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IS ALL THAT GLITTERS A NETWORK? SEARCHING FOR THE BOUNDARIES OF THE NETWORK APPROACH

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Network analysis has become a powerful tool in various fields. However, the increasing popularity comes with potential problems. Unfamiliarity with the characteristics of the systems under investigation complicates network model construction and interpretation of analysis outcomes. While these issues require special attention in studies that apply the increasingly complex higher-order connectivity models, similar problems are associated with all, even the most simple, network models. Alongside technical issues, network scientists face a philosophical question: can the network approach discover the fundamental nature of a system, on the one hand, and produce useful information, on the other hand. In this perspective, I review the potential problems of the network approach and propose two solutions to address them: active evaluation of the potential and limitations of the network framework before applying a network model and a transition toward an interdisciplinary research practice to interpret analysis outcomes in their right context.

Keywords: Complex networks; network science; modeling; interdisciplinarity; network neuroscience.

1. Introduction

Network science models diverse real-world systems as complex networks and studies their properties and structure with mathematical and statistical tools. The network approach has opened new horizons and contributed to an increased understanding on the world around us in several fields. Basic concepts and core ideas of network science are easy to understand even with little specialized education, as the Network Literacy project [97] has demonstrated. Network models appear intuitive to interpret and, in the best case, easy to build. Thus, it is no wonder that the application targets of the network approach have grown numerous and diverse, including, for example, social interactions taking place both face-to-face [23, 77] and remotely [24, 45], infrastructure [19], brain function [8, 65], genetics [96], economics [1, 44], and climate [40, 47].

The popularity of the network framework across fields speaks for its strong potential. However, a powerful framework can become even unnecessarily tempting. Indeed, the success of the network framework may mislead scientists into the assumption that *all that glitters is a network*: the network framework has similar potential to explore any system, and simply stating a system's networkness explains the very nature of the system. The tendency to make excessive claims about the universality of the network framework is recognized both within the field (see, e.g. Peel *et al.* [91]) and in a broader context of the philosophy of science [63]. This way of thinking is often accompanied by confusing a network model as a mathematical representation with the actual system of interest [91]. In the worst case, this may lead to building models and interpreting analysis outcomes solely in the context of network science, with little understanding on the other aspects of the system under investigation. At the same time, the spectrum of approaches under the network framework umbrella has grown more diverse, including models rather distant from the traditional definition of a network as a system of nodes connected by links.

In this perspective, I search for the boundaries of the network approach. To this end, I discuss both practical problems related to modeling a system as a network and the more fundamental question about the capacity of the network framework to produce usable and truthful information about the world around us.[a] Many network scientists may have addressed some of the concerns raised in the present perspective in the context of their own work. However, the network science community still lacks the explicit articulation of these concerns and ways to address them in a language shared across the highly multidisciplinary field. Through this perspective, I want to contribute to a shared understanding on the capacity and limitations of the network framework and thus help the framework to realize its full potential to open new insights on the various real-world complex systems.

[a] Addressing the later question, obviously, requires a definition for *truth*. This varies between fields of science depending on the underlying epistemological views. Here, I assume that each system has a fundamental *form* in Platonic sense so that each ideal measurement would observe this same form independently of the technical details of the measurement or the person performing it. Therefore, the information produced by a model is more truthful if it matches better the fundamental form of the system. Taking a different, relativistic view, where systems do not have fundamental forms and their existence depends on the observer, would make the question about the truthfulness of produced information, and thus the abscissa of Fig. 1, less relevant, as the definition of truth would vary from observer to observer. Instead, the question about usefulness, and thus the ordinate of Fig. 1, would remain relevant if we define *usefulness* as the ability to answer the research questions posed by the model user.

First, in Sec. 2, I consider technical challenges related to building network models. Section 3 addresses the philosophical question of networkness as the fundamental nature of systems. To this end, I introduce a space spanned by two questions: (i) is the system fundamentally a network and (ii) does some network model produce useful information about the system, and consider the location of different systems in this space. Next, in Sec. 4, I review the spectrum of models and approaches applied in the modern network science and ask if *network* still remains as the best term to describe all these approaches. Section 5 discusses the inherent multidisciplinarity and interdisciplinarity of network science, and emphasizes the importance of the dialog between fields of science for successful network studies. Finally, in Sec. 6, I summarize the risks presented in other sections and recommend lines of action to avoid them.

