Chapter 1

A whirlwind tour of network science

Network science has exploded in popularity since the late 1990s. But it flows from a long and rich tradition of mathematical and scientific understanding of complex systems. In this chapter, we set the stage by highlighting network science's ancestry and the exciting scientific approaches that networks have enabled, followed by a tour of the basic concepts and properties of networks.

1.1 Networks as a powerful analogical framework

System thinking

To understand the power of network thinking, it's worth taking a brief detour to the emergence of *system thinking* in the nineteenth century. The nineteenth century was a time of great advancements in science. As the industrial revolution upended how societies and economies function, science became a profession; physics, chemistry, biology, and so many other fields were established and advanced rapidly.

An important perspective that emerged during the nineteenth century was the recognition of *complex systems*—although the name came later—across domains. The idea is that our body, society, and *everything* consists of numerous individual elements. For instance, matter consists of "atoms" and "molecules." Although the idea of *basic elements* was suggested by ancient Greeks, this philosophical atomism turned into a concrete scientific theory—the *atomic theory*, propelled by the discovery of chemical laws through precise measurements of the chemical reactions (see Fig. 1.1). In other words, people began to look at *everything* as a system of atoms and molecules and realized that not only *what* constitutes the matter *matters*, but also *how it is arranged* matters.

Similar theories emerged across many fields around the same time. In biology, new instruments like lenses and microscopes led scientists to look at the structure of cells and organisms on a finer scale. This gave us *cell theory*, which postulates that every

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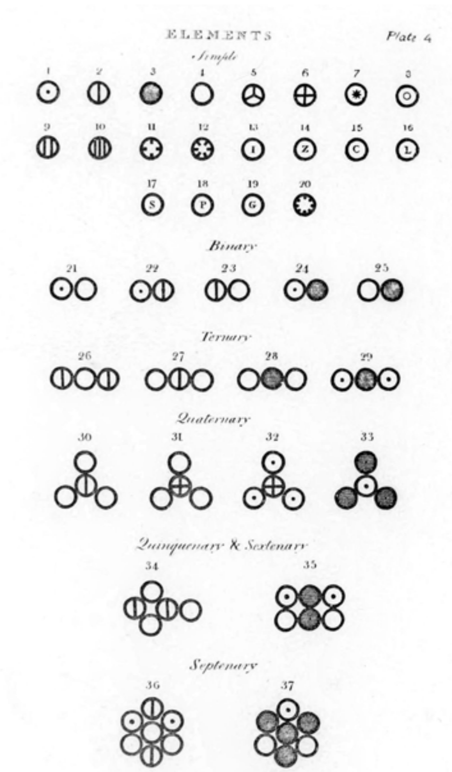

Figure 1.1 Atoms and molecules depicted in John Dalton's *A New System of Chemical Philosophy* (1808) [120].

living organism is made up of cells—the atoms of life. This is also the beginning of the realization that the rich biological phenomena originate not only from the nature of an individual cell, but also from *how* those cells interact with each other.

It was called "neuron doctrine" for the brain. With the ability to examine individual neurons and their dendrites, most notably in the work of Santiago Ramón y Cajal (1852–1934), scientists began to realize that a brain is essentially a giant, networked system of neurons. The realization began to take shape that the connections and interactions—rather than the make-up of different cells—are what the brain is all about.

Interestingly, the establishment of *social statistics* also happened around the same time. As cities grew and countries established themselves, there was strong need to get detailed information about the population within, and this led to the rapid development of *statistics*.[1] The same story again: the strong recognition of a *system* (cities, states, countries, etc.) as a collection of individuals and the ability to concretely think about and quantitatively measure this collection as a whole.

All these revolutions were about recognizing the *systems*, and the *elements* that make up the systems. Living organisms are made of *cells*; the brain consists of *neurons*; everything is made of *atoms*, and cities and countries are made of individual *people*!

[1] The term *statistics* originated from a German word "Statistik," which came from "statisticum" (Latin) or "statistica" (Italian). The term "Statistik" was introduced by Gottfried Cornwall (1719–1772) in 1749 to refer to the *analysis of data about the state*.

