monger <22>
Professor Ho Yinsen <10:45>
Lt. Col. James "Rhodey" Rhodes <8:15>
Raza <6>
Agent Phil Coulson <3:45>
Christine Everhart <3:45>
Abu Bakaar <1:45>
Harold "Happy" Hogan <1:15>
Director Nick Fury <1:15>
J.A.R.V.I.S. <v>

Data from IMDB



Movie	Year	Character	Time	Phase
Iron Man	2008	Tony Stark / Iron Man	77:15:00	1
Iron Man	2008	Pepper Potts	23:15	1
Iron Man	2008	Obadiah Stane / Iron Monger	22:00	1
Iron Man	2008	Professor Ho Yinsen	10:45	1
Iron Man	2008	Col. James "Rhodey" Rhodes / Wa	8:15	1
Iron Man	2008	Raza	6:00	1
Iron Man	2008	Agent Phil Coulson	3:45	1
Iron Man	2008	Christine Everhart	3:45	1
Iron Man	2008	Abu Bakaar	1:45	1
Iron Man	2008	Harold "Happy" Hogan	1:15	1
Iron Man	2008	Nick Fury	0:15	1
Iron Man	2008	J.A.R.V.I.S.		1
X-Men Origins: Wolverine	2009	Logan / Wolverine / Weapon X	50:30:00	
X-Men Origins: Wolverine	2009	Victor Creed / Sabretooth	17:00	
X-Men Origins: Wolverine	2009	William Stryker	11:15	



Clean data
Nick Fury = Director Nick Fury = Agent Nick Fury



Movie Data Collection & Preparation

Movie	Year	Character	Time	Phase
Iron Man	2008	Tony Stark / Iron Man	77:15:00	1
Iron Man	2008	Pepper Potts	23:15	1
Iron Man	2008	Obadiah Stane / Iron Monger	22:00	1
Iron Man	2008	Professor Ho Yinsen	10:45	1
Iron Man	2008	Col. James "Rhodey" Rhodes / War Machine / Iro...	8:15	1
Iron Man	2008	Raza	6:00	1
Iron Man	2008	Agent Phil Coulson	3:45	1
Iron Man	2008	Christine Everhart	3:45	1
Iron Man	2008	Abu Bakaar	1:45	1
Iron Man	2008	Harold "Happy" Hogan	1:15	1
Iron Man	2008	Nick Fury	0:15	1
Iron Man	2008	J.A.R.V.I.S.		1

Cleaned



Movie	char1	char2	Phase
3202 Iron Man	Tony Stark / Iron Man	Pepper Potts	1
3203 Iron Man	Tony Stark / Iron Man	Obadiah Stane / Iron Monger	1
3204 Iron Man	Tony Stark / Iron Man	Professor Ho Yinsen	1
3205 Iron Man	Tony Stark / Iron Man	Col. James "Rhodey" Rhodes / War Machine / Iro...	1
3206 Iron Man	Tony Stark / Iron Man	Raza	1
3207 Iron Man	Tony Stark / Iron Man	Agent Phil Coulson	1
3208 Iron Man	Tony Stark / Iron Man	Christine Everhart	1
3209 Iron Man	Tony Stark / Iron Man	Abu Bakaar	1
3210 Iron Man	Tony Stark / Iron Man	Harold "Happy" Hogan	1
3211 Iron Man	Tony Stark / Iron Man	Nick Fury	1
3212 Iron Man	Tony Stark / Iron Man	J.A.R.V.I.S.	1
3213 Iron Man	Pepper Potts	Obadiah Stane / Iron Monger	1
3214 Iron Man	Pepper Potts	Professor Ho Yinsen	1
3215 Iron Man	Pepper Potts	Col. James "Rhodey" Rhodes / War Machine / Iro...	1
3216 Iron Man	Pepper Potts	Raza	1
3217 Iron Man	Pepper Potts	Agent Phil Coulson	1
3218 Iron Man	Pepper Potts	Christine Everhart	1
3219 Iron Man	Pepper Potts	Abu Bakaar	1
3220 Iron Man	Pepper Potts	Harold "Happy" Hogan	1
3221 Iron Man	Pepper Potts	Nick Fury	1
3222 Iron Man	Pepper Potts	J.A.R.V.I.S.	1
3223 Iron Man	Obadiah Stane / Iron Monger	Professor Ho Yinsen	1

- **Itertools Combinations function**
- **pd.merge** with phases dataframe
- **pd.query** to slice into 3 different phases

```
from itertools import combinations

mcu = (MCU_char.groupby('Movie')['Character'].apply(lambda x: pd.DataFrame(list(combinations(x,2)))))

.mc.reset_index(level=1, drop = True)
.mc.reset_index()

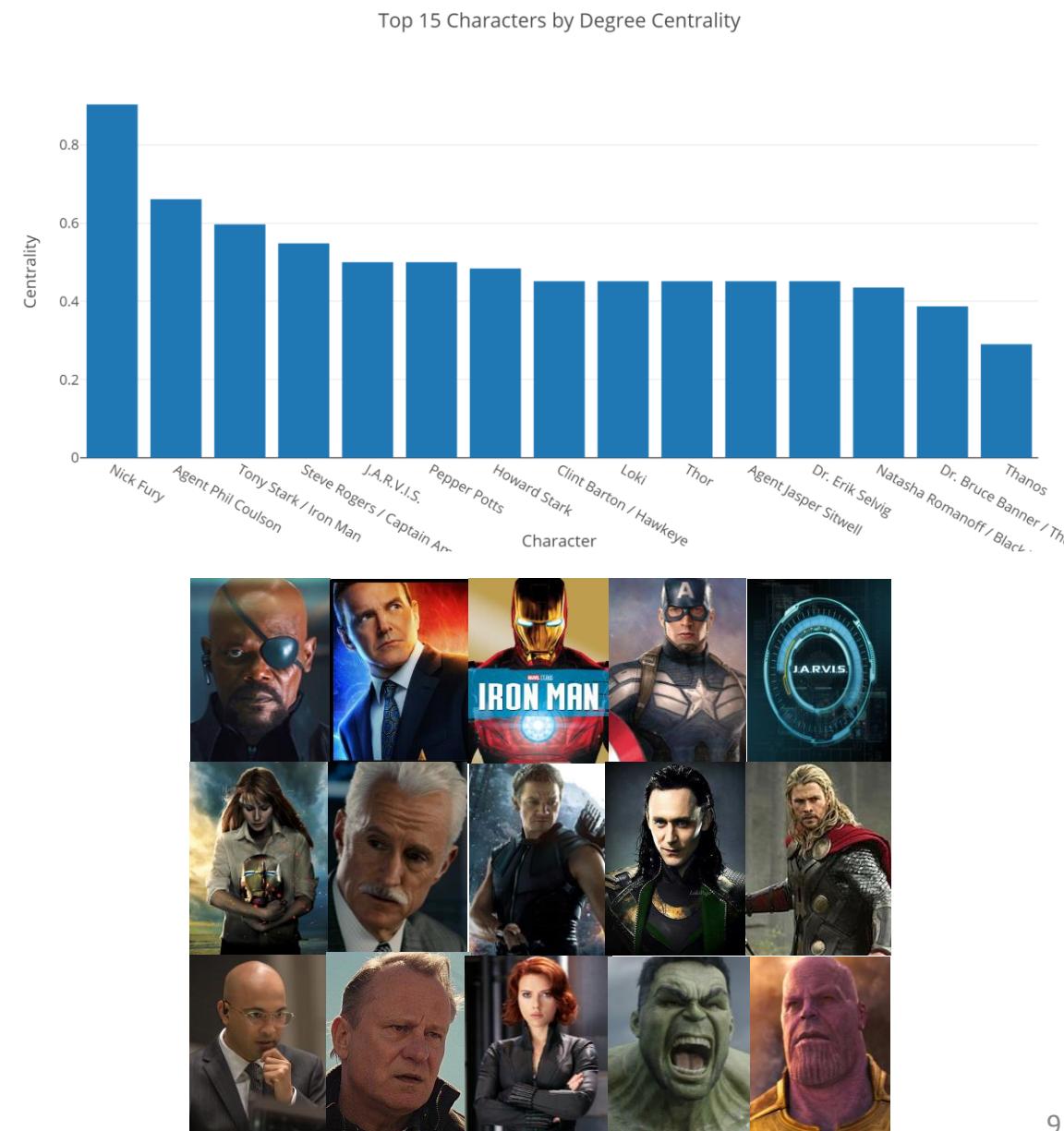
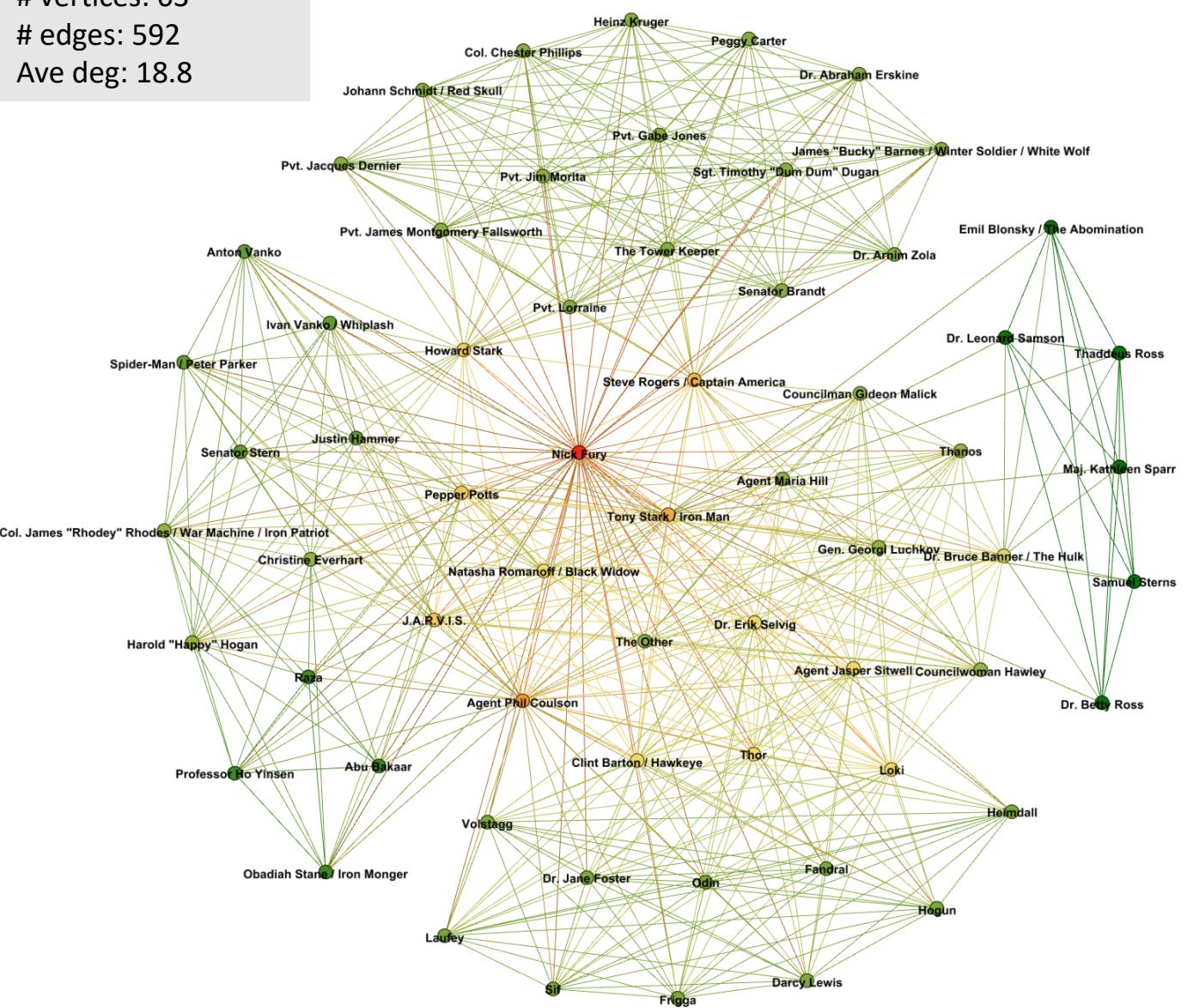
#rename column names
mcu.rename(columns={0:'char1',
                    1:'char2'},
           inplace=True)

#Add in phases column
#select phases from movie_info df
mcu_phase = movie_info[['Title', 'Phase']]
mcu_phase.rename(columns={'Title':'Movie'},
                  inplace = True)

#merge MCU with MCU_phases
mcu_new = pd.merge(mcu, mcu_phase,
                   left_on=['Movie'],
                   right_on=['Movie'],
                   how='inner')
```