2. Challenges in Network Construction and Interpretation

The well-known mathematical definition of a network is

$$\{V, E\} \text{ s.t. } E = (x, y), \quad x, y \in V, \tag{1}$$

where V is a set of nodes connected by links E. However, the everyday usage of the word covers various groups of entities, ranging from fishing nets to clubs and associations. Particularly, unlike the mathematical definition, the common language does not pay special attention on the connections between the entities. This is a potential source of confusion, as many fields of science use the term *network* in a way that reflects its everyday usage. For example, social science calls collaborative organizations of cities, countries, or other actors networks (see, e.g. Heikkinen *et al.* [43]), often following the terminology used by the organizations themselves. Similarly, neuroscientists refer to groups of brain regions that activate during the same task as networks (see, e.g. Tomše *et al.* [108], Bednarz *et al.* [12], or Damoiseaux *et al.* [27] and Fox *et al.* [38] for the most well-known example, resting-state networks that consists of regions with time series that correlate during rest). When network tools are applied in a field that uses the term also in a more everyday sense, special attention is required to avoid problems rising from the ambiguity of terminology. Many authors solve this problem by separating between *the network*, that is, the system under study, and *the graph*, its mathematical representation. Here, I call the system under study *a target system* or simply *a system*, while *a network model* is the mathematical representation (i.e. the graph) and the *network framework* refers to the paradigm of applying network models.

The rest of this perspective concentrates on studies that define a network as a system of nodes and links, either as the most simple form defined in Eq. (1) or as more complex models that allow non-dyadic connections between more than two nodes (for details, see Sec. 4). Further, in this section, I assume that it is possible to build for an arbitrary system of interest an accurate network model taking into account both the detailed research question and the specific features of the system under investigation.

Building a network model starts from the definition of nodes and links. These basic elements of a network fall into two categories based on their tangibility. Tangible nodes and links are concrete objects (e.g. people, bus stops, power lines), while intangible nodes and links are abstract or imaginary instances, such as brain regions with coherent activity as nodes or friendship or temporal similarity as links.

The presence of tangible node candidates makes node definition straightforward. For example, nodes of social networks depict people [83], while cell-level studies of neuronal systems use single neurons as nodes [29]. However, selection of node resolution requires attention even in presence of tangible nodes. For example, a study of policy networks [56] may operate at a coarse level, where nodes represent cities, but also zoom in to the more detailed levels of departments of city administration or even the employees of these departments. While each resolution level can produce meaningful, albeit different results, the aggregation level needs to be selected with care to avoid misinterpretations due to the interactions between subunits inside larger, aggregated nodes [20]. The correct choice of resolution for any given study depends on the exact research questions.

Tangible node candidates are not available in all cases. For example, imaging resolution and computational resources limit the usage of neurons as nodes in larger-scale brain network studies. Therefore, the definition and even number of nodes vary widely in the literature [2, 32, 35, 65], despite the undesired effects of inaccurate node definition on the observed network structure [35, 64, 115]. Similar problems arise in all systems where the basic units of activity are unknown or hard to measure. Apart from brain networks, another typical example are climate teleconnectivity networks [18, 40, 104, 119], where data are collected at measurement points placed either on a regular grid or following some geographical landmarks and nodes depict either the measurement points themselves or some aggregated combinations of them.

Similar to the case of nodes, link definition is most straightforward for physical systems with tangible link candidates. Links of the power grid network are power lines [19], while links of the neuronal network represent axon bundles [102]. Also intangible relationships (e.g. friendship, collaboration, community membership) may be natural candidates for link definition. However, the weight of these links is subjective, as demonstrated by surveys where subjects often report non-mutual social contacts [77, 100], or defined in terms of a proxy such as spatial proximity [23] or number of phone calls between individuals (see, e.g. Heydari *et al.* [45]). Definition and interpretation of intangible links require particular care in socially constructed networks, for example networks of scientific concepts [87, 120] and other semantic networks [99], where links often depict intangible relationships between intangible concepts, for example word associations.

Another extreme example of intangible links comes from similarity networks, where each node is assigned a time series, for example functional brain networks [65], stock market networks [1, 44], or climate teleconnectivity [40, 104]. The underlying relationship between the nodes is assumably causal (e.g. collaboration, information flow) but hard or impossible to measure directly. Therefore, links indicate temporal similarity of node time series instead of the underlying causal relationship, the most commonly used similarity measure being the Pearson correlation coefficient. Interpretation of the properties of these networks requires special care [91]. Apart from the common misinterpretation of correlation as a proxy for causality [78], many characteristic features of similarity networks, for example high clustering, follow directly from the mathematical properties of the Pearson correlation coefficient [89, 121] and may thus be less relevant for the system under investigation.