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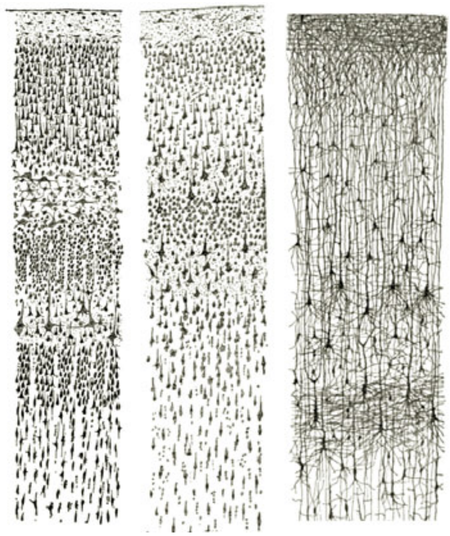

Figure 1.2 Ramón y Cajal's drawings of the human cortex, from *Comparative Study of the Sensory Areas of the Human Cortex* (1899). Figure from [386].

And every one of these revolutions was propelled by the development of new technologies, instruments, and capacities. Being able to see finer, measure more precisely, and calculate more accurately was the primary driving force behind these breakthroughs.

At the same time, although recognition was dawning of the importance of interactions in the system—for example, cells are remarkably similar to each other even when they belong to completely different systems and brains are different because of how they are wired—there was no way to accurately capture, at that time, the *interactions*.

Ramón y Cajal's drawings (see Fig. 1.2) beautifully illustrate how neurons produce incredibly complex branches (dendrites), but he could not see how these dendrites and axons are wired together. It took a hundred years until we could accurately connect the dots and measure the precise connections between individual neurons. Although scientists could *see* individual cells, it took a long time to be able to measure cellular interactions happening at the molecular level.

Yet, even without the science of *interactions*, system thinking could provide a powerful framework with which scientists crossed disciplinary boundaries. There was a plethora of analogy-making between disciplines and systems, unified by system thinking. Working with social *statistics* facilitated the development of probabilistic and statistical thinking and it had a huge influence on the way scientists think about the world. For instance, physicist Ludwig Boltzmann (1844–1906), one of the founders of statistical mechanics, drew inspiration from the social census, making an analogy between molecules and individuals. Boltzmann wrote (emphasis ours):

> *The molecules are like to many individuals*, having the most various states of motion, and the properties of gases only remain unaltered because the number of these molecules which on the average have a given state of motion is constant. (p. 69, *Critical Mass* by Philip Ball [33])

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Network thinking

The difficulty and trickiness of measuring interactions delayed recognizing and appreciating the importance of interactions in complex systems. It also limited scientists to the paradigm of *reductionism*—the approach that we need to understand each part of a system to understand the whole. Needless to say, reductionism is not inherently bad; it is indeed true that we should know the parts to understand the whole. The issue is that it is *not enough*, especially when we are dealing with complex systems that exhibit *emergent behaviors*.

It is not enough to understand how an individual neuron works to understand how cognition works; it is not enough to understand the chemical properties of individual molecules to understand how our body produces energy and renews itself; it is not enough to understand how individuals behave to understand large-scale social phenomena.

Network science arrived as it became clear that understanding the elements of a system is not enough, and as technology advanced to be able to measure interactions. But even without new scientific tools, there is a system where we could already measure interactions fairly easily—by asking the elements of the system directly. People can talk, and that is awfully convenient for network measurement. Because it is much easier to measure social networks, social network research has a much longer history than other fields of network science.

Jacob L. Moreno (1889–1974), a psychiatrist and social psychologist who pioneered psychodrama and group psychotherapy, was fascinated by the connections between inter-personal relationships (the social network!) and psychology. In the 1930s, he created a series of remarkable diagrams—which he called *sociograms*—by examining relationships between students at the New York Training School for Girls, a training institute for delinquent girls (see Fig. 1.3). The primary reason that he mapped the social relationships was to investigate why so many girls ran away from the school.[2]

To understand this phenomenon, Moreno proposed and conducted "*sociometry*"—a comprehensive measurement of the social interactions between students—with which he argued that the social network is what influences the eventual outcome of the students. In other words, he argued that the driving force of social dynamics is in the *network* of interactions.

The recognition of network interactions greatly affected sociology and related fields, allowing them to recognize the importance of *social structure* and the "*social forces*" that the social network can exert on the individuals. Network thinking arrived in other fields a bit later, mostly due to the difficulty of actually *seeing* and *recording* the connections. The aforementioned technology was still needed.