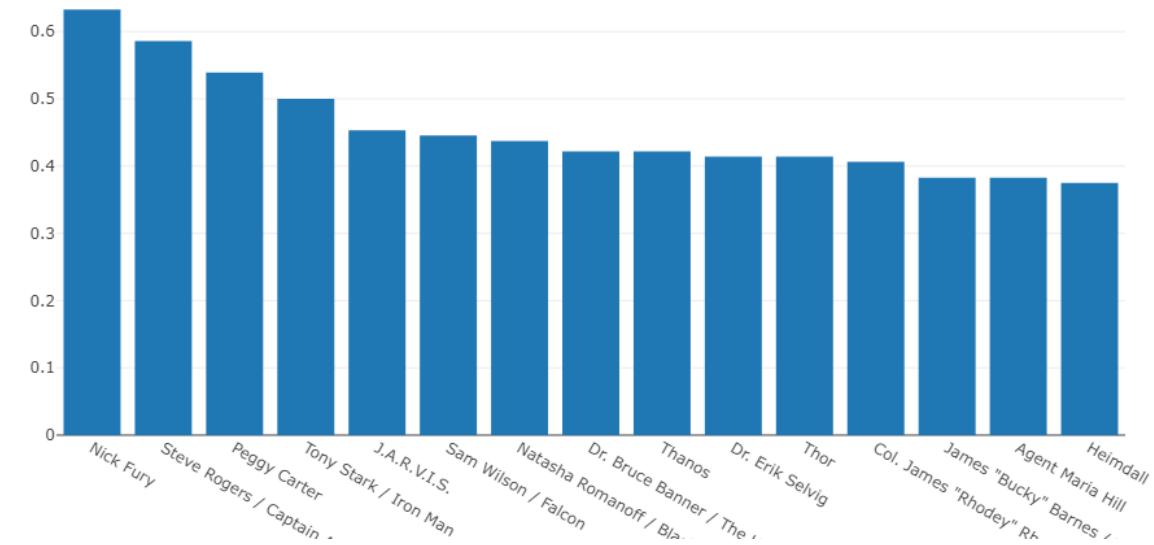
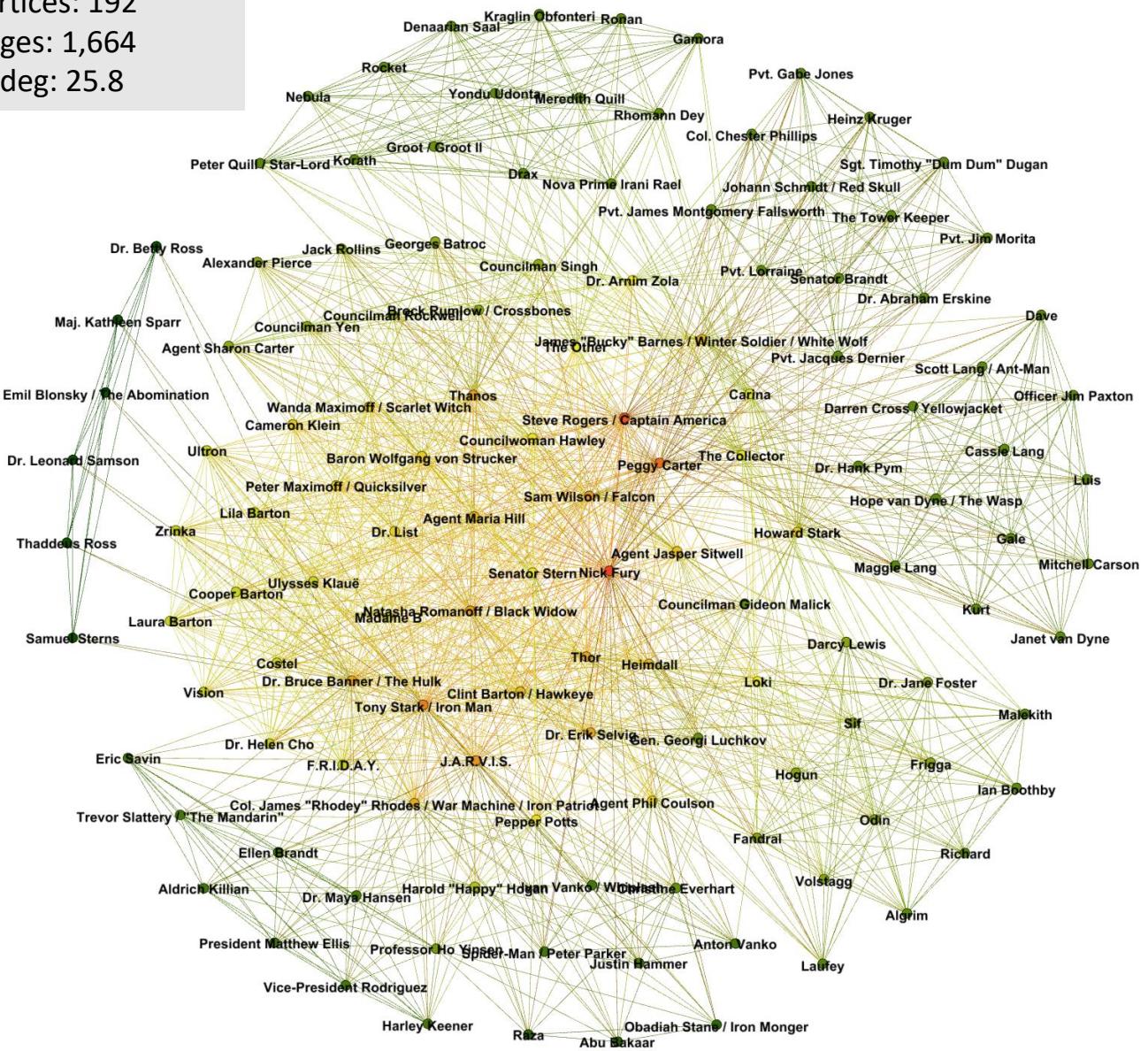
MCU Movies – Phase 1

