UNIVERSIDAD POLITÉCNICA DE MADRID

Assessing technological maturity of social network analysis: The four dimensions of SNA

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D. Camacho, A. Panizo-LLedot, G. Bello-Orgaz, A. Gonzalez-Pardo, E. Cambria.
The Four Dimensions of Social Network Analysis: An Overview of Research Methods, Applications and Software Tools
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Applied **I**ntelligence & **D**ata **A**nalysis
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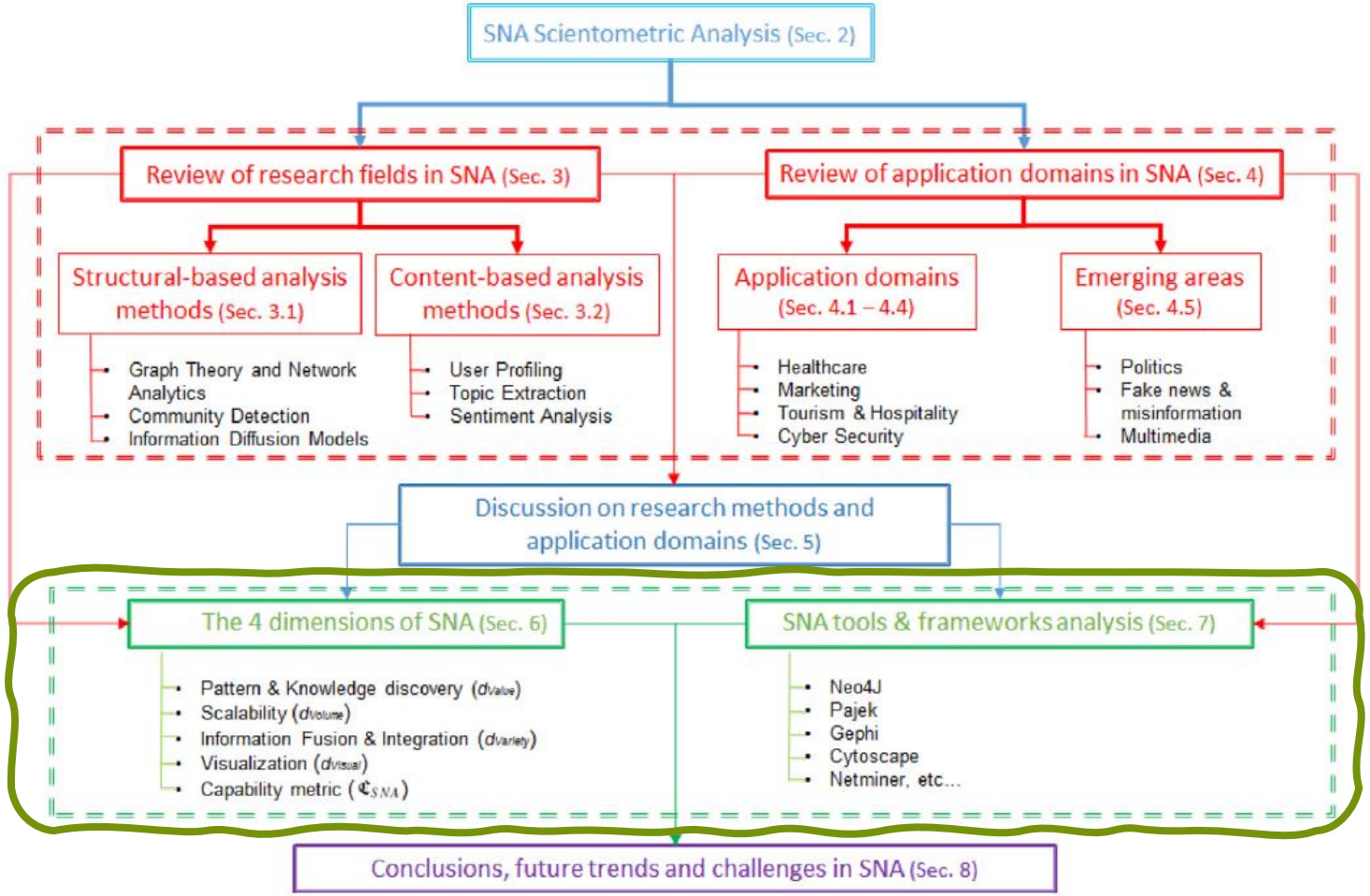
Outline


SNA Scientometric Analysis (Sec. 2)
Review of research fields in SNA (Sec. 3)
Review of application domains in SNA (Sec. 4)
Structural-based analysis methods (Sec. 3.1)
Content-based analysis methods (Sec. 3.2)
Application domains (Sec. 4.1 – 4.4)
Emerging areas (Sec. 4.5)
Graph Theory and Network Analytics
Community Detection
Information Diffusion Models
User Profiling
Topic Extraction
Sentiment Analysis
Healthcare
Marketing
Tourism & Hospitality
Cyber Security
Politics
Fake news & misinformation
Multimedia
Discussion on research methods and application domains (Sec. 5)
The 4 dimensions of SNA (Sec. 6)
SNA tools & frameworks analysis (Sec. 7)
Pattern & Knowledge discovery (d_{value})
Scalability (d_{volume})
Information Fusion & Integration ($d_{variety}$)
Visualization (d_{visual})
Capability metric ($\mathfrak{C}_{SNA}$)
Neo4J
Pajek
Gephi
Cytoscape
Netminer, etc...
Conclusions, future trends and challenges in SNA (Sec. 8)

Motivation

- Currently, Online Social Network (OSN) have billions of active users around the world.
- OSNs are a social structure made up of people, or entities, connected by some type of relationship or common interest (professional relationship, friendship, kinship, etc.).
- These networks allow:
  - To define a public (or semi-public) profile.
  - To manage a list of other users with whom the individual (or entity) will share a connection.
  - To view and traverse their list of connections and those made by others within the social site

Motivation

- There are several factors that has make OSNs to gain the attention of the research community:
  - The easy access to this type of information.
  - the availability of vast amounts of data.
  - the simple and straightforward codification in form of graph-based representation
  - the direct application of any practical results drawn from them.
- Nowadays, OSNs are one of the hot research areas in several disciplines:
  - Data Mining
  - Big Data
  - Machine Learning
  - Information Visualization
  - Complex systems…

Motivation

- Examples of different problems that can be studied in OSNs are:
  - Community detection problem: the division of the graph into clusters of nodes based on the network structure.

CPD

Motivation

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  - Community detection problem: the division of the graph into clusters of nodes based on the network structure.
  - Information Diffusion models: to study how the information is propagated through the network, and how users influence each others.

CPD

IDM

Motivation

- Examples of different problems that can be studied in OSNs are:
  - Community detection problem: the division of the graph into clusters of nodes based on the network structure. CPD
  - Information Diffusion models: to study how the information is propagated through the network, and how users influence each others. IDM
  - User Profiling: to categorize the different users in the network based on his content published. UP

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  - Community detection problem: the division of the graph into clusters of nodes based on the network structure. CPD
  - Information Diffusion models: to study how the information is propagated through the network, and how users influence each others. IDM
  - User Profiling: to categorize the different users in the network based on his content published. UP
  - Topic Extraction: discovering the abstract "topics" that occur in a collection of documents. TE

Motivation

- These problems are solved in a wide variety of application domains.
- In this talk, we are going to briefly describe some works published in the following research areas:
  - Healthcare
  - Marketing
  - Tourism & Hospitality
  - Cyber security
  - Politics
  - Fake news and misinformation

CPD

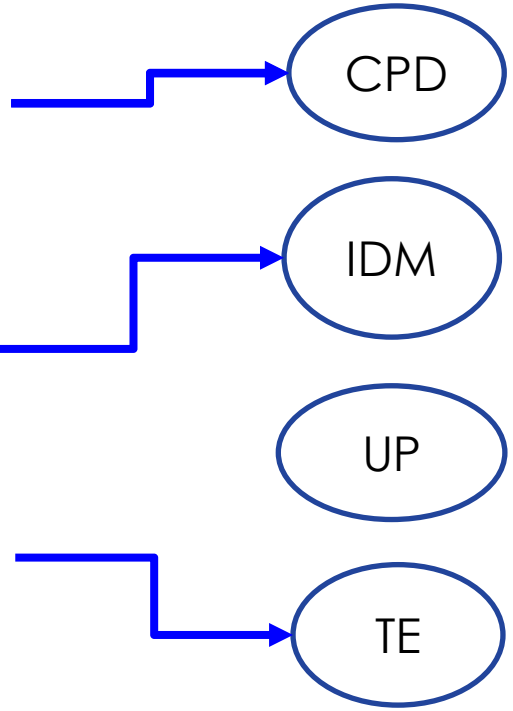
IDM

UP

TE

Motivation

- **Healthcare**
  1. **Bello et al. (2017)** focused the research on the detection and tracking of discussion communities on vaccination arising from OSNs as Twitter.
  2. **Huang et al. (2014)** carried out a study to investigate peer offline and online friendships, for determining how online activities with friends might broker the peer influence processes.
  3. **Weichselbraun et. al. (2017)** analyzed the text published to the early identification, assessment, and verification of potential public health risks.