Independently of the definition of nodes and links, a network model is never a direct replication of the underlying connectivity structure of the system of interest. Instead, every model is a reconstruction based on the observations of the model user [91]. This is particularly evident in the case of intangible nodes and links, where the node and link definition itself requires operations on data collected from the system under investigation, for example calculating time series correlations. However, also in the presence of tangible nodes and links, the observed network structure is prone to errors related to the observer and data collection process [91]. For example, observing the entire connectivity structure is possible in small-scale, closed case example systems. However, the network models of larger, more open-ended systems are constructed through sampling [26, 91], and the structure of a sampled subnetwork is not guaranteed to resemble that of the whole system [91, 105]. Errors in network model construction cumulate when network metrics are applied on the models [91]. While accounting for noise and uncertainty in network model construction, for example through Bayesian reconstruction techniques, is important for correct interpretation of network analysis outcomes, usage of these techniques remains rare in most application fields of the network framework [91].

In most network models, nodes and links do not have physical location, and thus their location does not affect most network measures. However, physical location plays a role in many real-world systems modeled as networks, for example brain [60], climate [79], or transportation [68, 114] systems. Thus, omitting the physical space easily leads to misinterpretations in the network analysis of these systems. For example, clustering, modularity, or small-worldness may reflect economical or spatial limitations of constructing physically long links, instead of being fundamental properties that explain system's function [60].

Thresholding, the standard step after node and link definition, is necessary for similarity networks that typically have full adjacency matrices. Further, thresholding is useful in all networks where weak links (e.g. short periods of proximity, small numbers of phone calls, narrow axon bundles) are insignificant or noisy. Selecting the optimal threshold requires balancing: stringent thresholding minimizes noise but risks discarding data. Further, the optimal thresholding approach depends on the research question. For example, absolute thresholding with a fixed numerical threshold detects between-condition differences in the overall level of connectivity, while proportional thresholding (i.e. discarding a fixed proportion of weakest links) works better if expected differences are merely in the location than the number of links [111]. Often, finding a single optimal threshold is outright impossible as each network metric depends on the threshold in a different way and would thus require a different optimal threshold value [91].

To summarize, modeling a system as a network is a highly nontrivial task. So far, I have assumed that this task can be accomplished with careful methodological choices. The following section, however, will raise a more fundamental question: to what extent does the network approach help us to reveal the true nature of the systems under investigation?

3. Fundamentally a Network?

3.1. *What makes a good model?*

The evaluation of the capacity of the network framework to model real-world systems builds on the broader discussion on the ontology and epistemology of models. A model is commonly defined as a representation of a target system or phenomenon [39, 91]. In other words, the minimum requirement for a model, known as the surrogative reasoning condition, is that investigating the model allows inducing information about the target system [39].

Literature has proposed several explanations for how this induction is possible, that is, in what sense a model represents its target. The viewpoint of structuralism is particularly relevant for the network framework: a model represents its target if and only if it is isomorphic to the target, that is, if the model contains elements that correspond to those of the target and the model elements are connected with similar relations as the target elements [110].[b] From this perspective, building a model is equivalent to identifying the structure, that is, the elements and relations between them, of the target system. Importantly, modeling requires the presence of an intentional actor, the model user: accidentally isomorphic systems do not model each other [39]. Therefore, in structuralistic modeling, the model user forces a structure on the target system. If this structure matches the underlying features of the target, the model produces correct and useful information about the target, while a badly matching model structure can, for example, cause mispredicting the behavior of the target. If the target has no underlying structure — that is, it is not fundamentally a network —, using a network model leads to misinterpretations about not only the function but also the very nature of the target system.

Model selection sets limits to what can be learned about the target system. Each model is developed in the context of a given target system and builds on the related assumptions on what kind of features the target system has and which of them are relevant for the specific research questions under investigation [31]. The assumptions behind a model define the model's possibility space, spanned by the possible states of the target system that the model can capture [31]. A model cannot address the

[b] Also other accounts on modeling, for example the denotation, exemplification, keying-up, imputation (DEKI) account [39] allow isomorphism as one possible representation style.

features or behaviors of its target that fall outside the possibility space; for example, static models cannot capture dynamic behaviors [30, 31].

In the case of network models, the definition of nodes and links belongs to the most important assumptions that span the possibility space and thus define what information the model can produce [20]. Another relevant assumption covers the dependencies between links, that is, how and to what extent the existence of one link predicts the existence of other links [109]. Dependencies can be, for example, temporal (i.e. the presence of a link at moment t affects the presence of other links at moment $t + 1$), spatial (i.e. the presence of a link in a specific spatial location affects the presence of other links in spatially close locations), or of subclass type (i.e. a polyadic connection between a set of nodes indicates dyadic connections between each pair of the set members) [109]. As we have seen in Sec. 2, especially spatial dependencies can be relevant for network construction but are often ignored and thus excluded from the possibility space.