vertices: 63
 # edges: 592
 Ave deg: 18.8



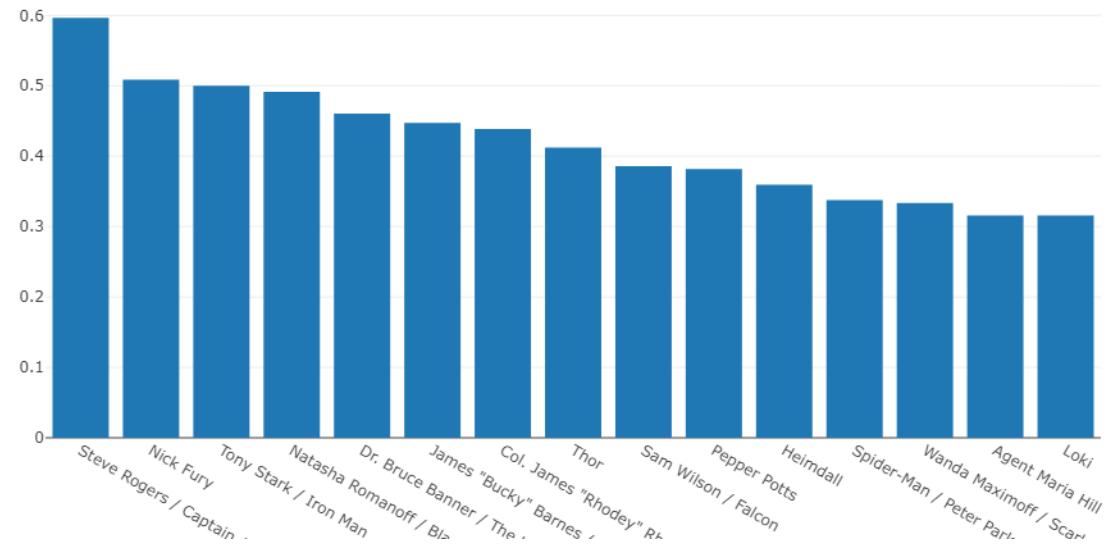
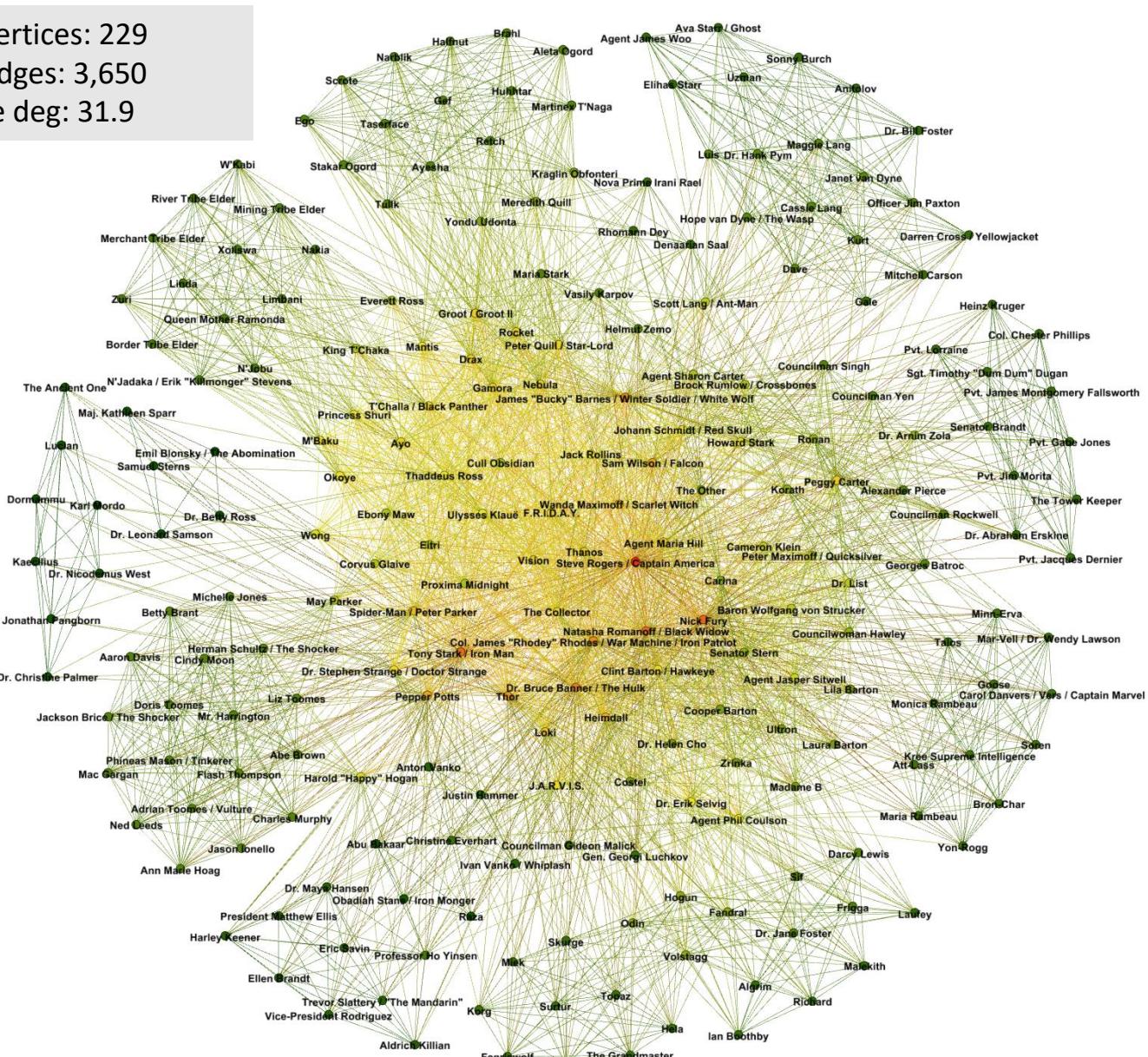
MCU Movies – Phase 2