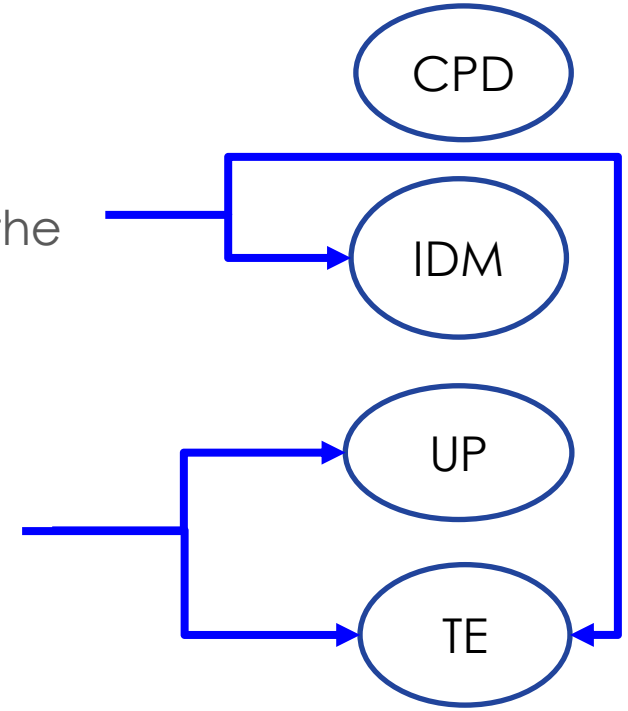


Motivation

- **Healthcare (focused on COVID-19)**

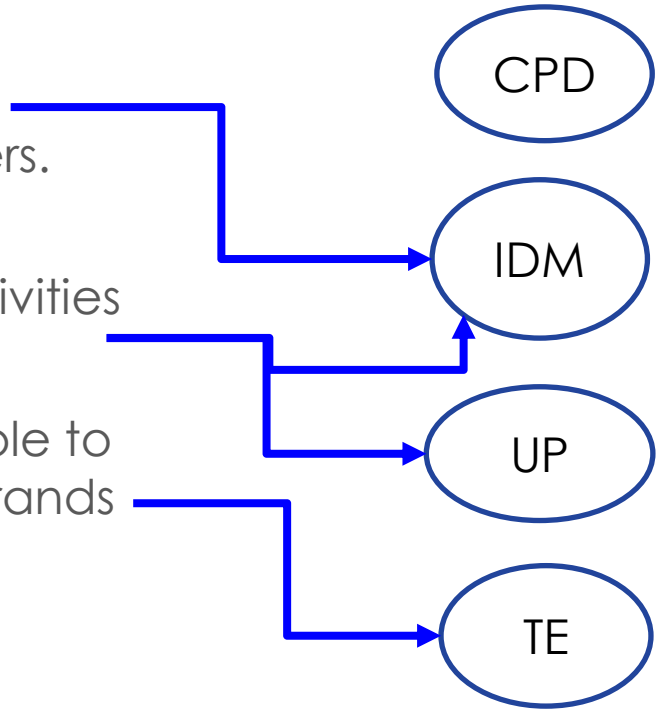
1. **Cinelli et al. (2020)** measured the engagement and interest in COVID-19 by analysing the comments and the reactions, and then, compared the evolution of the discourse in each social media platform

2. **Singh et al. (2020)** develop a risk assessment tool to quantify the rate at which any user from the selected region is exposed to unreliable post.



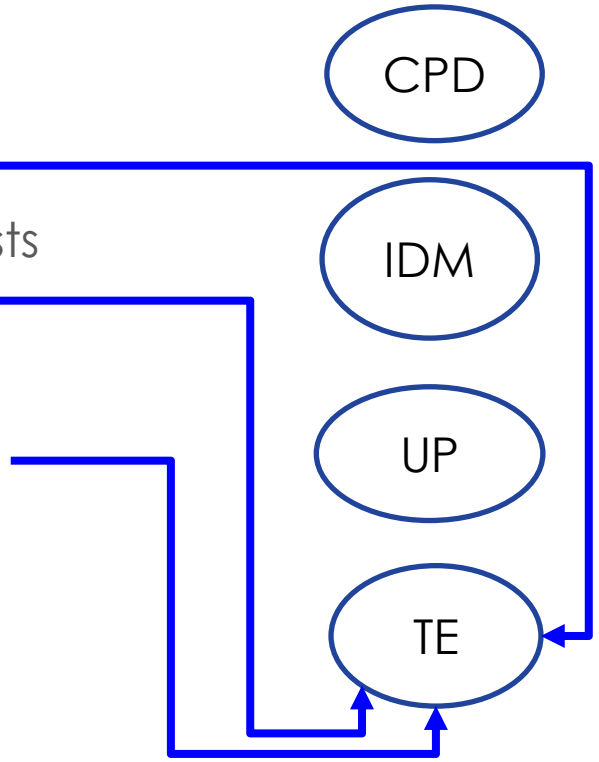
Motivation

- **Marketing**
  1. **R. G. Duffet (2015)** performed a study how the advertising of Facebook influences to the customers.
  2. **Harrigan et. al. (2017)** analyzed how social media platforms can be used to perform promotional activities to communicate with the targeted customers.
  3. **Hudson et. al. (2016)** studied that customers are able to express their opinions about specific products or brands to many other customers in OSNs.



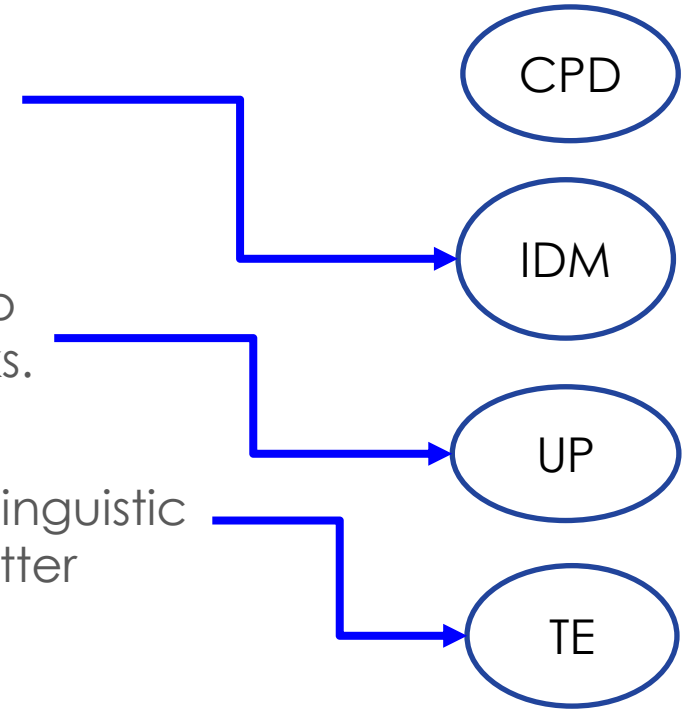
Motivation

- **Toursim & Hospitality**
  1. **Guo et. al. (2017)** measured tourist satisfaction by analyzing the different posts created in OSNs.
  2. **Hu et. al. (2017)** used sentiment analysis to extract tourists attitude and opinion toward tourism products such as hotel services.
  3. **Deng and Li (2018)** selected photo elements from the viewers' perspective and assist marketing organizations



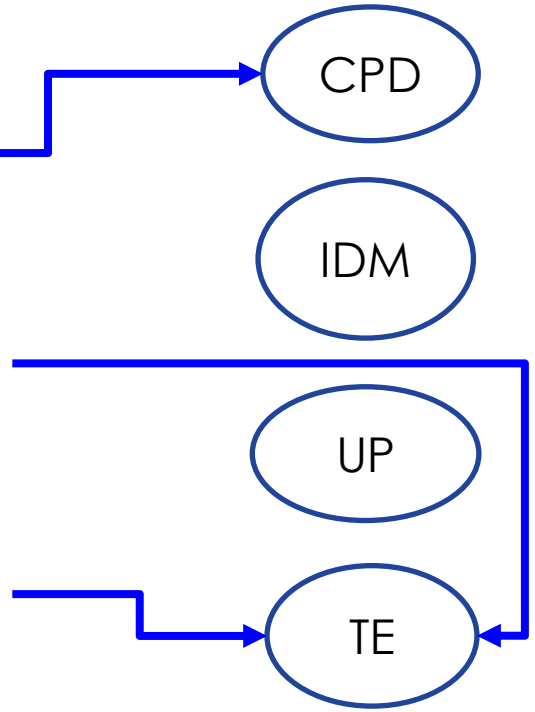
Motivation

- **Cyber security**
  1. **Fernandez et. al. (2019)** studied how radical users influence the other users in the OSN.
  2. **Lozano et. al. (2017)** used the network topology to identify the critical node in online terrorist networks.
  3. **Lara-Cabrera et al. (2017)** analyzed the different linguistic aspects of the tweets to determine whether a Twitter account belongs to a radical user or not.



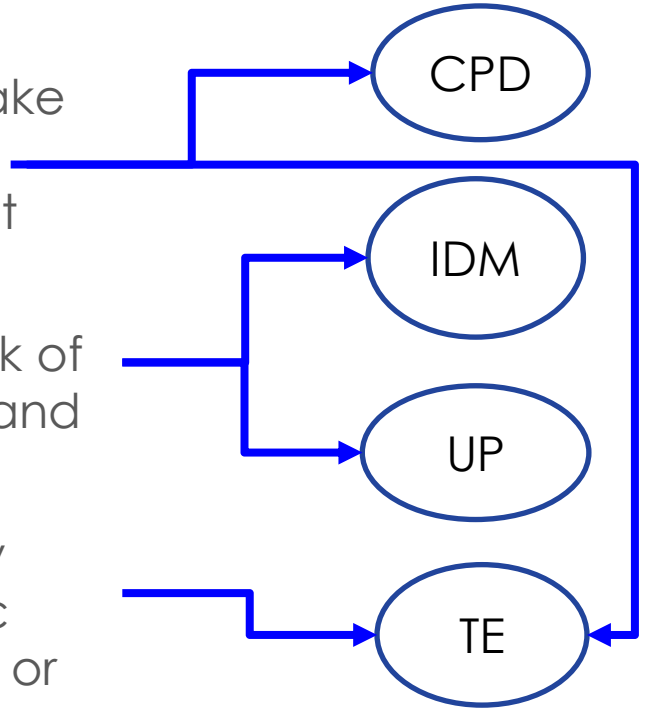
Motivation

- **Politics**
  1. **Ozer et al. (2016)** investigated the contributions of different types of user connectivity and content information in clustering politically users into pure political communities.
  2. **Davidson et. al. (2017)** designed a system that automatically classify the posts or comments based on its content and determine whether the corresponding post contains hate speech or not.
  3. **Panizo-Lledot et. al. (2019)** analyzed alt-right communities by taking into account their discourse on twitter.