In addition to the target system itself, dependencies may originate also from external conditions, such as the transitivity dependency (i.e. tendency to form triangles) in networks, where links are defined in terms of the Pearson correlation coefficient [109]. If an external dependency is not correctly embedded in the model, it may be misinterpreted as a feature of the target system. For example, while the high small-worldness of functional brain networks is known to originate from the transitivity dependency [121], it is still often considered a fundamental feature behind the normal brain function [7, 89] and used both to investigate effects of diseases (e.g. [6, 103]) and to evaluate the goodness of network construction approaches (e.g. [37, 42, 115]).

While models typically originate from a specific research setting, many of them are later transferred to new research fields and thus become model templates [61–63]. The application of network models in various fields is a typical example of model transfer (see Knuuttila and Loettgers [63] for an analysis of the Barabási–Albert model [5] as a model template). In this transfer, the new field adopts not only mathematical tools applicable outside of their original context but also ontological assumptions about the target system [62]. The new application field inherits the possibility space developed for the original target system of the model template [31, 62]. This limits the analysis in the new application field: as features possessed by the new but not by the old target fall outside of the possibility space, posing a research question about these features may seem irrelevant and the old and new target systems appear more similar than they actually are. Further, concepts with a well-defined meaning in the original context (i.e. phase transition in the field of physics in the case of a widely studied model template, the Ising model) may become merely metaphorical in the new context (e.g. study of social segregation), which may lead to a misguided or limited interpretation of the new target system [61, 62]. Therefore, while model transfer opens new insights in many fields, applying model templates also requires special care especially in fields that are distant from the one the template originates from [31, 62, 63].

3.2. *Introducing the networkness space*

Let us define the networkness space as a space spanned by two axes that describe properties of a system (Fig. 1(a)). The abscissa tells to what extent the system *is a network*, or a system, where connectivity essentially defines the function [47, 83]. By this definition, a mathematical *graph* object with no properties except connectivity is maximally networky, and the networkness of a system tells how accurately the corresponding graph represents the system or, using the terminology of DiFrisco *et al.* [31], how well the possibility space of a network model matches the underlying features of the system. On the other hand, the ordinate tells *how useful information* the network approach produces about the system and its function or to what extent the possibility space of a network model allows answering relevant research questions about the system. Together, the two axes correspond to two complementary views on the purpose of science: understanding the nature of the world on the one hand and producing useful applications on the other hand. It is important to notice that locating a system in the networkness space is not a strict categorization: while a system can be more or less network, few systems are fully networks or no networks at all. Similarly, while the network approach can be more or less useful for describing a system, it rarely is the only usable framework or completely useless.

Earlier literature has demonstrated the shortcomings of the classical network model (as per Eq. (1)) in modeling target systems with dynamic behaviors [30, 31] or polyadic relations between elements [109]. In this section, I apply a slightly broader definition of a network. Therefore, to define a system's position along the abscissa, I consider a system a network if connectivity of any sort, dyadic or higher-order, is fundamentally relevant for it. Further, to define the position along the ordinate, the network model that produces useful information about the system can contain also dynamic components, for example processes simulated on top of a network structure as proposed by DiFrisco and Jaeger [30] or time-stamped links as in temporal networks [48]. I will return to the possibilities and problems of the higher-order connectivity and other more complex network models in Sec. 4.

The top right part of the networkness space features systems that are networky due to their physical nature and, while they can be studied in terms of other analysis approaches as well, the network analysis outcomes are almost guaranteed to be useful. Examples of these systems include the WWW, power grids, and transportation networks. Often, these systems are characterized by tangible nodes and links (see Sec. 2). However, high networkness and usefulness of the network approach are typical of also social relationships with intangible links and completely intangible mathematical models, for example the Erdős-Rényi [33] and Barabási-Albert [5] models or the small model networks proposed by Holme [46].

Importantly, the potential of the network approach to produce useful information about these systems does not mean that they could not be studied successfully with

[c] See Carpelan [22] for a review of the archeological studies of the Antrea Net Find, a stone-age fishing net and related objects.