vertices: 192
 # edges: 1,664
 Ave deg: 25.8

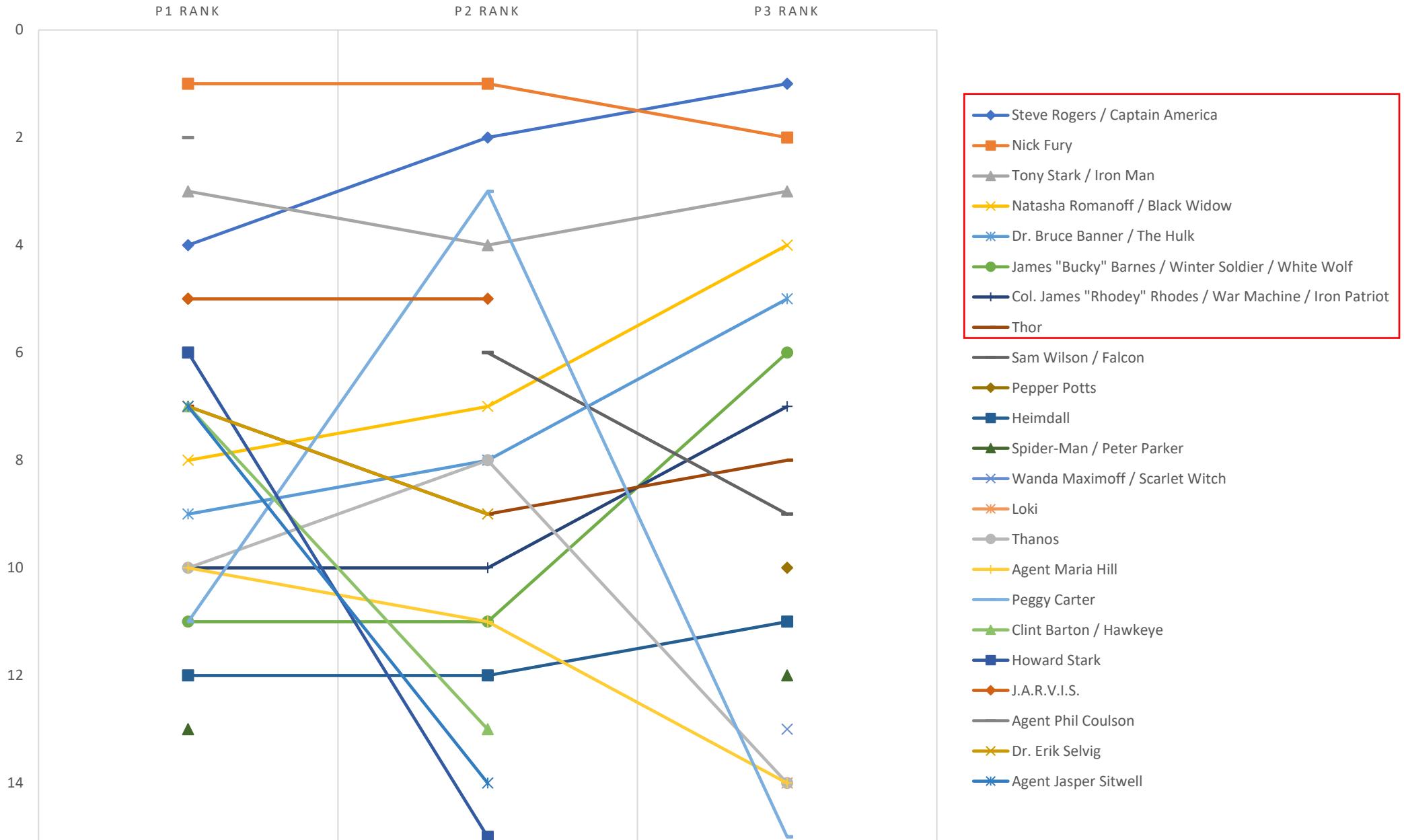


MCU Movies – Phase 3

vertices: 229
 # edges: 3,650
 Ave deg: 31.9



How did characters' centrality fare in 3 phases?



All 50 'Marvel' related movies

vertices: 495
edges: 6,100
Ave deg: 24.6

Interesting Findings:

Top 10 Central Characters

Steve Rogers / Captain America

Nick Fury

Tony Stark / Iron Man

Spider-Man / Peter Parker

Natasha Romanoff / Black Widow

Dr. Bruce Banner / The Hulk

James "Bucky" Barnes / Winter Soldier / White Wolf

Col. James "Rhodey" Rhodes / War Machine / Iron Patriot

Logan / Wolverine / Weapon X

Professor Charles Xavier

Bridge between “communities”:

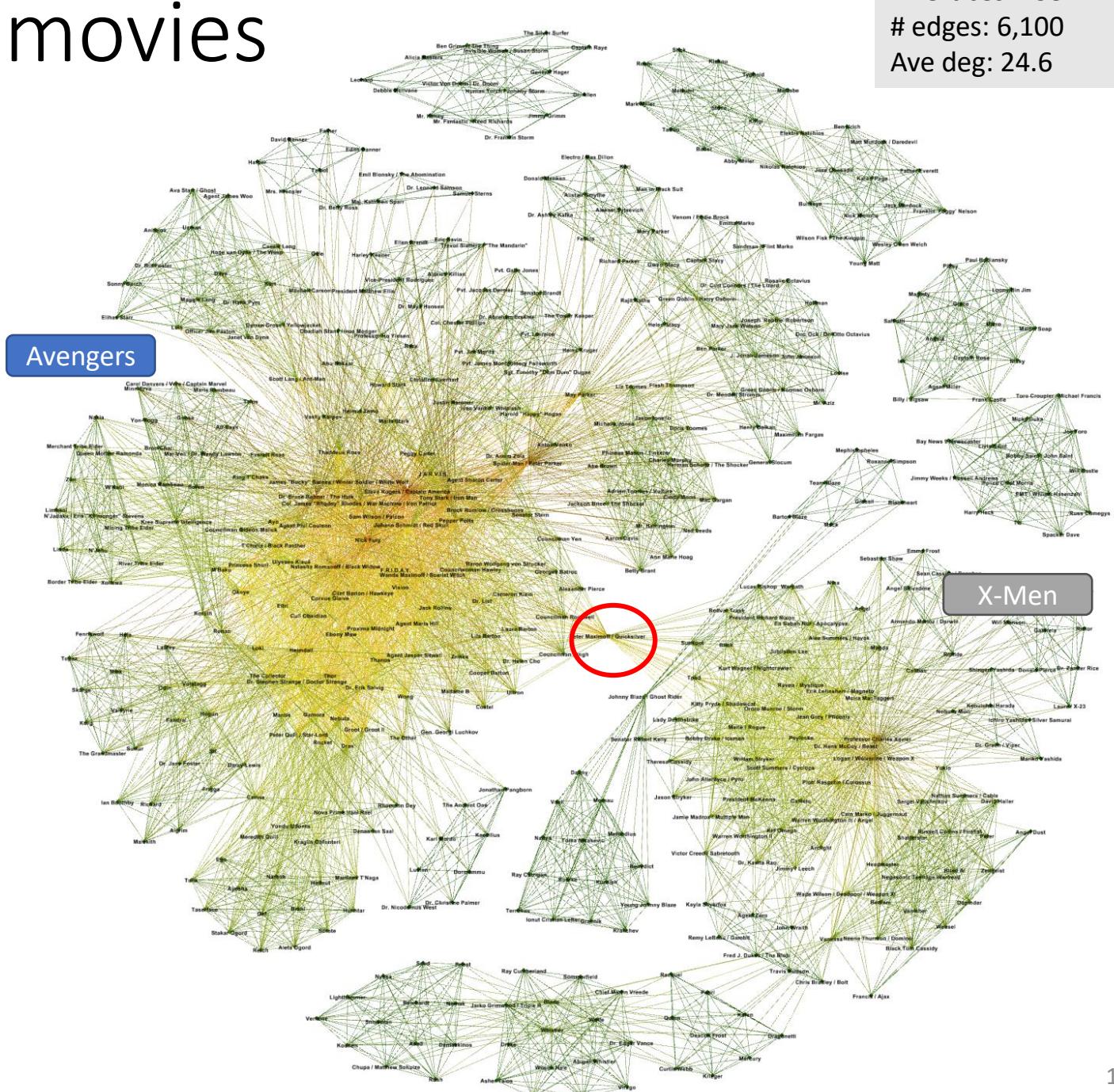
- **Quicksilver** (Avengers to X-Men)