Motivation

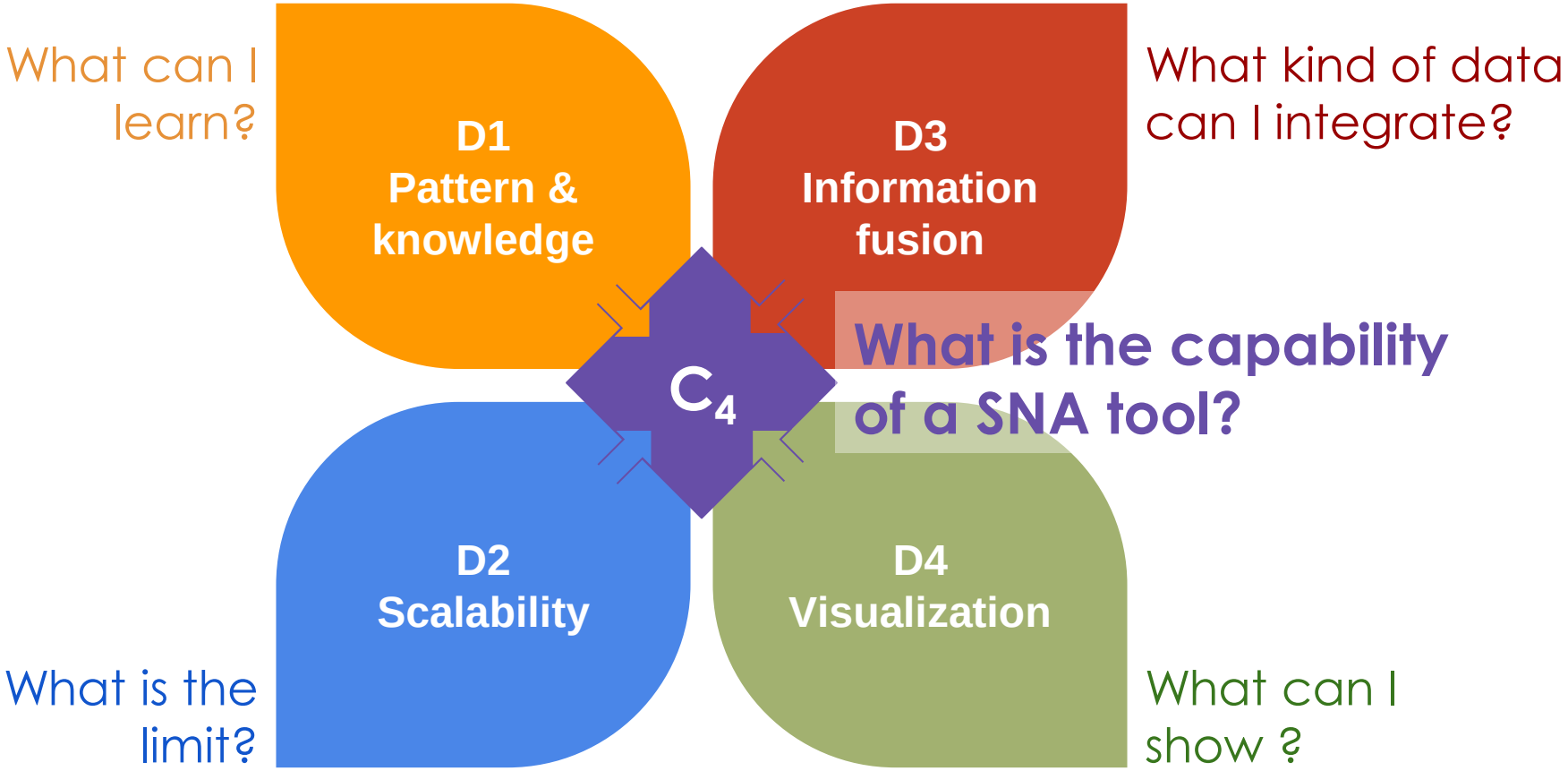
- **Fake news and misinformation**
  1. **Ruchansky et. al. (2017)** identified users that create fake news by analysing the co-occurrence network that represent how many times two users have written post relevant to the same news articles.
  2. **Kwon et. al. (2013)** characterized the diffusion network of fake news by analyzing the co-occurrence network, and the degree and clustering coefficient.
  3. **Potthast et. al. (2017)** tried to detect the fake news by analyzing the user created content by using syntactic features, such as "n-grams "and bag-of-words (BOW) or parts-of-speech (POS) tagging.



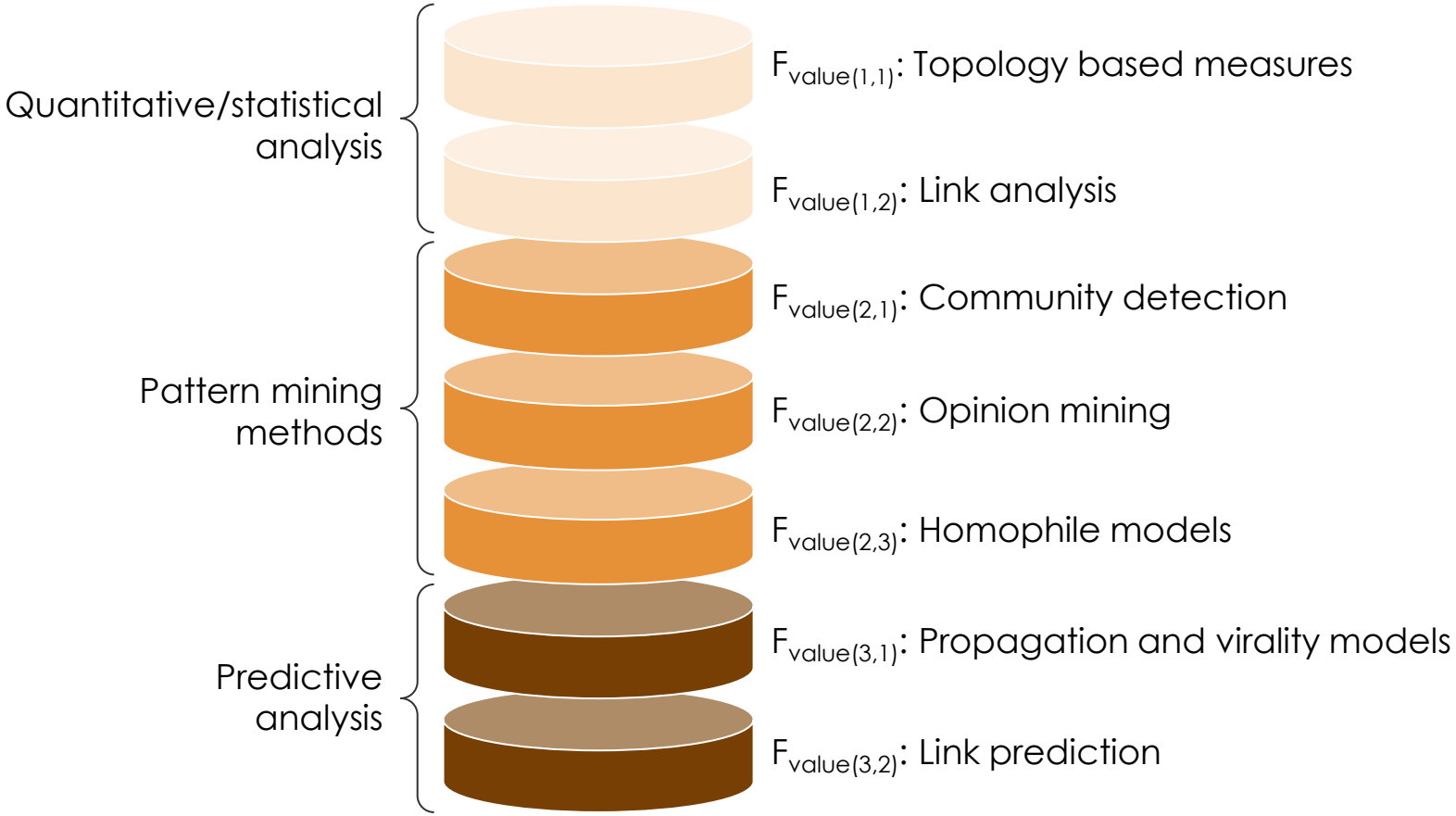
Motivation

- As it can be observed, there is a wide variety of algorithms and methods around **Social Network Analysis** (SNA).
- Any researcher who wants to start his/her research in SNA can be *overwhelmed* by this bunch of papers, algorithms, and systems.
- The goal of this work is to define a **set of metrics (dimensions)** that allow to evaluate the **maturity** of any SNA algorithm, system or platform.

The four dimensions

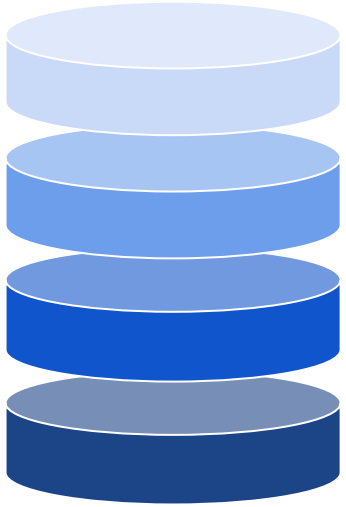


D1- Pattern & knowledge



$$D_{value}(x) = a/2 * \sum_{i=1}^{2} F_{value(1,i)}(x) + \beta/3 * \sum_{j=1}^{3} F_{value(2,j)}(x) + \gamma/2 * \sum_{k=1}^{2} F_{value(3,k)}(x)$$