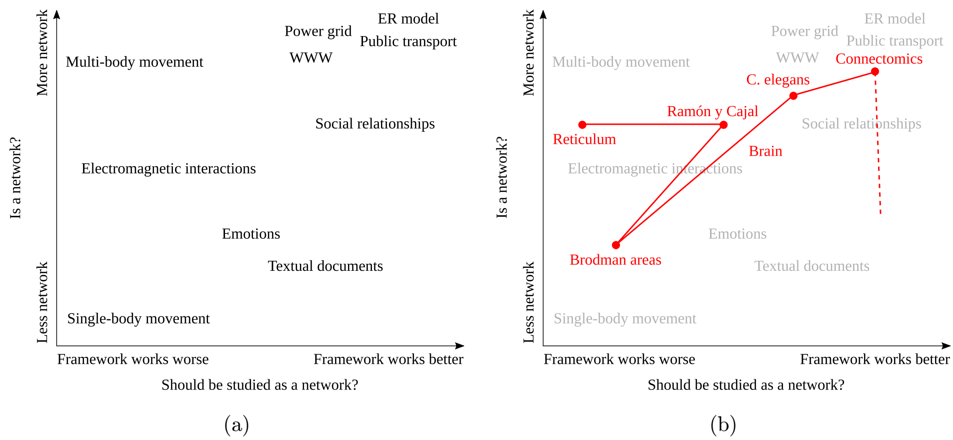

Fig. 1. The space spanned by system's fundamental networkness and the application potential of the network approach to study the system. (a) Locations of several example systems in the space. Locating systems under investigation in this space helps to evaluate the potential and limitations of the network framework. (b) The case of the brain demonstrates changes in a system's location in the space over time. While the reticulum theory and Ramón y Cajal's neuronal diagrams recognized the role of connectivity in brain function, the neurological tradition shifted the focus from connectivity to mapping isolated areas. The development of imaging and analysis methods led to a new era of connection mapping and finally to the connectomics that views the brain as highly networky and studies it with network tools. The recent criticism of particularly functional brain networks does not question the usefulness of the network approach but may change the view of brain's fundmental networkness (the dashed line).

other methods. Qualitative methods are, alongside mathematical and numerical models, often important for analyzing some aspects of both social relationships and fundamentally networky cultural artifacts such as power grids. Ironically, methods of archaeology, anthropology, or cultural studies may beat network tools when studying the probably most networky of all objects, a fishing net.[c]

The popularity of the network approach has given rise to several examples of meaningful network analysis of less networky systems. For example, textual documents or experienced human emotions may not intuitively appear network. However, network analysis of these phenomena has revealed structures of policy making and coalition formation [4, 69–71], action strategies [49], and emotion concepts [107]. These systems often lack tangible node and link candidates and thus node and link definition requires special attention. Often, the most fruitful analysis frameworks for these systems combine network methods with other fields of study: for example, Papin [88] investigates transnational municipal networks of climate governance armed with a combination of network science and organizational theory.

Multi-body movement and electromagnetic systems are examples of the rare systems where interactions play a key role but that are still better studied with other methods than the network approach. Finally, single-body movement in presence of friction is an extreme example of a system with low networkness and little application potential for the network framework.

The location of a system in the networkness space can, and often does, change over time (Fig. 1(b)). A system's trajectory in the space reflects both increased understanding on the system and the development of network tools. For example, the 19th century *reticulum* theory assumed that the brain consists of a continuous mesh of matter, the *reticulum*. Thus, connectivity was recognized as an essential part of brain function, yielding high networkness. However, there were no attempts to analyze the brain with network tools, probably because of the lack of both tangible node candidates and suitable analysis tools. The discovery of neurons by Santiago Ramón y Cajal offered such node candidates and thus opened the possibility for more network-oriented analysis of the brain. The neuron drawings of Ramón y Cajal are indeed similar to later connectivity diagrams. However, the history of neuroscience took a different course, thanks to the enormous work Cécile Vogt-Mugnier, Oskar Vogt, Corbinian Broadmann, and other neurologists that divided the brain into regions characterized by different neuron types. The neurologists never denied the connections between brain areas. However, the brain remained at the bottom left corner (low networkness, little useful network applications) of the space till 1980s, when White *et al.* [116] published the full structural mapping of the *C. elegans* neuronal system. Later, the theory of connectomics, or structural mapping of brain connectivity [41, 102], and the dawn of network neuroscience [8, 81] identified the brain firmly as a system with high networkness and notable application potential for network analysis methods. However, questions about the essential network nature of the brain have risen again in the recent years. These questions relate to the well-known problems in construction and analysis of functional brain networks, including challenging definition of nodes and links, less intuitive interpretation of analysis outcomes, and misinterpretation of correlation as causation [65, 78]. Some researchers have addressed these issues with more complicated connectivity models, for example the chronnectome framework [21, 51, 53]. As we will see in Sec. 4, these models are sometimes rather distant from the classical definition of a network.

3.3. *The networkness space: Step-by-step*

The location of a system in the space spanned by the system's networkness and the application potential of the network framework is important for defining the limits of the network approach. Locating a system in the space helps both to select reasonable research questions and to predict the research impact. Next, I will describe how the location of a system in the networkness space is estimated in practice. Importantly, the space is a qualitative rather than a quantitative tool. Therefore, while the following instructions aim to help in evaluating the networkness of a target system and the usefulness of a network model to study this system, these evaluations are not typically strictly binary and can, as discussed above, change in response to changes in the ontological views on the target system and the development of analysis tools.