This difficulty has been gradually overcome with better engineering and new tools, especially combined with computers and digital technologies. With computers and the Internet, numerous databases of network data emerged across fields. Although our knowledge of chemical reactions is as old as human civilization, it was in the 1990s when the first computerized and shared databases of chemical reactions were created. Similar databases for protein interactions were also created. The Internet itself—a pretty useful

[2] Ella Fitzgerald, legendary jazz singer, attended the school and also ran away after about a year. She might be in one of the sociograms that Jacob Moreno created!

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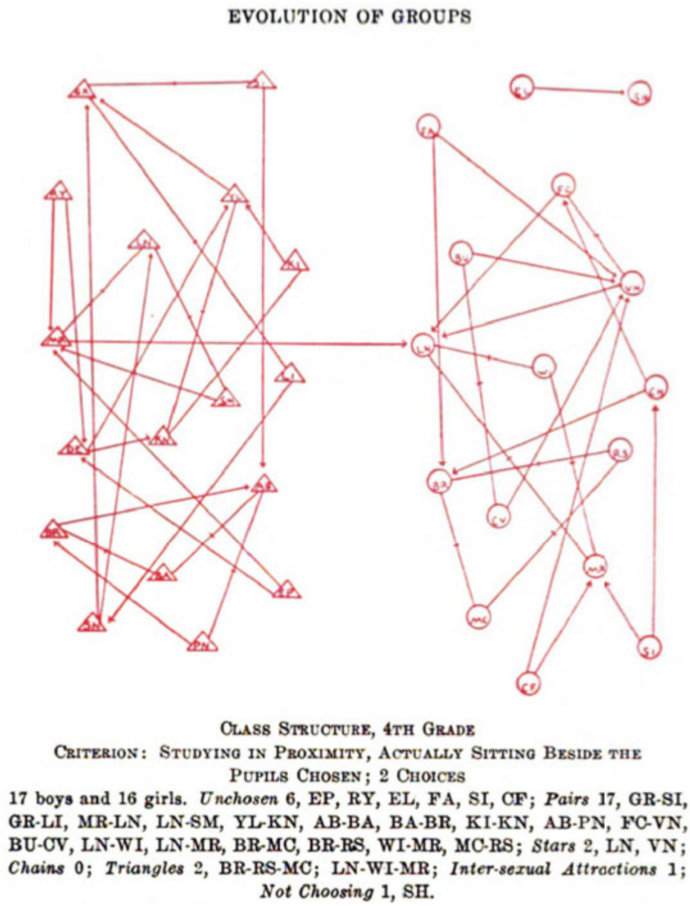

Figure 1.3 Jacob L. Moreno's sociogram of 4th grade students at the New York Training School for Girls. Figure from [318]; originally published in [317].

network—was mapped and compiled into a network dataset. Online social networking services emerged and provided a completely new way to map social interactions at a societal scale.

The fact that network datasets and maps began to emerge *across many fields* also nudged scientists to think more analogically; network thinking flourished. In particular, statistical physicists who are used to the idea of complex systems and computer scientists who are used to computer networks and data structures emerged as the primary driving force to look for universal patterns in these network data.

By identifying and abstracting the *network structure* in all kinds of systems, many universal or prevalent characteristics of these networks have been discovered. Networks now serve as an analogical framework to translate insights and methods from one system to another. For instance, based on our intuition and understanding of the major travel hubs in the network of airports, we can ask whether major "hubs" appear between

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our proteins or among people. Or, we can apply an algorithm developed to discover groups of people, or "communities," in a social network to instead find "communities" of proteins in the network of interacting proteins.

Network thinking often gives us a superpower to cross rigid disciplinary boundaries. As Boltzmann used the *system analogy* between people and molecules to develop statistical mechanics, network scientists use the *network analogy* to transcend disciplinary boundaries and understand the universal patterns of complex systems.

1.2 Data and theory—the pillars of network science

Our ability to *measure* interactions has been critical to the blooming of network science. Network science, as an empirical science, is largely driven by measurements and data. New *network data* have always driven the understanding of networks around us.