Spider-Man / Peter Parker

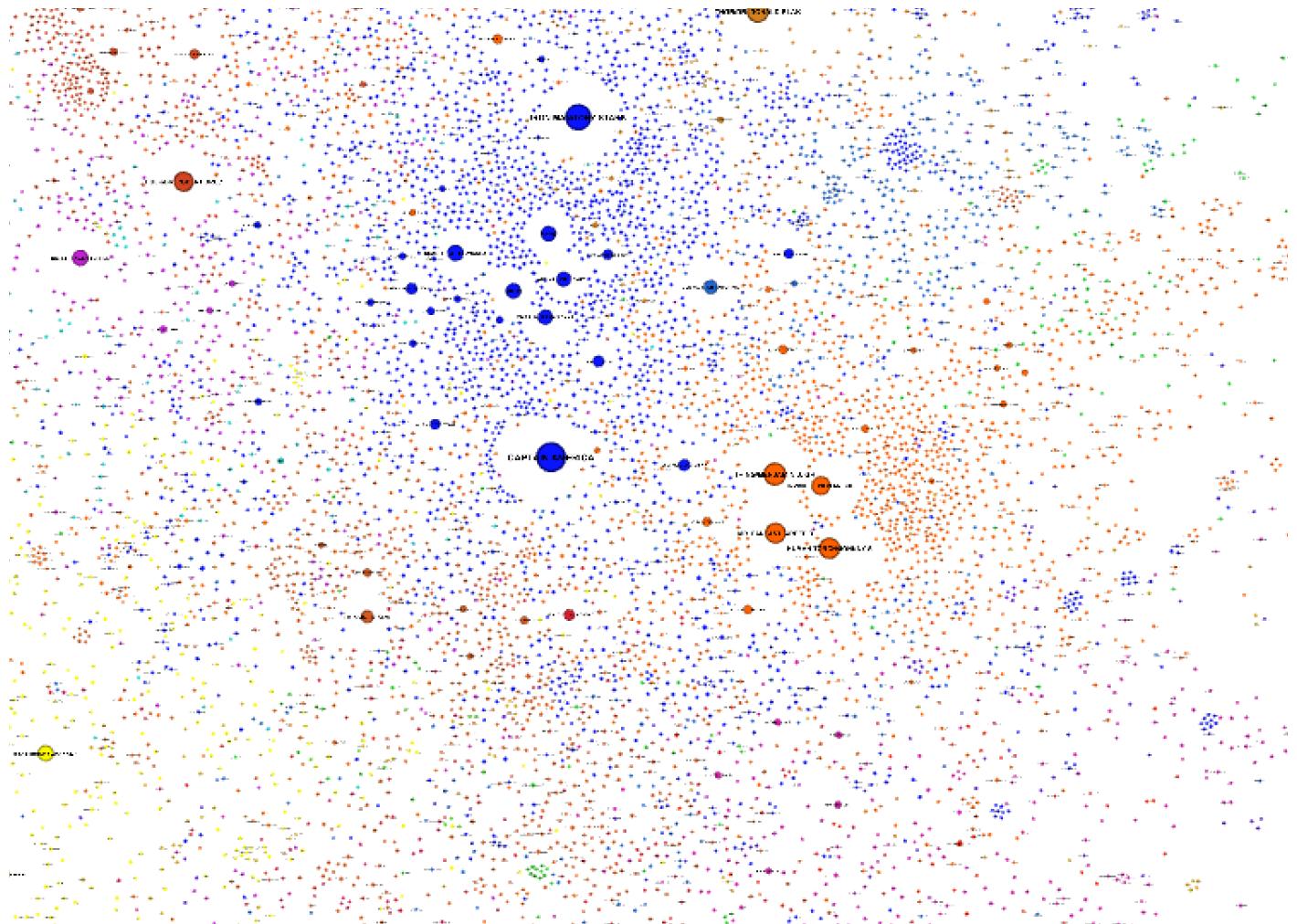
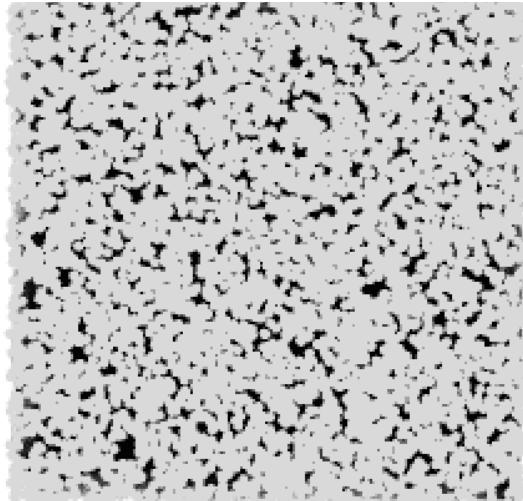
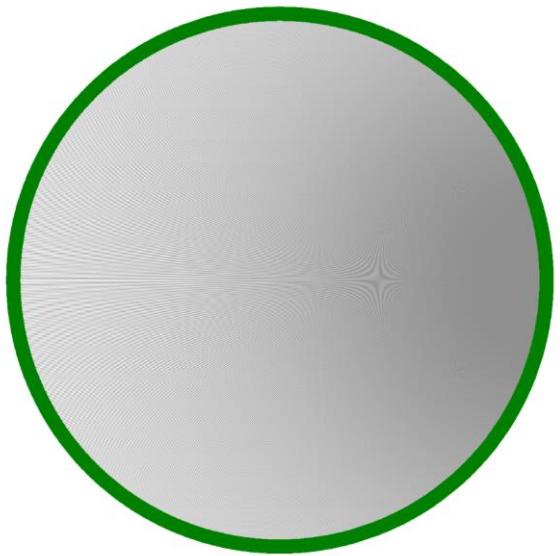
Logan / Wolverine / Weapon X

Professor Charles Xavier

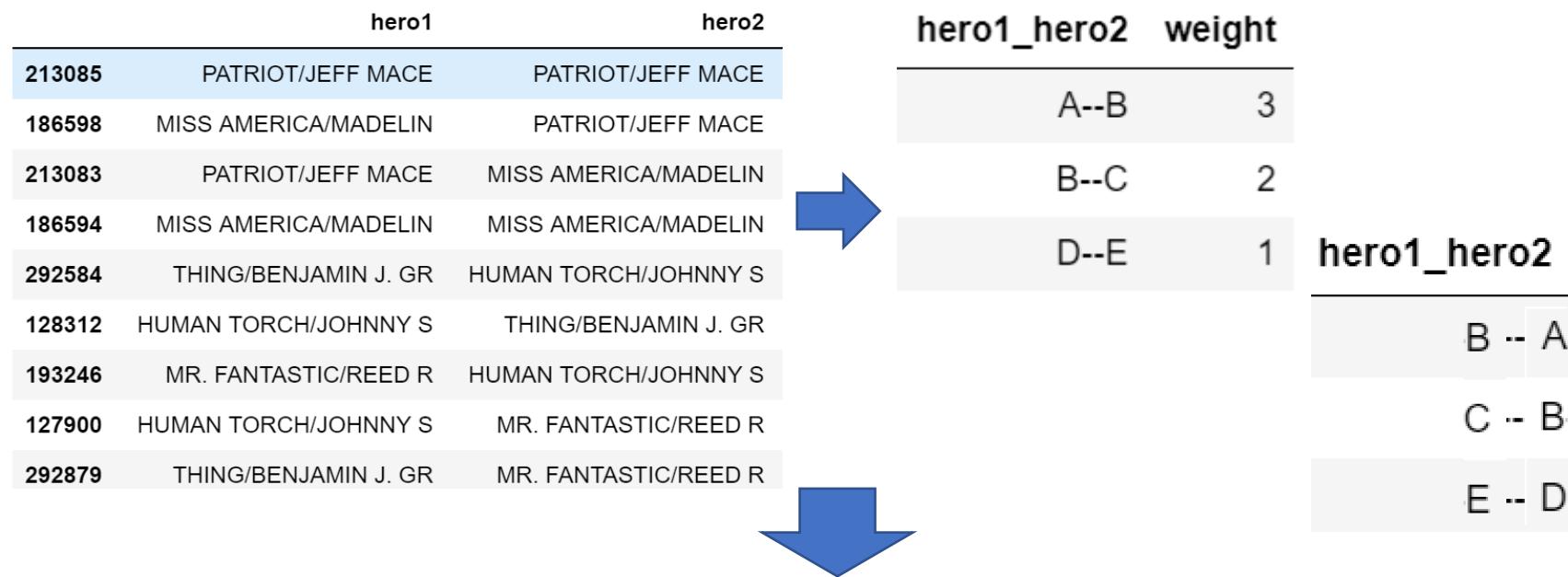
Steve Rogers / Captain America



Comic Data Preparation



Comic Data Preparation



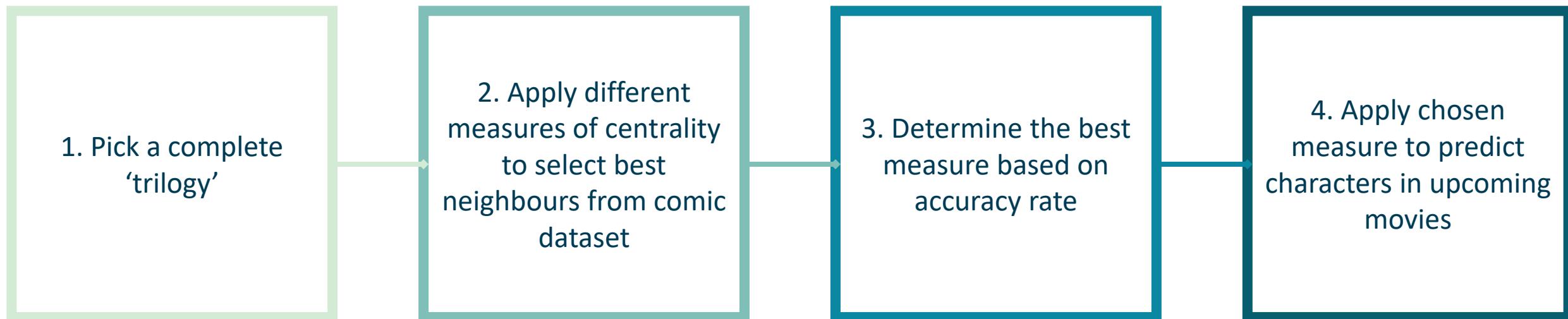
hero1	hero2	weight
213085	PATRIOT/JEFF MACE	2550
186598	MISS AMERICA/MADELIN	1894
213083	PATRIOT/JEFF MACE	1894
186594	MISS AMERICA/MADELIN	1344
292584	THING/BENJAMIN J. GR	744
128312	HUMAN TORCH/JOHNNY S	744
193246	MR. FANTASTIC/REED R	713

How do Movies Compare to the Comics?