D2 - Scalability



$F_{volume1}$: Space - Time

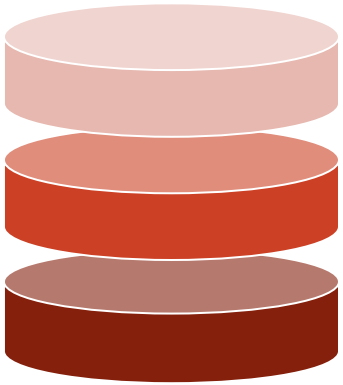
$F_{volume2}$: Parallelism

$F_{volume3}$: Functional

$F_{volume4}$: Heterogeneous integration

$$D_{volume}(x) = a/4 * \sum_{i=1}^{4} F_{volume\ i}(x)$$

D3 - Information Fusion & Integration



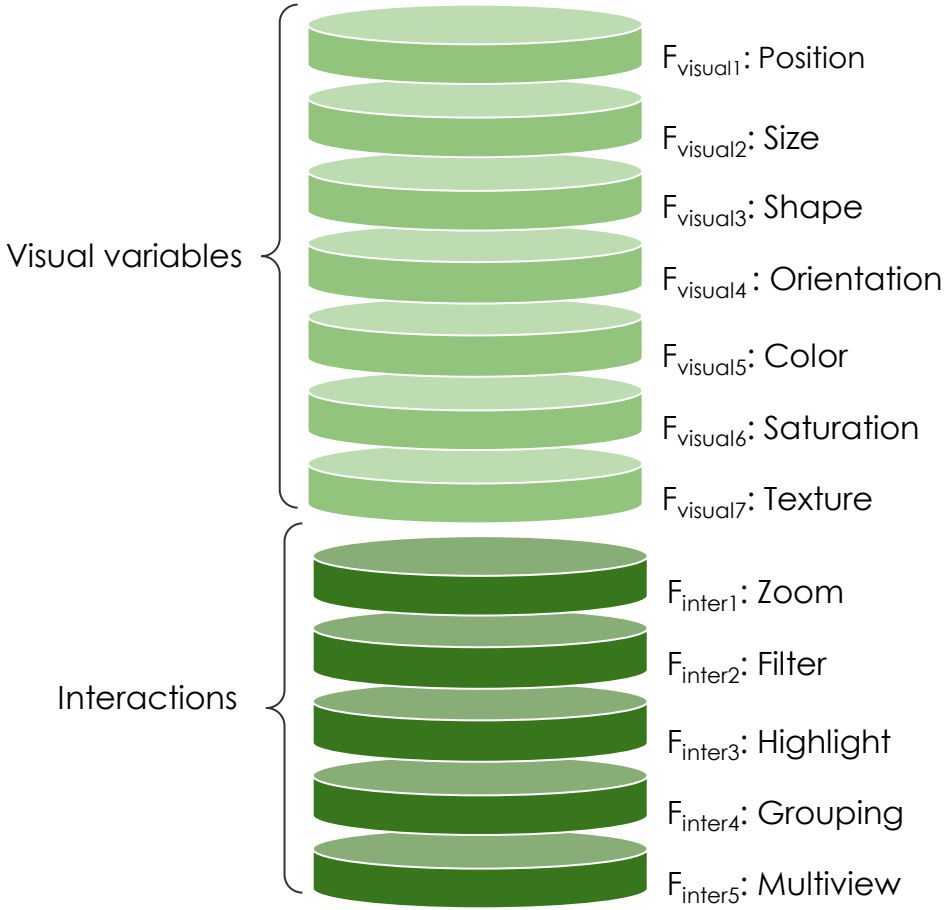
$F_{variety1}$: Multichannel

$F_{variety2}$: Multimodality

$F_{variety3}$: Multirepresentation

$$D_{variety}(x) = a/3 * \sum_{i=1}^{3} F_{variety\ i}(x)$$

D4 - Visualization



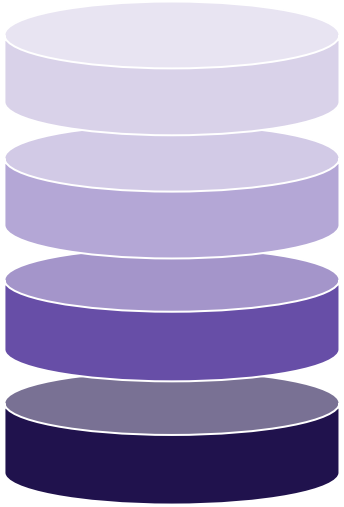
$$D_{visual}(x) = a/7 * \sum_{i=1}^{7} \gamma_i * F_{visual\ i}(x) + \beta/5 * \sum_{j=1}^{5} \theta_j * F_{inter\ j}(x)$$

Summary

Research Question	Dimension	Degree	Range
What can I learn ?	D1. Pattern & Knowledge Discovery	Dvalue(x) = $\alpha/2 * \sum_{i=1}^{2} Fvalue(1,i)(x) + \beta/3 * \sum_{j=1}^{3} Fvalue(2,j)(x) + \gamma/2 * \sum_{k=1}^{2} Fvalue(3,k)(x)$	[0, 1]
What is the limit ?	D2. Scalability	$Dvolume(x) = \alpha/4 * \sum_{i=1}^{4} Fvolume\ i(x)$	[0, 1]
What kind of data can I integrate ?	D3. Information Fusion & Integration	$Dvariety(x) = \alpha/3 * \sum_{i=1}^{3} Fvariety\ i(x)$	[0, 1]
What can I show ?	D4. Visualization	Dvisual(x) = $\alpha/7 * \sum_{i=1}^{7} \gamma i * Fvisual\ i(x) + \beta/5 * \sum_{j=1}^{5} \theta j * Finter\ j(x)$	[0, 1]

Summary on dimensions and the quantitative measures (degrees) defined.

C_4 - Global tool capability



D_{value}: Pattern & knowledge discovery

D_{volume} : Scalability

$D_{variety}$: Information Fusion & integration

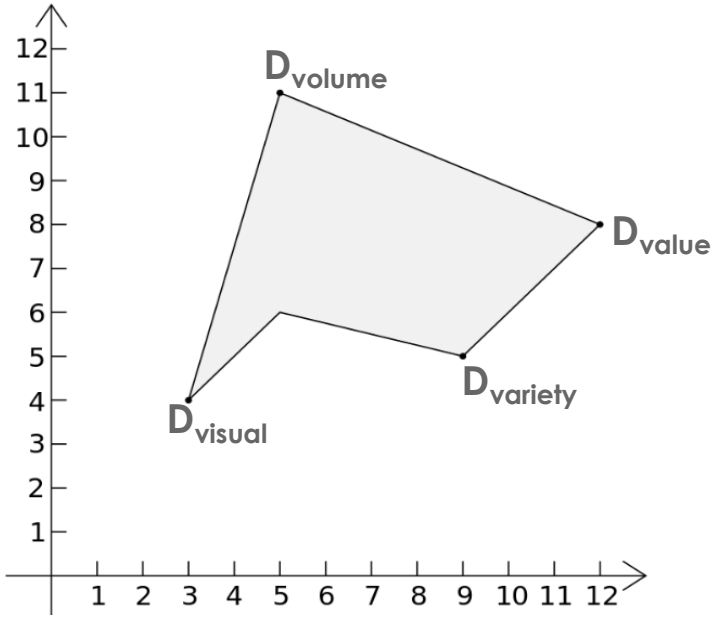
D_{visual}: Visualization

$$C_4(x) = \frac{1}{2} * \left| (D_{value}(x) + D_{volume}(x)) * (D_{variety}(x) + D_{visual}(x)) \right|$$

C_4 - Global tool capability

$$A = \frac{1}{2}\left|\sum_{i=1}^{n-1}(x_i y_{i+1} + x_n y_1) - \sum_{i=1}^{n-1}(x_{i+1} y_i - x_1 y_n)\right|$$

Shoelace formula *(Gauss's or surveyor's area formula)*



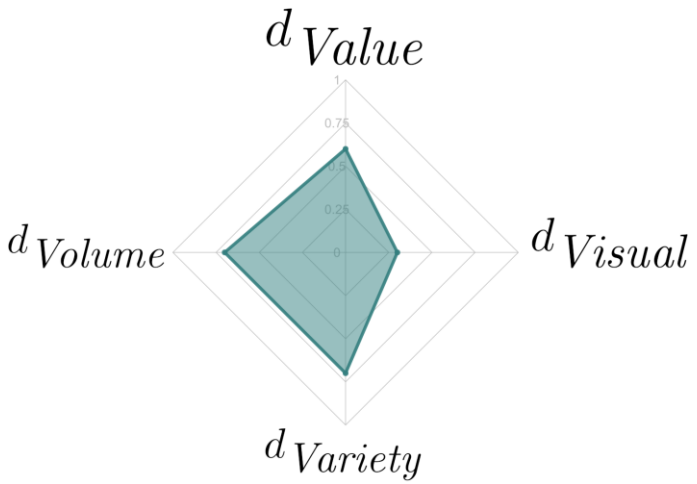
$$\mathfrak{C}_4(t) = \frac{1}{2} \cdot \left|\sum_{i=1=Value}^{3=Variety}\left(d_i^{x_i}(t) \cdot d_i^{y_{i+1}}(t) + d_i^{x_n}(t) \cdot d_i^{y_1}(t)\right) - \sum_{i=1=Value}^{3=Variety}\left(d_i^{x_{i+1}}(t) \cdot d_i^{y_i}(t) - d_i^{x_1}(t) \cdot d_i^{yx_n}(t)\right)\right|$$

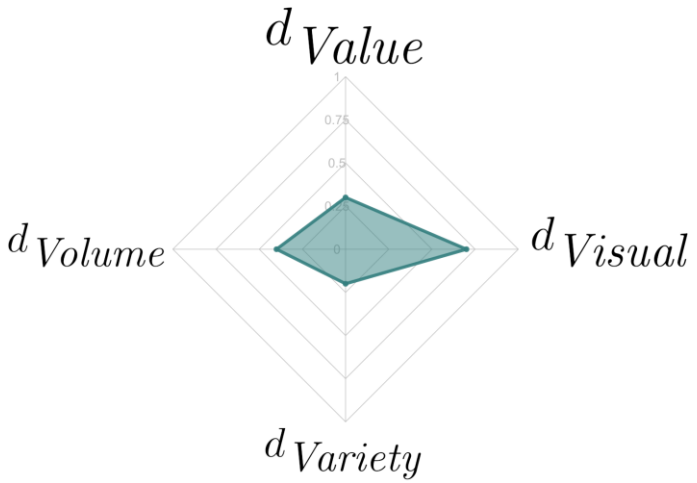
$$\mathfrak{C}_4(t) = \frac{1}{2} \cdot \left|\left(d_{Value}^{x_1}(t) + d_{Volume}^{y_2}(t)\right) \cdot \left(d_{Variety}^{x_3}(t) + d_{Visual}^{y_4}(t)\right)\right|$$

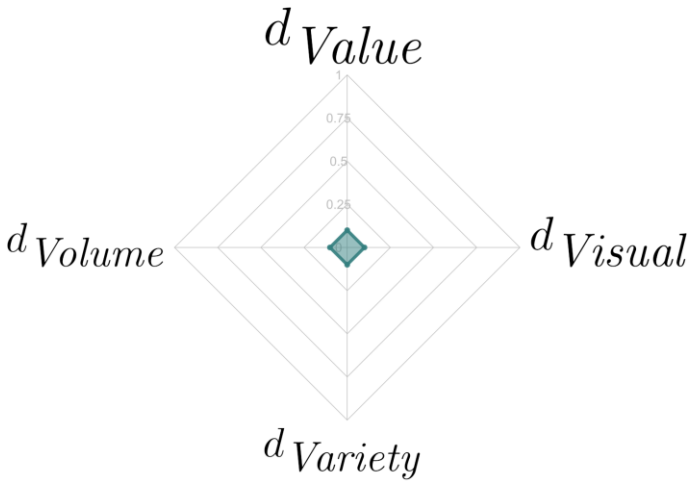
C_4 - Global tool capability

Rank	$\mathfrak{C}_4(t)$	Dimensions				SNA technology
		d_{Value}	d_{Volume}	$d_{Variety}$	d_{Visual}	
1	0.315	0.6	0.7	0.7	0.3	Tool 1 (high value)
2	0.170	0.3	0.4	0.2	0.7	Framework 1 (medium value)
3	0.010	0.1	0.1	0.1	0.1	Tool 2 (low value)

Example of $\mathfrak{C}_4$ metric application over three different hypothetical SNA tools and frameworks.