Locating a system in the networkness space takes place through answering two sets of questions, the first one addressing the networkness of the system (i.e. the location along the abscissa) and the second one considering the usefulness of the network framework (i.e. the location along the ordinate). Optimally, these questions should be addressed in interdisciplinary collaboration with experts in the application field to ensure a sufficiently profound understanding on the ontology of the target system. Since the response to any of the questions does not depend on the responses to the other questions, the questions do not need to be answered in any specific order. Table 1 demonstrates the answers to these questions for two example systems, public transport and experienced emotions, and how the answers are interpreted to locate the systems in the networkness space.

Questions to address a system's networkness:

(i) Are there obvious, in particular tangible, candidates for nodes and links? Systems with more natural node and link candidates are more probably fundamentally networks.

(ii) Are the obvious node and link candidates present at a single spatial resolution or across various spatial (and possibly temporal) resolutions? While systems with easily identifiable nodes and links at various scales require special attention when selecting the reasonable aggregation level [20], they are more probably fundamentally networks than systems where nodes and links can be identified only at a single, optimized scale.

(iii) What other features does the system have apart from connectivity? If these features are numerous and relevant to the system's function, the system is less probably fundamentally a network. Further, these features will be excluded from the possibility space of any network model and cannot thus be addressed through the network framework.

(iv) Are there other established or otherwise reasonable models for the system apart from network models? If such models exist, the system is less probably fundamentally a network since it has relevant features that fall outside network models' possibility space but are successfully captured by other models.

(v) To what extent connectivity structure explains the system's function? If connectivity determines the function, the system is by definition fundamentally a network. However, even in systems commonly considered fundamentally networks, connectivity may rather restrict than determine function [30].

Questions to address the usefulness of the information the network framework produces about the system:

(i) Is enough sufficiently high-quality data available for estimating the relations between the nodes? If the data are limited or of low quality, network analysis outcomes will be corrupted by errors in network model construction [91].

Table 1. Examples of locating a system in the networkness space.

Question	Public transport	Experienced emotions
Networkness (abscissa)		
Obvious node/link candidates?	Obvious, tangible candidates for nodes (stops) and links (transport lines)	Obvious, intangible node candidates (emotion concepts), no obvious link candidates (often defined in terms of experienced similarity of emotional concepts evaluated by experiment participants)
Resolution?	Node and link candidates at various spatial scales (city, country, international)	Node candidates at a single scale only
Other features than connectivity?	Alongside connectivity, e.g. economy and emissions are relevant for some research questions	Neuroscientific, psychological, and biological components are very relevant for experiencing emotions
Other models	Mathematical and computational models for system parts (e.g. single lines [54], stops [36]), no alternative model for the whole system	Various qualitative and quantitative emotion models in neuroscience and psychology
Importance of connectivity for function?	The transportion system function and user trajectories strongly explained by connectivity	Similarity structure between emotion concepts does not explain how and why emotions are experienced
Interpretation	Fundamentally a network	Has connectivity features but is not fundamentally a network
Usefulness (ordinate)		
Data availability?	Public data (see von Ferber *et al.* [113]) and even curated datasets [67] available	Data can be collected from participants without notable sources of error, some public data available [85]
Existing network models?	Various network analyses (e.g. Kujala *et al.* [67], von Ferber *et al.* [113]) have developed different models and measures for them	Some earlier network analyses (e.g. Toivonen *et al.* [107])
Interpretation of network metrics?	Node and link definition allow easy interpretation of path length as distance or travel time	Link definition as experienced similarity may obscure the interpretation of some measures but e.g. detected communities are easy to interpret
Role of connectivity in research question?	Numerous potential connectivity-related research questions about e.g. route planning (travel time, number of transfers), some questions (e.g. user's motivation to choose public transport) are not answerable through a network model	Network analysis can answer questions related to e.g. grouping and classification of experienced emotions
Interpretation	The network framework can produce highly useful information	The network framework, among other approaches, can produce useful information

(ii) Are there existing network models for the target system? Producing useful results is more probable if prior network models and related mathematical tools are available.

(iii) Does the definition of nodes and links allow a meaningful interpretation of network analysis outcomes? Many network measures (e.g. shortest path length and its derivatives) rely on interpreting network links as concrete connections, not, for example, correlations or probabilities [91], and thus producing useful information is less probable if link definition does not allow such an interpretation.

(iv) How central is connectivity for the present research question? If the connection between the research question and the system's assumed network structure is not clear, producing useful information is less probable.