Degree Centrality:

Rank	Movies	Comics
1	Steve Rogers / Captain America	Captain America / Steve Rogers
2	Nick Fury	Spiderman / Peter Parker
3	Tony Stark / Iron Man	Iron Man / Tony Stark
4	Natasha Romanoff / Black Widow	Thing / Benjamin Grimm
5	Dr. Bruce Banner / The Hulk	Mr. Fantastic / Reed Richards
6	James "Bucky" Barnes / Winter Soldier / White Wolf	Wolverine / Logan
7	Col. James "Rhodey" Rhodes / War Machine / Iron Patriot	Human Torch / Johnny Storm
8	Thor	Scarlet Witch / Wanda Maximoff
9	Sam Wilson / Falcon	Thor / Dr. Donald Blake
10	Pepper Potts	Beast / Hank McCoy

Predicting Future Characters



- There are 2 complete trilogies in the entire MCU – Iron Man & Thor
- Identify all unique characters in the trilogy to use for verification of our measures
- Apply the following measures to the comic dataset to predict characters that will appear in the Thor movie series:
 - Top weighted neighbours
 - Degree Centrality
 - Similarity
- Compare accuracy rate of three measures to determine which one is the best
- Apply the chosen measure to upcoming movies:
 - Black Widow
 - Black Panther 2
 - Doctor Strange 2
 - Gambit

Identify Unique Characters of a Series

1. 2. 3. 4.



```
for char in g.adj['Thor']:
    print(char)
```



```
for char in
g.adj['Thor: The Dark World']:
    print(char)
```



```
for char in g.adj['Thor: Ragnarok']:
    print(char)
```

1. Thor

Thor	Frigga
Loki	Heimdall
Dr. Jane Foster	Agent Phil Coulson
Dr. Erik Selvig	Laufey
Odin	Agent Jasper Sitwell
Darcy Lewis	Nick Fury
Sif	Clint Barton / Hawkeye
Volstagg	Hawkeye
Fandral	Doctor Strange
Hogun	

2. Thor: The Dark World

Thor	Frigga
Loki	Heimdall
Dr. Jane Foster	Malekith
Dr. Erik Selvig	Algrim
Odin	Ian Boothby
Darcy Lewis	The Collector
Sif	Richard
Volstagg	Carina
Fandral	
Hogun	

3. Thor: Ragnarok

Thor	Surtur
Loki	Dr. Stephen Strange
Dr. Bruce Banner / Hulk	Topaz
Valkyrie	Fenriswolf
Odin	Miek
Hela	Hogun
Skurge	Volstagg
The Grandmaster	Fandral
Heimdall	Natasha Romanoff / Black Widow
Korg	

There are 35 unique main characters in the Thor Trilogy (excluding Thor)

Measures to identify potential neighbours

Top Weighted
Neighbours

- Create a weighted graph
- Select all neighbours of key character
- Rank neighbours by weight
- Select top neighbors



Character	Weight
Captain America	386
Iron Man/Tony Stark	344
Odin	266
Vision	255
Scarlet Witch/Wanda Maximoff	254
Wasp/Janet Van Dyne	238
Hawk	210
Balder	209
Sif	204
Ant-Man/Dr. Henry J. Pym	189
Volstagg	187
Fandral	186
Hogun	186
Loki	182
Jarvis, Edwin	160
Mr. Fantastic/Reed Richards	129
Thing/Benjamin J. Grimm	126
Wonder Man/Simon Williams	125

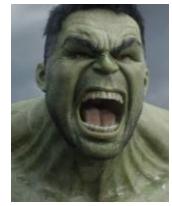


Character	Weight
Human Torch/Johnny Storm	124
She-Hulk/Jennifer Walters	123
Hercules	114
Kincaid, Dr. Jane Foster	112
Heimdall	111
Invisible Woman/Sue Storm	111
Black Panther/T'Challa	103
Quicksilver/Pietro Maximoff	99
Spider-Man/Peter Parker	95
Beast/Henry Hank Mccoy	90
Captain Marvel II/Monica Rambeau	84
Enchantress/Amora	78
Karnilla	76
Hulk/Dr. Robert Bruce Banner	72
Vizier	72
Sub-Mariner/Namor Mackenzie	62
Black Widow/Natasha Romanoff	61

Neighbours with top centrality scores

Centrality

- Use the weighted graph previously created
- Get all the neighbors of one character
- Rank with degree centrality
- Select top neighbors

Character	Degree Centrality	Character	Degree Centrality
Captain America	0.296965		Dr. Strange/Stephen Strange 0.16607
Spider-Man/Peter Parker	0.27035		Hulk/Dr. Robert Bruce Banner 0.164202
Iron Man/Tony Stark	0.236887		Wonder Man/Simon Williams 0.160778
Thing/Benjamin J. Grimm	0.220389		Professor X/Charles Xavier 0.160623
Mr. Fantastic/Reed Richards	0.21463		Colossus II/Peter Rasputin 0.159533
Wolverine/Logan	0.213385		Marvel Girl/Jean Grey 0.15642
Human Torch/Johnny Storm	0.211829		Hercules 0.154241
Scarlet Witch/Wanda Maximoff	0.206226		Jarvis, Edwin 0.153463
Beast/Henry Hank Mccoy	0.197198		Sub-Mariner/Namor Mackenzie 0.152374
Vision	0.193152		Daredevil/Matt Murdock 0.150506
Invisible Woman/Sue Storm	0.192374		Iceman/Robert Bobby Drake 0.147082
Hawk	0.182879		Black Widow/Natasha Romanoff 0.143502
Wasp/Janet Van Dyne	0.169805		Fury, Col. Nicholas 0.143502
Ant-Man/Dr. Henry J. Pym	0.168405		Jameson, J. Jonah 0.143191
Cyclops/Scott Summers	0.168249		Quicksilver/Pietro Maximoff 0.136187
Angel/Warren Kenneth Worthington III	0.167004		Nightcrawler/Kurt Wagner 0.133385
Storm/Ororo Munroe	0.166848		Rogue 0.129339
She-Hulk/Jennifer Walters	0.166693		

Neighbours with top centrality scores

Centrality

- Use the weighted graph previously created
- Get all the neighbors of one character
- Rank with eigenvector centrality
- Select top neighbors

Character	Eigenvector Centrality	Character	Eigenvector Centrality
Captain America	0.291174519	Professor X/Charles Xavier	0.116516396
Thing/Benjamin J. Gr	0.232840152	She-Hulk/Jennifer Walters	0.114708977
Human Torch/Johnny Storm	0.228728903	Jarvis, Edwin	0.109228344
Iron Man/Tony Stark	0.225055946	Quicksilver/Pietro Maximoff	0.107505041
Mr. Fantastic/Reed Richards	0.224791665	Colossus II/Peter Rasputin	0.10650563
Invisible Woman/Sue Storm	0.216340253	Marvel Girl/Jean Grey	0.105099105
Scarlet Witch/Wanda Maximoff	0.212751467	Angel/Warren Kenneth Worthington III	0.104304004
Vision	0.209606757	Iceman/Robert Bobby Drake	0.102478167
Thor/Dr. Donald Blake	0.199501378	Hulk/Dr. Robert Bruce Banner	0.100038363
Wasp/Janet Van Dyne	0.197125043	Hercules	0.096838714
Hawk	0.176999356	Patriot/Jeff Mace	0.095058577
Ant-Man/Dr. Henry J. Pym	0.171095374	Sub-Mariner/Namor Mackenzie	0.089066117
Beast/Henry Hank Mccoy	0.157246619	Black Widow/Natasha Romanoff	0.085247196
Wonder Man/Simon Williams	0.143439689	Rogue	0.083888824
Cyclops/Scott Summers	0.135707624	Nightcrawler/Kurt Wagner	0.077362686
Wolverine/Logan	0.131486003	Black Panther/T'Challa	0.077100814
Spider-Man/Peter Parker	0.129055006	Richards, Franklin B	0.076174818
Storm/Ororo Munroe	0.122635321		



Neighbours most similar to Thor

Similarity

- Create a node vector model
- Get Similarity with main character in the movies
- Rank with similarity
- Select top characters



Character	Similarity
Executioner II/Skurge	0.928727
Odin	0.907808
Loki	0.8981
Enchantress/Amora	0.889757
Sif	0.877101
Heimdall	0.873244
Balder	0.870802
Surtur	0.86834
Kincaid, Dr. Jane Foster	0.862963
Krista	0.862055
Harokin	0.859799
Hogun	0.85884
Fandral	0.855293
Utgard-Loki	0.851918
Volstagg	0.847318
Tyr	0.844327
Hobbs, Harris	0.837497
Vizier	0.837075

Character	Similarity
Frigga	0.836512
Volla	0.828432
Destroyer III	0.825879
Seth II	0.824532
Hildegarde	0.823125
Lorelei II/Melodi	0.818588
Karnilla	0.813871
Neffethesk	0.813761
Pentigaar	0.812846
Designate/Tarene	0.805783
Nichols, Lorna	0.788973
Horus	0.78628
Toothgnasher	0.784995
Malekith/Malcolm Keith	0.784638
Case, Col. Preston	0.782062
Kurse/Algrim	0.781911

How did our measures do?