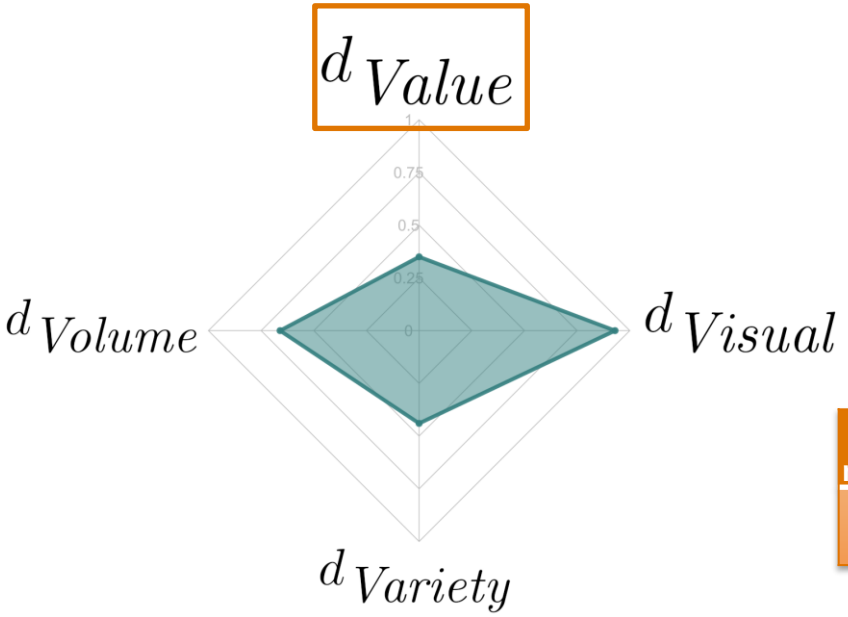


Tool evaluation example - Gephi

Total (C4)	Pattern and Knowledge discovery	Information Fusion	Scalability	Visualization
0.346482	0.345238	0.444444	0.664167	0.928571

Gephi : it's a powerful open-source solution for graph visualization. The larger datasets tend to have a hair-ball look and are hard to understand via Gephi. (300000 y 1000000 edges)

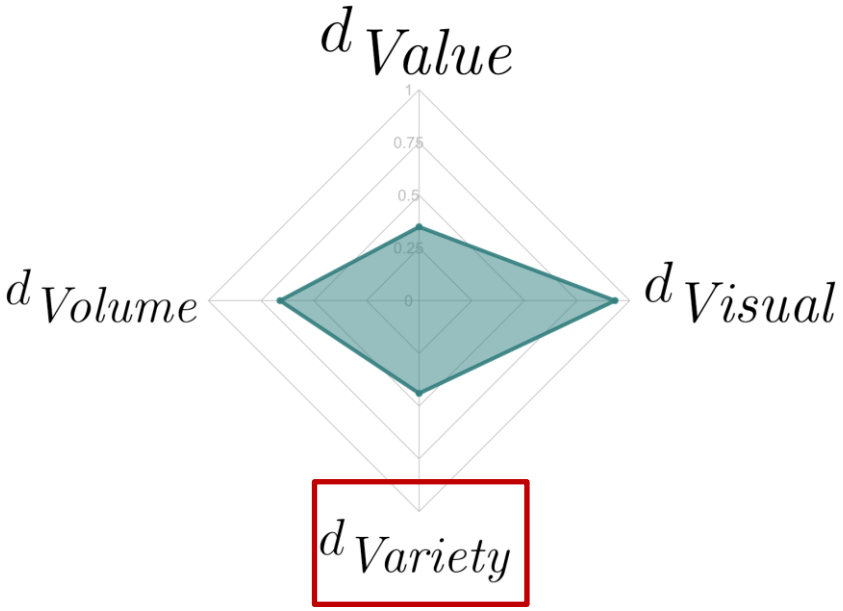
Tool evaluation example - Gephi



Total (C4)	Pattern and Knowledge discovery	Information Fusion	Scalability	Visualization
0.346482	0.345238	0.444444	0.664167	0.928571

measures topology	link analysis	community detection	oppinion mining	virality	homophily	link prediction
1,00	0,75	0,67	0,00	0,00	0,00	0,00

Tool evaluation example - Gephi



Total (C4)	Pattern and Knowledge discovery	Information Fusion	Scalability	Visualization
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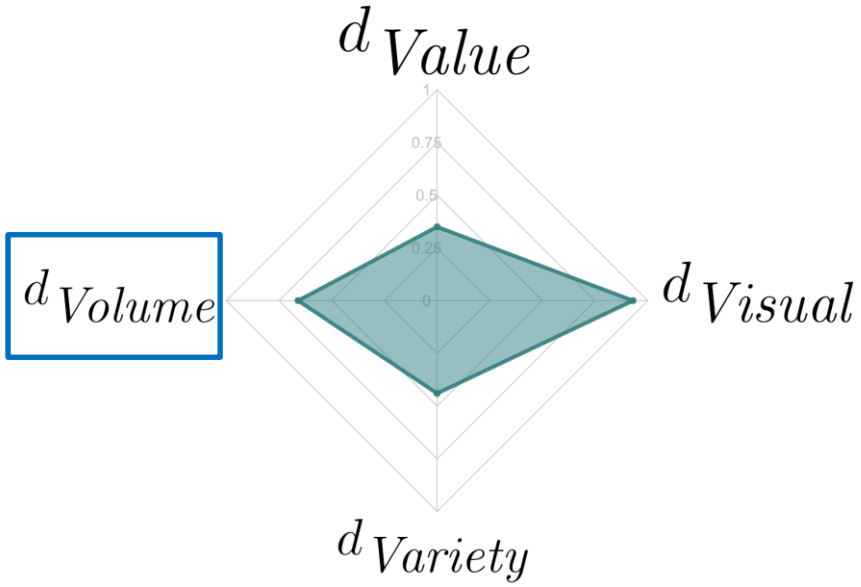
miltichannel	miltimodality	multi-representation
0,33	0,33	0,67

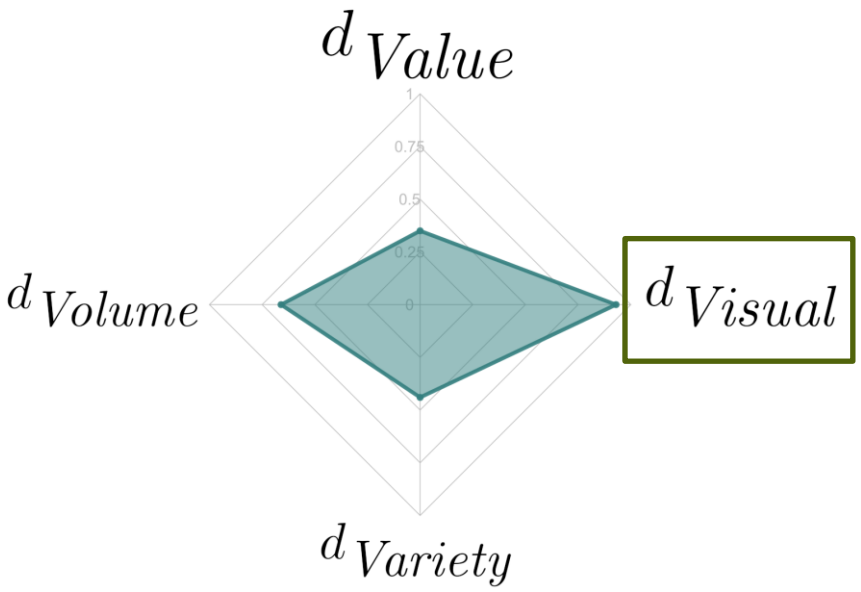
Tool evaluation example - Gephi



Total (C4)	Pattern and Knowledge discovery	Information Fusion	Scalability	Visualization
0.346482	0.34523	0.444444	0.664167	0.928571

space-time	parallelism	functional	heterogeneous-integration
0,66	0,33	1,00	0,67

Tool evaluation example - Gephi



Total (C4)	Pattern and Knowledge discovery	Information Fusion	Scalability	Visualization
0.346482	0.34523	0.444444	0.664167	**0.928571**

Visual variables	Interaction
0,86	1,00

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Frameworks and tools analized

- **20 SNA tools** were selected for the analysis from *Github*[22], *KDNuggets*[23, 24] and *Infoviz wiki*[25].
- It was considered:
  - The type of software **license**
  - The quantity and quality of the software **documentation**
  - Its current **impact** among the community
- A **rubric** was created to **homogenize** the **analysis** among researchers

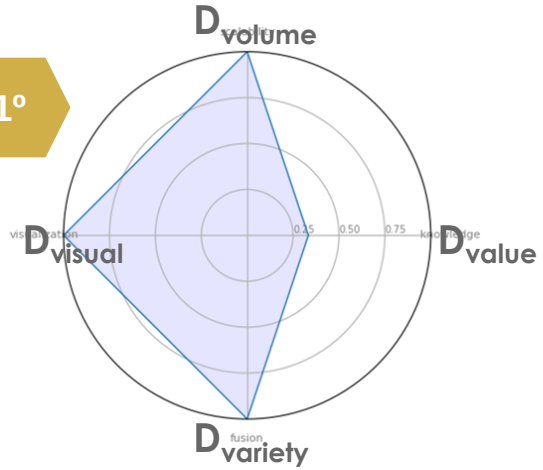
20 analysed tools

IGraph	AllegroGraph	LaNet-vi	SNAP
ORA-LITE/PRO	Network Workbench	NetMiner	Circulo
Cytoscape	JUNG	SparklingGraph	NetworkX
Pajek	GraphX Apache Spark	Gephi	UCINET
Prefuse	Graphistry	GraphViz	Neo4J