The answers to the above questions, and thus the location of a system in the networkness space, should be considered in the context of each specific research project. Is the goal a deeper understanding on the characteristics of the target system, or are practical applications more central? If connectivity is not essential for a system, network analysis cannot explain its fundamental nature. However, as stated above, a system rarely is strictly either a network or a non-network. Therefore, even if network analysis cannot fully explain a system, a network model can serve as an efficient description of the system from a specific viewpoint or at a specific scale. Further, the network analysis outcomes can have valuable practical applications even in systems with relatively low networkness, and limited computational and measurement resources may make network analysis the most reasonable way to analyze a system even if it was not the theoretically optimal one. For example, Baijot *et al.* [3] hypothesize that the observed differences in functional brain network structure between patients and control subjects may reflect increased movement of patients during the measurement instead of changes in brain function. Should this be the case, the observed differences would shed little light on the origin of the disease. However, this does not compromise their potential as a useful diagnostic biomarker.

4. Stretching the Network Definition

In the previous sections, I have considered all models based on connectivity, regardless of whether dyadic or polyadic, static or dynamic, network models. Indeed, while the popularity of the network approach has increased, the set of tools under the network umbrella has grown both in number and in diversity. Next, I will consider approaches that stretch the boundaries of the network framework at both ends, that is, are either notably more simple or significantly more complicated than the traditional definition of a network in Eq. (1). Note that a system can be modeled with a more simple or complex model independently of its location in the networkness space.

The most simple network studies concentrate on connection mapping, while mathematical and statistical analyses of the obtained connectivity structure play a minor role. This is typical, for example, of the early work on connectivity in neuronal systems (e.g. [13, 90, 116]) and studies on the effects of diseases on functional brain networks (e.g. [73, 73, 82]). Sometimes the results of the most simple network analysis could be easily reached with other, less complex tools. For example, counting the participation actions can reveal the most active event participants without the need to build a participation network and detect its hubs. Occasionally such simple studies use *network* purely as a buzzword. However, the network framework can be advantageous even in simple studies. For example, a clear visualization of a complex phenomenon [49, 88] or the possibility to compare obtained degrees to a null model [43] may justify the network approach.

While the popularity of the network approach has lead to *networkification* of the methods at the simpler end of the spectrum, the approaches at the other end have become increasingly complex. The first extensions of the classical network models included link weights to represent the importance, tightness, or frequentness of the links, directed links to represent non-mutual connections between nodes, and multigraphs that allow multiple links between a single pair of nodes. Among the more complex connectivity models, multilayer networks [17, 57] represent different types of links on different layers, while higher-order connectivity models such as hypergraphs and simplicial complexes model polyadic connections between more than two nodes [10, 15, 109]. Connectivity dynamics can be captured through temporal networks, where each link exists only at certain moments of time indicated by its time stamp [48], and time-dependent multilayer networks, where intralayer links represent connectivity inside each time window while interlayer links connect consecutive windows [9, 86, 106]. All these models share features with classically defined networks but also stretch the boundaries of the definition. While a detailed model of dynamic or higher-order connectivity with node-specific attributes can yield an increased understanding on the system under study, for example by embedding the subclass dependency omitted by the classical network model [109], the success of these models depends on data availability and quality. If the access to high-quality data is limited, a simple network model can yield more reliable information than a more complex one. Further, the increased amount of details in the more complex models risks the feature that makes the network approach so powerful: the ability to represent complex systems by simple, even intuitive models of connectivity. Therefore, for studies that require a particularly high level of detail, overloading a network model with these details may not be the best approach. Instead, more complex numerical simulation frameworks can include connectivity among other features.

Many mathematical tools that have been developed for studying classical networks generalize for more complex connectivity models; the examples include triadic closure and clustering [14, 25, 34, 59, 98], community detection [55, 66, 80, 92], and path analysis [16, 28, 76, 84, 93] in hypergraphs, simplicial complexes, and multilayer networks as well as the analysis of multilayer motifs [11, 58]. However, such generalizations are rarely unequivocal and often require additional assumptions and conditions. Further, the interpretation of network metrics that is intuitive in classical networks easily becomes blurred in more complex models. In the worst case, this leads to interpretations that concentrate solely on the mathematical properties of the model and are weakly connected to the concrete system under investigation.

Sometimes the existing tools are not sufficient for analyzing the structure and function of the new, more complex connectivity models. In these cases, the ends of the network spectrum get close to each other: the most complex models become maps of connectivity and node attributes, while the network analysis needs to wait until the development of tools and metrics matches the complexity of the models. For example, the chronnectome paradigm of network neuroscience [21, 51] represents brain function as time-dependent connectivity between temporally and spatially fluctuating sources and thus offers a theoretical framework for investigating brain dynamics along multiple dimensions at once. While pioneering work on mapping the fluctuating source boundaries has taken place [51, 52, 94, 95, 117, 118], network analyses with sources as nodes remain scarce.[d]

5. How Interdisciplinary is Network Science?

Interactions between the fields of science can be described in terms of a three-level framework [50]. *Monodisciplinary* research is based on a single field only. *Multidisciplinary* studies combine components from different fields, but each component remains independent and easy to recognize. *Interdisciplinary* research, on the other hand, aims for synthetic interactions between the fields and may lead to the emergence of completely new fields.