	Weight of Next Neighbour	Degree Centrality	Eigenvector Centrality	Node2Vec Similarity
Predicted number	35	35	35	35
Matched number	10	4	2	15
Accuracy	28.6%	11.4%	5.7%	42.9%

Predicting Future Characters of these Movie

1. 2. 3. 4.



Black Widow (2020)

Character	Similarity
DEATHCRY	0.827196
ANT-MAN/DR. HENRY J. PYM	0.778099
HERCULES	0.763727
MANTIS	0.759803
IVAN PETROVITCH	0.757092
NEUT	0.755555
ZA'KEN	0.734836
MADAME MASQUE III	0.734648
TUC	0.733714
SWORDSMAN III/PHILIP JAVERT	0.730123
CARINA/CARINA WALTER	0.730029
JOCASTA II	0.728925
VISION	0.726362
T'KYLL ALABAR	0.718949
TABULA RASA	0.710955
STORM, CHILI	0.710499
WATCHLORD	0.706668
WASP/JANET VAN DYNE	0.705857
PROCTOR	0.698965
NELIT	0.698442



Black Panther 2 (TBD)

Character	Similarity
LYNNE, MONICA	0.821174
NECRODAMUS	0.789341
ADAMS, NICOLE NIKKI	0.775762
SWORDSMAN/JACQUES DUQUESNE	0.77544
ROSS, EVERETT KENNETH	0.76188
WHITE WOLF/HUNTER	0.753689
KILLMONGER, ERIC/N'JADAKA	0.751231
RED GUARDIAN II/ALEXEI SHOSTAKOV	0.750105
TAKU	0.743949
PRESTER JOHN	0.742969
STINGER II	0.741208
ANT-MAN/DR. HENRY J. PYM	0.740225
MASTER PANDEMONIUM/MARTIN PRESTON	0.731731
BLACK KNIGHT III/EOB	0.728046
GRIM REAPER/ERIC WILLIAMS	0.727991
VISION	0.72677
ZURI	0.726121
WASP/JANET VAN DYNE	0.725275
AMENHOTEP	0.723408
LLOIGOROTH	0.721435

Predicting Future Characters of these Movie

1. 2. 3. 4.



Gambit (TBD)

Character	Similarity
PSYLOCKE/ELISABETH BRADDOCK	0.884617
CHROME	0.884347
ROGUE	0.874492
DELGADO	0.863572
MACTAGGART, JOE	0.859872
HAZARD/CARTER RYKING	0.853572
RASPUTIN, MIKHAIL	0.849118
EJULP	0.847835
STORM/ORORO MUNROE	0.843426
TRION	0.842097
MARROW/SARAH	0.841992
MR. SINISTER/NATHAN	0.838692
SISTER MARIA	0.82992
BRAIN CELL	0.82423
WANDERER	0.821231
MEME	0.818377
WOLVERINE/LOGAN	0.816266
RYKING, ALEXANDER	0.813096
PAM	0.812597
AVATAR	0.81259

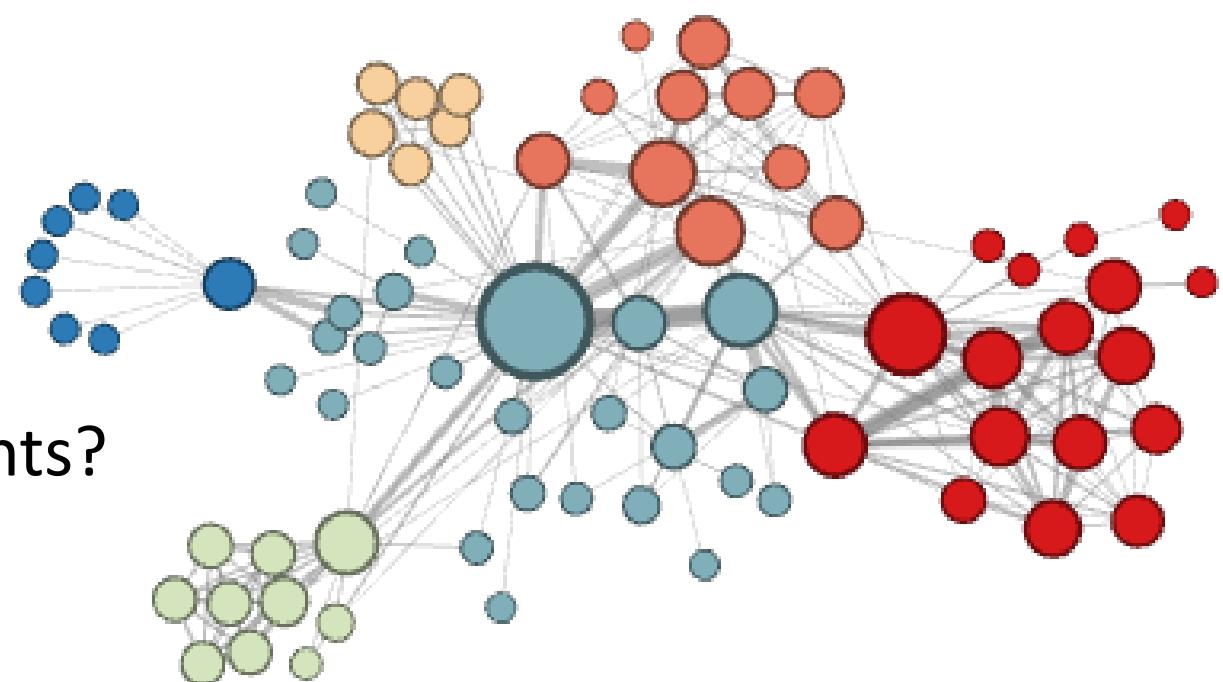


Doctor Strange 2 (TBD)

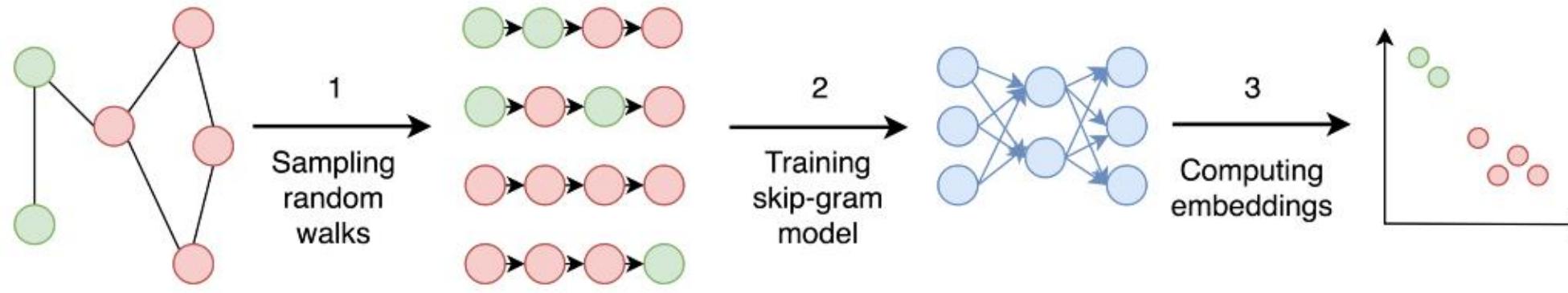
Character	Similarity
CLEA	0.967789
WONG	0.959589
CHANG, IMEI	0.904088
ANCIENT ONE	0.899713
RINTRAH	0.890948
WOLFE, SARA	0.885755
BLESSING, MORGANA	0.859316
DORMAMMU	0.855099
BARON MORDO/KARL MORDO	0.834619
BLACK, CYRUS	0.828678
ASMODEUS	0.825324
AGAMOTTO	0.820484
AZRAEL	0.820051
SHADOW QUEEN/SHIALMAR	0.817132
UMAR	0.816197
AGGAMON	0.816153
DR. STRANGER YET	0.814923
INTERLOPER	0.813463
SHUMA-GORATH	0.81115
APPALLA	0.810538

Node2Vec Package – What is Node2Vec?