TOP 5 tools

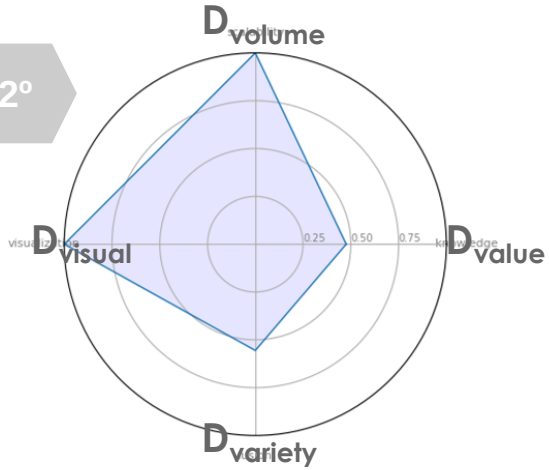
1º

PyGraphistry



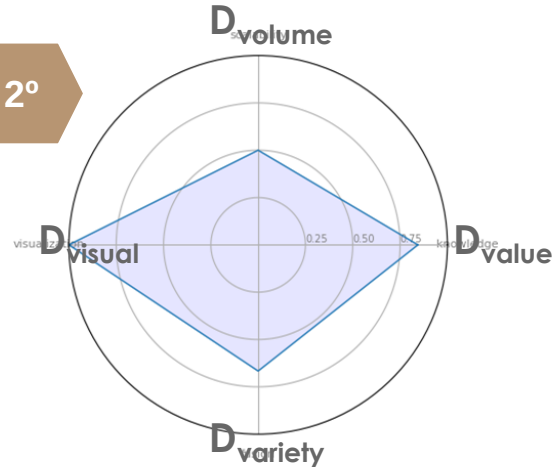
2º

Neo4j



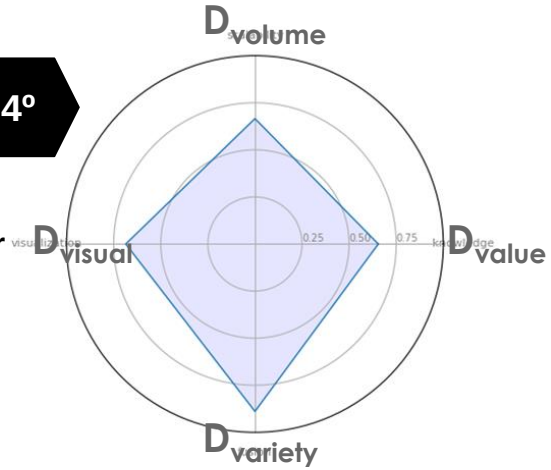
2º

Ora-lite



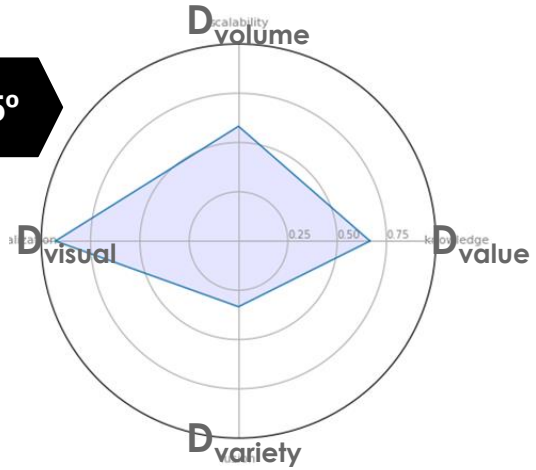
4º

NetMiner



5º

Cytoscape



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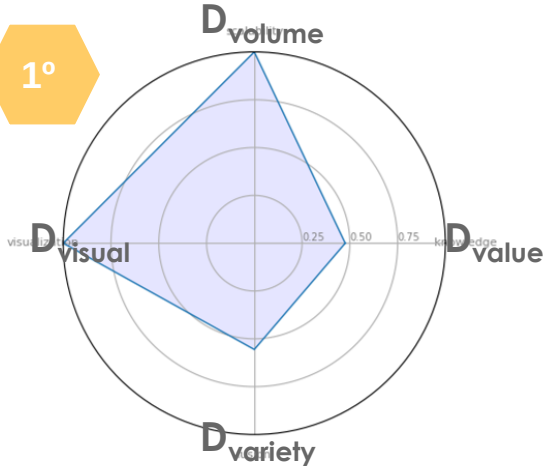
TOP 5 tools open source tools

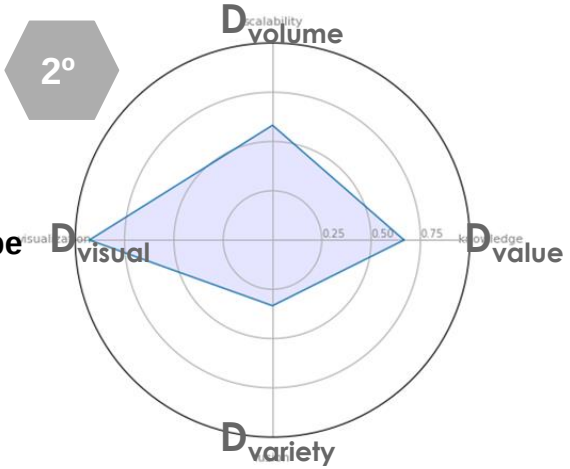
1º

Neo4j



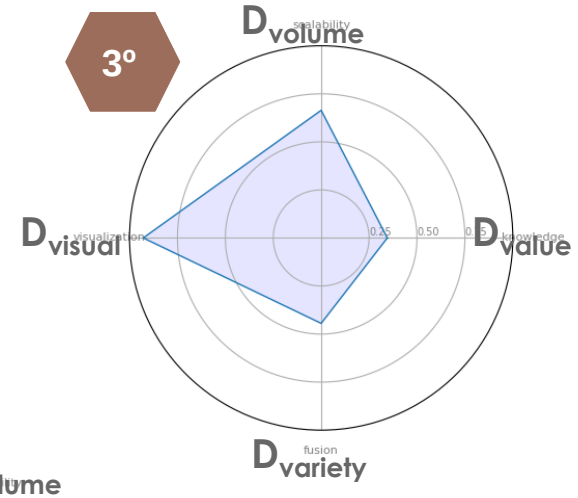
2º

Cytoscape



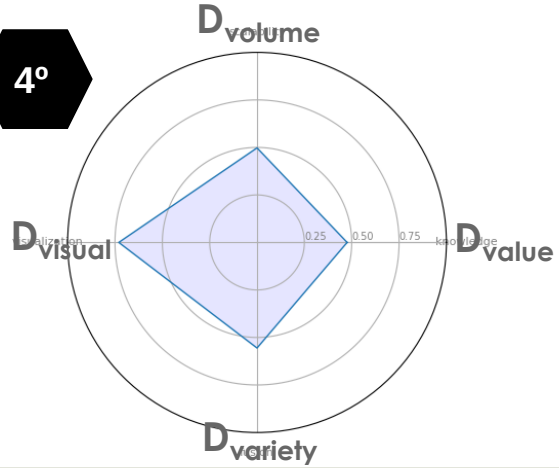
3º

Gephi



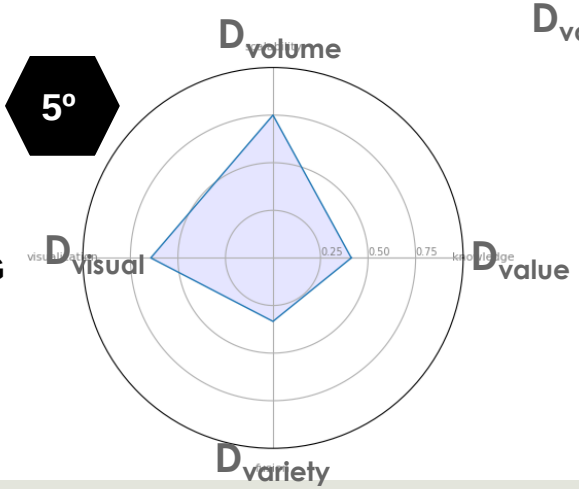
4º

Pajek



5º

JUNG



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TOP 5 - by dimension

Dimension	SNA Tool	Score	Dimension	SNA Tool	Score
Knowledge Discovery	**ORA-LITE/PRO**	0.84	Scalability	**Graphistry**	1.0
	SNAP	0.67		**AllegroGraph**	1.0
	Cytoscape	0.67		**Neo4J**	1.0
	NetMiner	0.65		GraphX Apache Spark	0.92
	NetworkX	0.52		Sparkling Graph	0.92
Information Fusion	**Graphistry**	1.0	Visualization	**ORA-LITE/PRO**	1.0
	NetMiner	0.89		**Graphistry**	1.0
	Network Workbench	0.67		**Neo4J**	1.0
	ORA-LITE/PRO	0.67		Ghepi	0.93
	Pajek	0.56		Cytoscape	0.93