Graph theory, the area of mathematics behind network science, combines combinatorics, topology, and algebra. However, despite its interdisciplinary origins, graph theory has a prolonged history as an established, independent field and may thus appear an example of monodisciplinary research. Network science itself is typically merely multidisciplinary than interdisciplinary. Network studies combine data collected in some field and analysis performed by experts in another field: network scientists. However, the interactions between the fields often remain limited. Although data collectors may participate in setting the research question and interpretation of the analysis outcomes, often data come from an open database, and there is no direct interaction between data collectors and network scientists who analyze the data.

The lack of interdisciplinarity makes it difficult to locate the system under investigation in the networkness space introduced in Sec. 3.2 and thus to understand the potential and limitations of network analysis. The problem is two-fold. On the one hand, network methods easily become a silver bullet in the fields that provide data for network analysis. Data collectors are unfamiliar with network methods and thus may expect too much from the capacity of the network approach to answer

[d] However, see Luo *et al.* [75] and Long *et al.* [74] for network analyses with time-dependent nodes that resemble the chronnectome sources.

fundamental questions. On the other hand, network scientists may lack a field-specific understanding. This complicates recognizing noise and biases embedded in the research data, especially in the data extracted from publicly available databases, and accounting for the uncertainty in network structure [91]. A further risk is an unnecessary narrow interpretation of analysis outcomes, emphasizing more the mathematical descriptions than the meaning of the results in the context of the data. For example, during the COVID pandemic, numerous network studies introduced spreading models that were mathematically feasible but lacked epidemiological validation. In genetics, misinterpretation of analysis outcomes has occurred when studying gene regulation systems with static network models without sufficient understanding on the related dynamic and causal processes [112, 30]. Similarly, in sociophysics, problems arise when network science and simulation models originating from physics are applied to study social phenomena such as opinion formation or innovation spreading but results are interpreted without sufficient contribution from sociologists or psychologists [62, 101].

In summary, the field of network science would benefit from a more interdisciplinary research practice. Increased communication between network scientists developing models for different application targets allows more fluent transfer of model templates [109]. Similarly, closer collaboration between network scientists and their colleagues from the fields, where network models are applied, is needed to avoid misguided posing of research questions and interpretation of results due to a sub-optimal model template transfer [62]. Further, maintaining an active connection between the theory and applications of network science supports handling noise and model uncertainty [91].

Establishing a novel interdisciplinary practice requires genuine, mutual interaction between researchers from different fields throughout each research project, instead of the separated work on a shared topic that characterizes the current multidisciplinary paradigm. Shared epistemology, language, and understanding on the potential and limitations of the network framework become particularly important when the background of actively collaborating researchers grows more heterogeneous [91]. The interdisciplinary schools and study programs that are already emerging, for example, in the field of network neuroscience, can support this transition.

6. Closing Remarks

The ever-increasing popularity of the network approach in diverse fields of research has opened new insights on various real-world systems. Meanwhile, *network* has become a buzzword that appears in the titles and toolboxes of countless articles, often without deeper consideration of the potential of network analysis to tackle the research questions at hand. The eagerness to expand the application area of network science has given rise to several problems that fall roughly into two groups.

First, a typical network study combines analyses performed by network scientists with data collection and possibly question setting by experts in some other field. Too often, such studies suffer from the lack of understanding on the potential and limitations of the network approach on one side and the characteristics and context of the data under investigation on the other side. In the worst case, this leads to problems in network model construction, for example suboptimal node and link definition. Such inaccuracies in the network analysis question the reliability of the analysis outcomes.

On the other hand, the quest for greater accuracy has led to increasingly complex models that stretch the traditional definition of network. While the classical network definition is relatively intuitive, understanding the mathematics behind the more complex models and interpreting their outcomes require special expertise. Therefore, these models come with the risk of narrow, mainly mathematically oriented interpretations weakly rooted in the context of the data under investigation.

Above, I have proposed two solutions for these problems. First, the current multidisciplinary approach keeps the contributions of different fields separated. Therefore, transition toward a more interdisciplinary setting, including continuous mutual interaction between contributors, would support both a more accurate construction of network models and more profound interpretations of research outcomes.

Second, evaluating the potential of the network framework on a given research problem is necessary before applying a network model. This potential consists of two components: to what extent a network model can reveal fundamental truths about the target system and, independently, to what extent the network analysis outcomes are useful. Locating the systems under investigation in the space spanned by these two components (see Fig. (1)) can support planning an optimal network analysis, avoiding the excessive hype around the framework, and asking the research questions that network analysis can best answer.

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