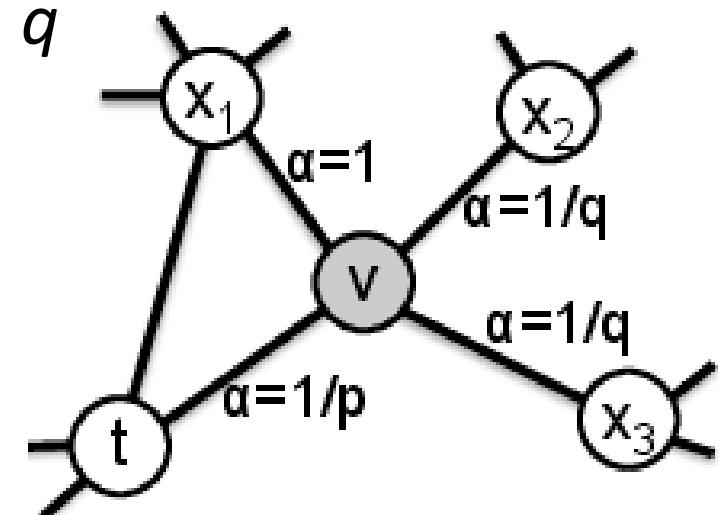
- Same principle as word2vec
- But!
 - Text => Linear, directed, contextual
 - Graphs => No natural order
- Can a network graph be made analogous to a corpus of documents?



Node2Vec Package – What is Node2Vec?



- Select 1 node from the network
- Do m random walks from the node with n steps in each random walk, governed by parameters p, q
 - p : returning to the previous node
 - q : going to/"discovering" a part of the graph unconnected to the previous node
- Repeat for all nodes



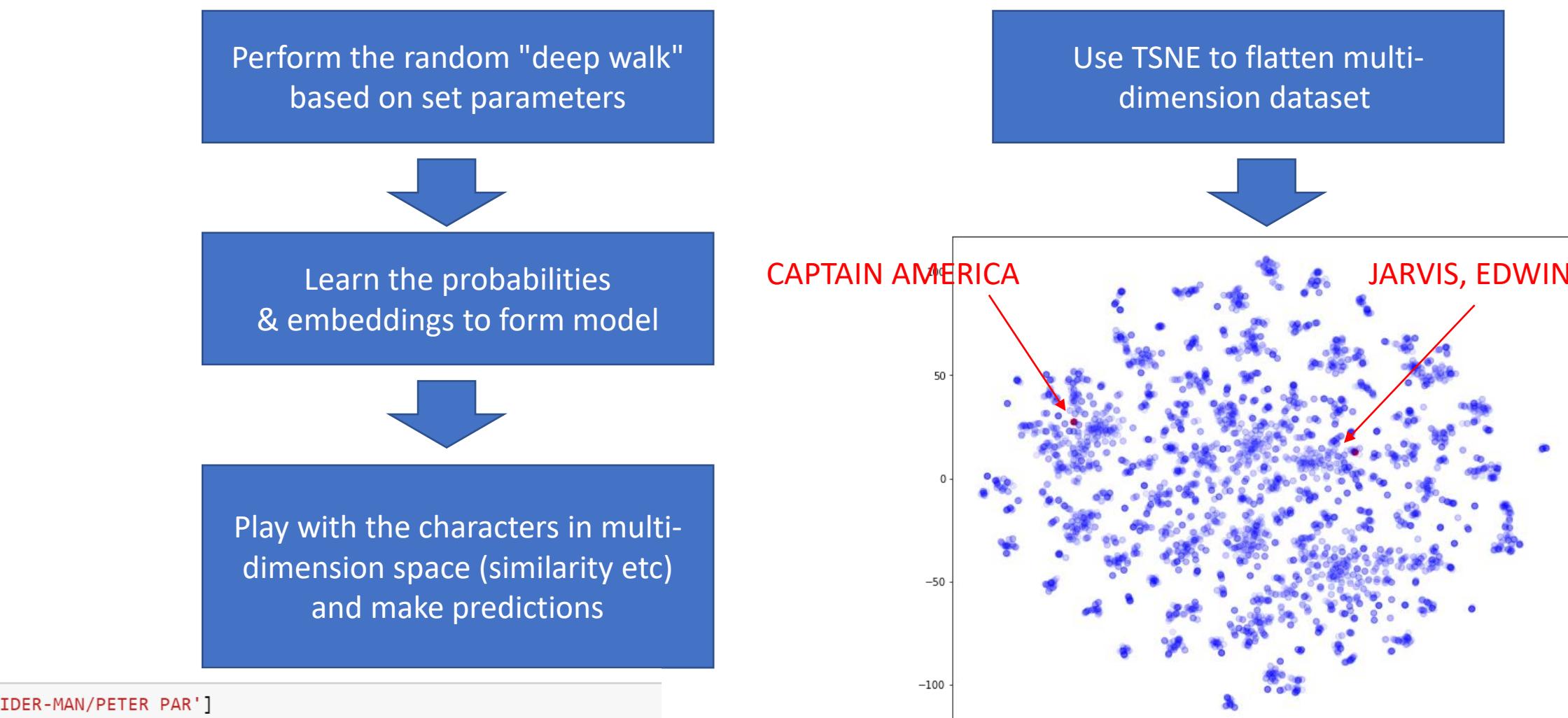
Node2Vec Package

```
In [5]: # Generate walks
# will take a while
node2vec = Node2Vec(g, dimensions=20, walk_length=25, num_walks=125)

Computing transition probabilities: 100%|██████████| 6426/6426 [05:01<00:00, 21.33it/s]
Generating walks (CPU: 1): 100%|██████████| 5/5 [00:06<00:00, 1.34s/it]
```

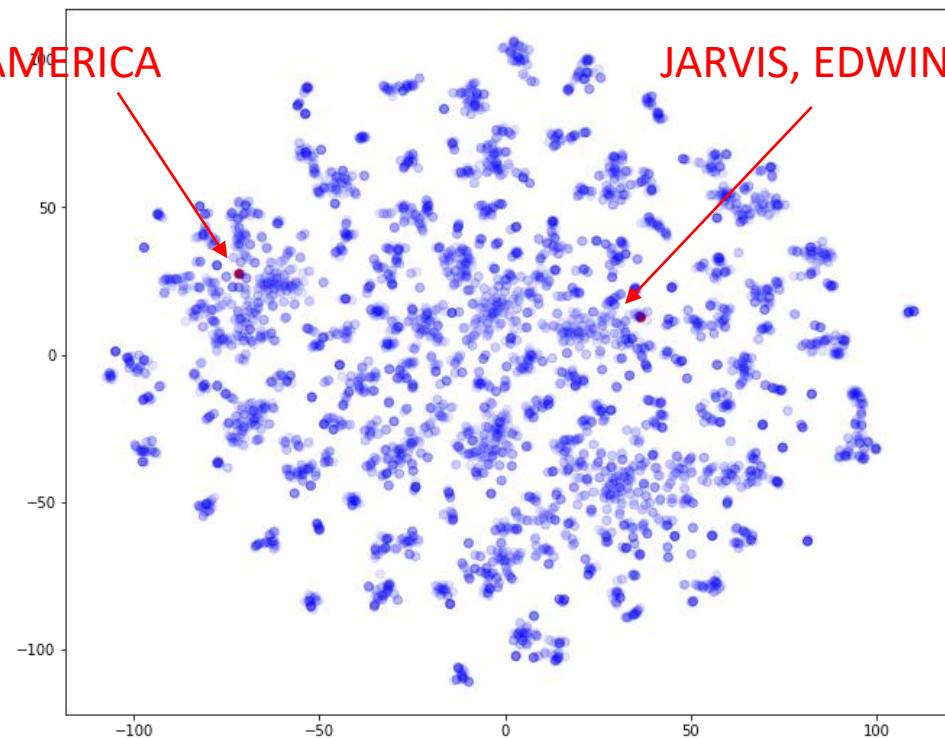
- Each random walk is analogous to a "sentence"
- All random walks together is analogous to a "corpus"
- Skip-Gram model to determine similarity

Node2Vec Package



[IDER-MAN/PETER PAR']

```
38346 , 3.8081942 , -2.813464 , 3.8015187 , -0.44214833,  
15962 , -0.3458974 , 2.7286322 , -4.449345 , -2.7225494 ,  
778554, 2.3601246 , 2.4234307 , -2.4428544 , -3.0922093 ,  
21474 , -0.9120338 , -2.5853953 , -1.6498612 , -2.6722753 ],  
float32)
```



Limitations and Further Work

- Exploration of Node2vec with weighted edges. Experimenting with more parameters eg. Number of dimensions, length of walks
- Include other MCU properties, such as Marvel TV series, Agents of SHIELD, Jessica Jones, Daredevil, Iron Fist, Luke Cage, The Defenders, etc, and other MCU produced One-Shots.
- Inability to mine comics dataset for completely new superheroes

Questions?