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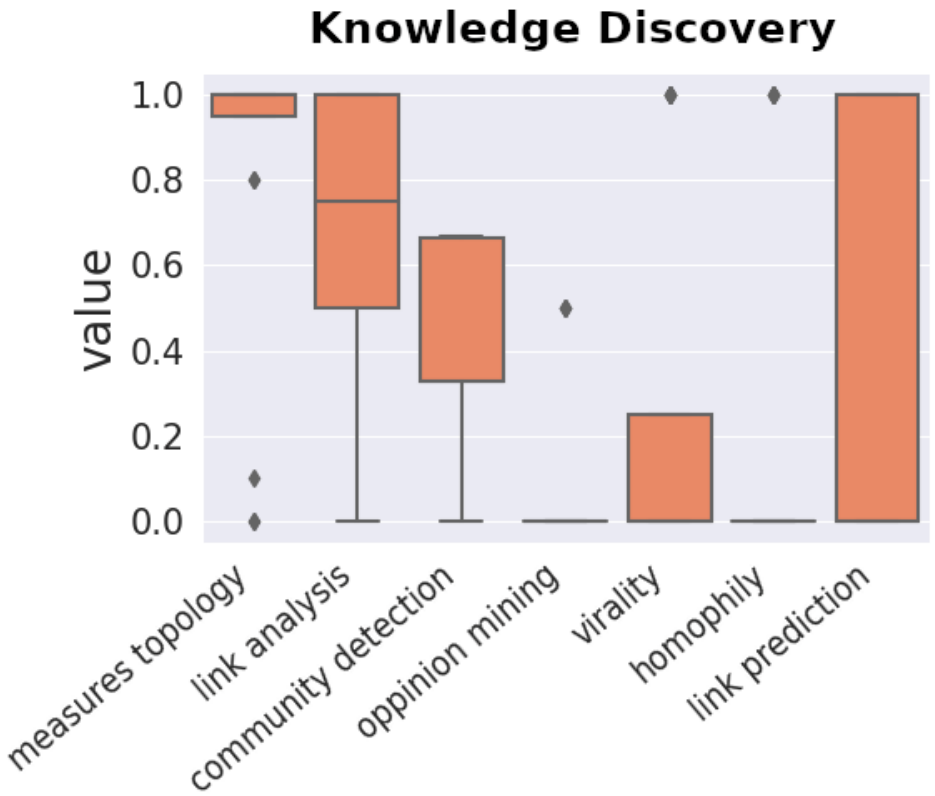
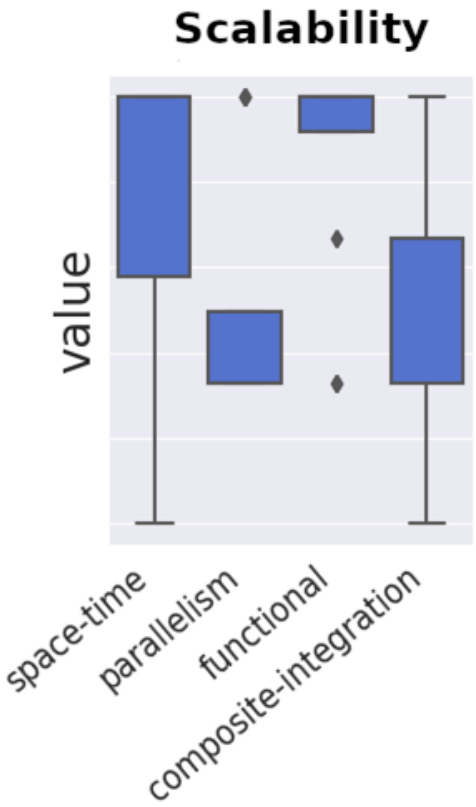
Knowledge Discovery tool's analysis



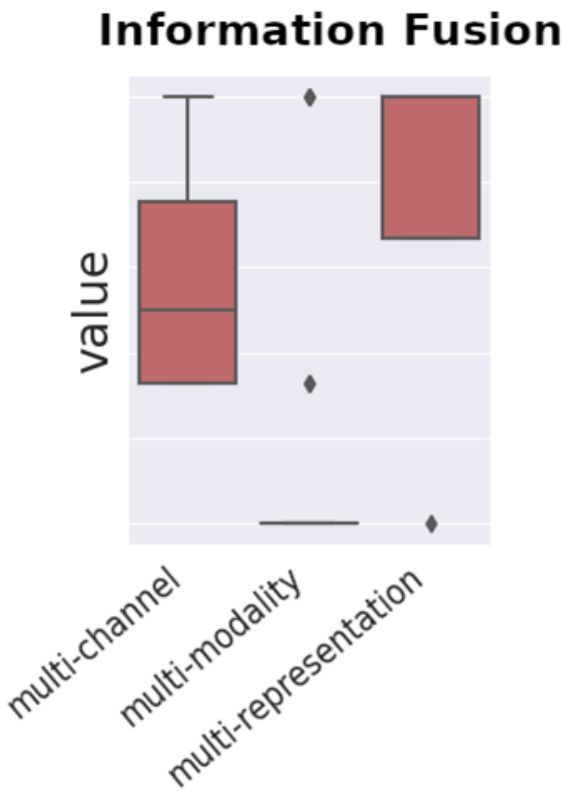
- *Topology measures*, *Link analysis* and *Community detection* are fairly **common**
- *Homophily*, *Virality* and *Opinion mining* can only be **found** in a **few tools.**
- **No tool completely develop** the *Community detection* or the *Opinion mining* degrees.

Scalability tool's analysis



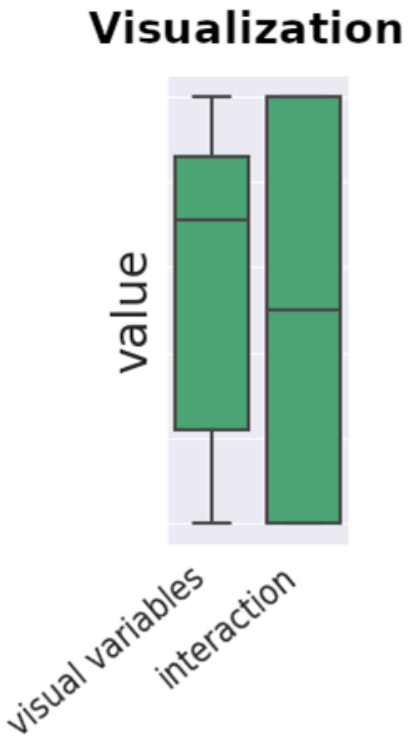
- **All** degrees are **fully developed**
- **Few tools** achieve **high** values of **parallelism**
- **Space-time** scalability is usually **high**

Information fusion tool's analysis



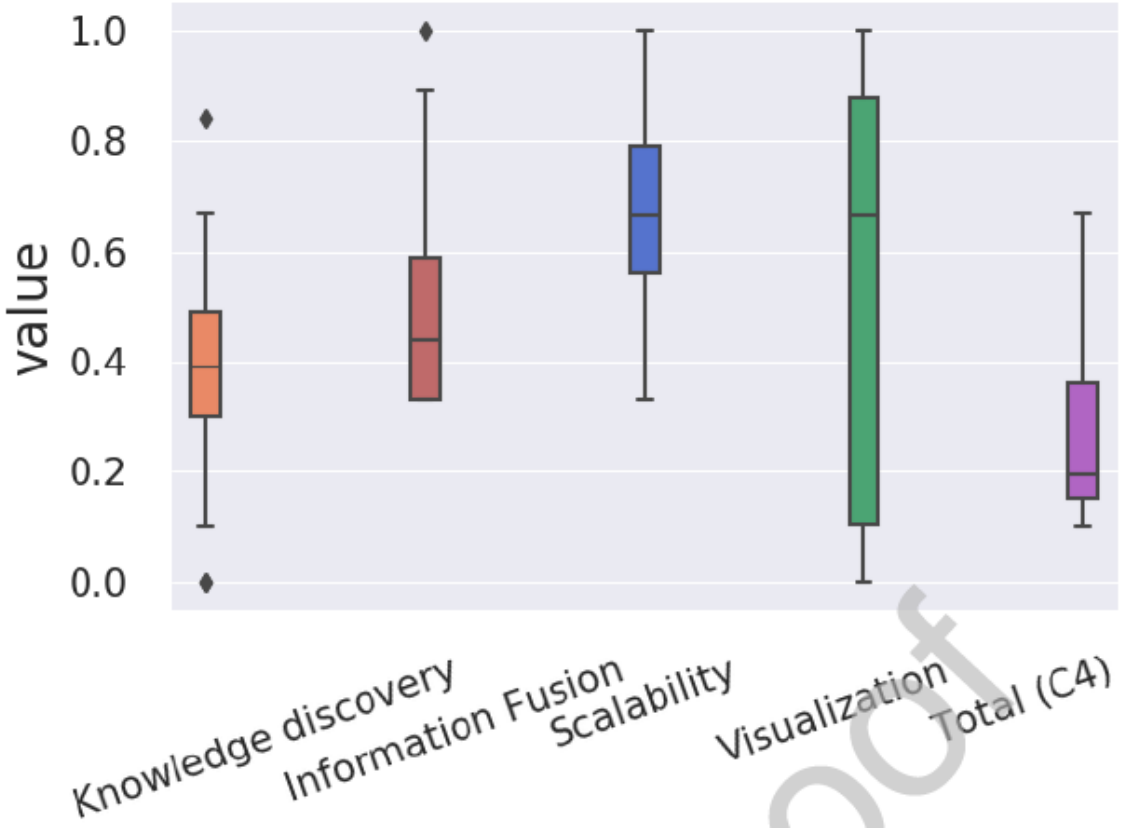
- **All** degrees are **fully developed**
- **Few tools** achieve **high** values of **multi-modality**
- **multi representation** is usually **high**

Visualization tool's analysis



- If a tool contains **visualization** capabilities they are **usually high**
- Is most common to find **a lot of visual variables** for usage **compared** to the **interactions** available
- Tools **interactivity** is **average**.

Summary



Distribution of the different dimensions values achieved by the analyzed tools

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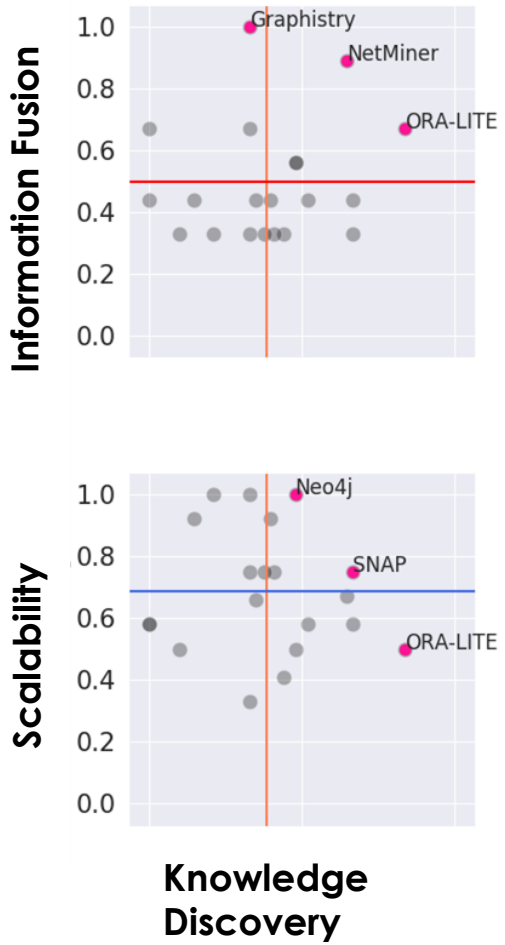
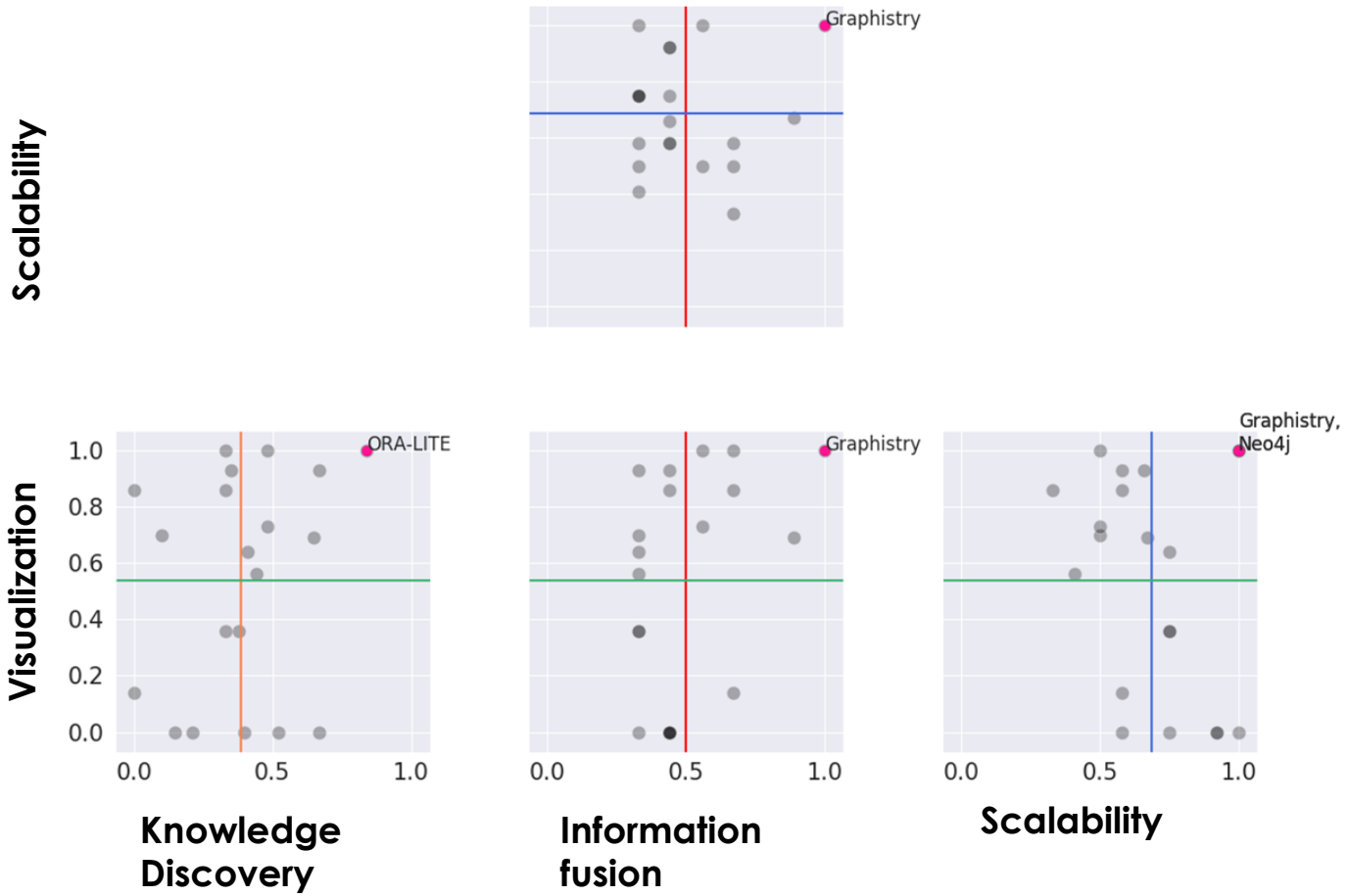
Relationship between dimensions (I)



- **No clear superior** tool when comparing Knowledge discovery with Scalability or Information Fusion
- **Scalability** values were **expected** to **drop** when doing fancier analysis are these usually are more complex
- Surprisingly, adding **more** sources of **information** is **not enhancing** the **knowledge** discovery. This shows **mis potential**.

Relationship between dimensions (II)



- There are clear **tools** that **dominates** all others
- Tools with **above average Knowledge** discovery or Information **Fusion** and **Visualization** are **common**
- Tools with **above average** Information **Fusion** or **Visualization** and **Scalability** are **rare**.

Conclusions

What can I discover? (D1)

- The goal of this question is to ***quantify the capacity of the tool to extract valuable knowledge from the data.***
- Some measures are fairly common: topology measures, link analysis or static community detection.
- Whereas others are quite rare such as *dynamic community detection*, *opinion mining*, *virality* or *homophily*.
- This suggests that the **content** of OSNs is **not** being **fully exploited** by actual tools.

Conclusions

What is the limit? (D2)

- This question is **focused** on the **scalability** of the tool and it takes into account the **amount of data that can be extracted** from OSNs.
- Most of the analyzed tools are capable of handling fairly big graphs (around 100.000 nodes), they are very customizable (their code is publicly available), and allow communication with other tools via APIs.
- Although just a few of them achieves fully integration with other applications.
- Few tools are capable of doing BigData analysis and the ones that can, have a low/medium average Knowledge Discovery capabilities.
- These tools needs to **improve**: the **size** of handled networks, the **fusion** and **integration** from different sources, and the **knowledge discovery**.

Conclusions

What kind of data can I integrate? (D3)

- This question is related to the capacity to **integrate** and **fusion** information.
- The quantitative analysis of the tools shows that most of the analyzed tools used complex graph representation (multilayered graphs or hypergraphs), are able to process two or three different data types.
- But they extract data from one unique OSN.
- There is a **wide range of improvement** in this dimension, related to the **fusion** and **integration of information using different types of data** formats, and when possible, **from different OSNs**.

Conclusions

What can I show? (D4)

- This last question measures the **capacity** of the tools, frameworks, and methods **to visually represent the information** stored in the network.
- Although there exist a large number of information visualization, this is still an open problem in the area.
- The visualization capabilities of the analyzed tools where more evenly distributed compared to the rest of the dimensions.
- There is a **lack of tools** with **high Scalability** and **Visualization capabilities**.
- More complete visualization tools needs to be developed. These tools will be highly welcomed in areas such as dynamic community finding, data analytics or pattern discovery.

Conclusions

- What is proposed here is an **initial work**.
- These **dimensions**, and the defined metrics, **should not be considered** as the **only possible** ones and are meant to be **extended** and **improve** as technology evolves.
- **Maximum values** in any dimensions does **not mean** that these **features cannot be improved** in the future only indicate that, given the current state of technology, a higher value is achieved compare to other tools.
- In order to **allow researchers** not only to **access** the data used in this article, but to foster for a future **collaboration** among the community a **website** has been designed

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AIDA Social (or how to contribute)

https://ai-da-sna.github.io/

AI+DA - Social Network Analysis

AI+DA is a multidisciplinary research group located at Escuela Técnica Superior de Ingeniería de Sistemas Informáticos de la Universidad Politécnica de Madrid. Our main research areas are Machine Learning (Classification, Hidden Markov Models, Deep Learning), Decision Support Systems, Computational Intelligence, Evolutionary Computation, Data Mining, Social Network Analysis, Big Data, and Intelligent Systems for Industry. With more than 300 publications and 40 research and industrial projects, the group has an outstanding experience in both research cooperation and partnership consortium.

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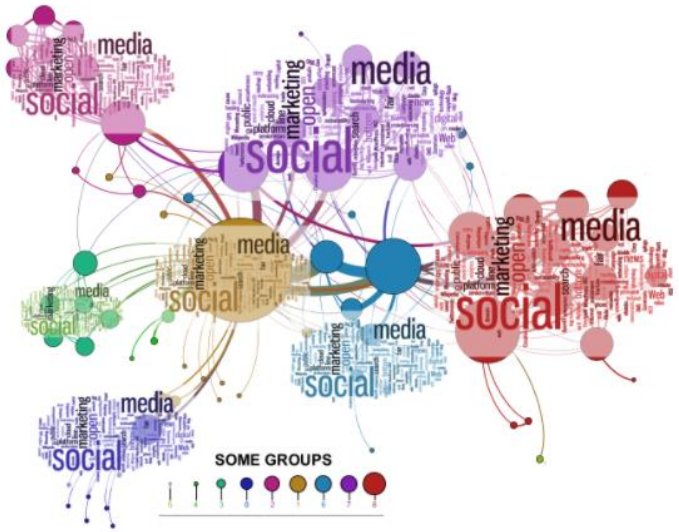

An overview of Social Network Analysis software tools

This repository provides a quantitative analysis of a set of popular Social Networks Analysis (SNA) tools and frameworks that we hope will help software engineers, SNA researchers, and any other SNA practitioners, selecting the best and most adequate technology for their goals, and

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AIDA Social (or how to contribute)

- A collaborative website to evaluate SNA-software (tools, frameworks, algorithms, etc.) by the community, as a GitHub repository.
- The evaluation rubric designed to assess the SNA-software tools
- The specific evaluation made for all the SNA-software tools carried out in this paper.
- A brief summary of this paper

https://ai-da-sna.github.io/

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Assessing technological maturity of social network analysis: The four dimensions of SNA

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The four dimensions of social network analysis: An overview of research methods, applications, and software tools

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Big data

ABSTRACT

Social network based applications have experienced exponential growth in recent years. One of the reasons for this rise is that this application domain offers a particularly fertile place to test and develop the most advanced computational techniques to extract valuable information from the Web. The main contribution of this work is three-fold: (1) we provide an up-to-date literature review of the state of the art on social network analysis (SNA); (2) we propose a set of new metrics based on four essential features (or *dimensions*) in SNA; (3) finally, we provide

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