The explosion of network science coincided with the explosion of our capacity to systematically collect data. In biology, the Human Genome Project opened up molecular understanding of human biology in the 1990s; scientists began to assemble the *metabolic network* (the widely used metabolic network database KEGG[3] was initially released in 1995); methods for systematically probing interactions between proteins were first developed in the late 1980s and early 1990s. In neuroscience, techniques like *diffusion tensor imaging* (DTI) were also proposed around this time [42, 43] and computerized measurements of brain networks began. In social science, although network research had a long history since Moreno, the emergence of the Internet and the "social web" allowed us to collect unprecedented, high-resolution, societal-scale social interaction data.[4]

This sudden deluge of network data drew a lot of attention from scientists, leading to the discovery of universalities and commonalities across real-world networks, which then sparked the emergence of network science theories. This pattern continues today, whenever there is new network data from important complex systems, it pushes network science forward by forcing scientists to perform new measurements, develop new methods, and invent new theories.

However, despite being our focus, ***data alone cannot paint a full picture***. Big data without any insight or useful theoretical framework is expensive junk. We need coherent theories that equip us to understand the data and make predictions. For instance, network growth models allow us to ponder the mechanisms *behind* the growth of networks; the theory of random graphs can tell us what should we expect to see in a network under certain assumptions about the system; statistical inference can help us identify large-scale patterns in the networks. Finally, theories make *predictions*, which are powerful directives that lead to useful measurements and data collection.

Network science, like all science, stands upon the dual pillars of data and theory.

[3] Kyoto Encyclopedia of Genes and Genomes.

[4] Whether social web data can be a good proxy of social relationships is another interesting question that we will discuss more later.

1.3 Networks are everywhere

One of the primary reasons why networks can serve as such a powerful analogical framework to study complex systems is that networks are *everywhere*. Just look at ourselves. Society is a giant network of people. It is intriguing that so many of the "Big Tech" companies are built on the power of social networks. Google's secret sauce was recognizing the value of the network between web pages and developing the algorithm, *PageRank*, that can harness it. Facebook (Meta) was literally built as a platform to share and communicate with people through the social network. Once it reached a dominant position—pulled enough people into the platform—it became extremely *sticky*. Because so many of our friends use Facebook, it is difficult for any one person to leave and this is true for everyone on the platform. The more people use an online social networking service, the harder it is to quit due to this *network effect*.

If we look inside ourselves, we can find that we (and every living organism) rely on many levels of networks, from the network of biochemical reactions to the network of neurons in the brain. All biological phenomena (and diseases) arise from the interactions between molecules, cells, and organs.

You can also easily find networks in unexpected places. For instance, it has been suggested that there is an interesting network in forests called the "*mycorrhizal network*," which is a network between plants, underground, formed by fungi.[5] This fungal network has been described as the "Internet" or postal network between plants, through which plants can exchange nutrients and communicate with each other. "Mycorrhizal network" doesn't exactly roll off the tongue, but fortunately there is a more memorable name for this network; it's the "*wood wide web*"!

Speaking of plants and fungi, we can construct another interesting network between the foods we eat, based on their flavor similarity. This network—the "*flavor network*"[6]—was inspired by the "food pairing hypothesis," which argues that two ingredients go well together if they share the same flavor-producing chemical compounds because the flavor gets enhanced by the combination (see Fig. 1.4). You can see why this hypothesis calls for a network—look at all those intricate patterns!

When we inhale and exhale these flavor molecules, *olfactory receptors* (proteins) in our nose need to do their job to recognize the flavors. Because they bind with the flavor molecules (like a lock and a key), it is critical to know the exact shapes of the proteins that constitute the receptors. Although the sequences of proteins are well-known, deducing three-dimensional (3D) structure from them is far from trivial; rather, it is the opposite of trivial. This is called the *protein folding* problem and has been a notoriously difficult open problem.

The biggest challenge is that pretty much any pair of amino acids, regardless of their distance in the genetic sequence, might be right next to each other in the final, folded protein. In other words, the amino acids in a protein have a lot of non-trivial long-range *interactions* and each protein can be thought of as a *network* of amino acids that are eventually *connected* in the final 3D shape. Surprisingly, this elusive problem was effectively solved by the *AlphaFold* team at Google's Deep Mind in 2021, and this

[5] Note that there is a controversy over the existence of this network. Some scientists criticize that it is unproven and over-hyped.

[6] It was constructed and studied in part by yours truly, see Ahn et al. [6].

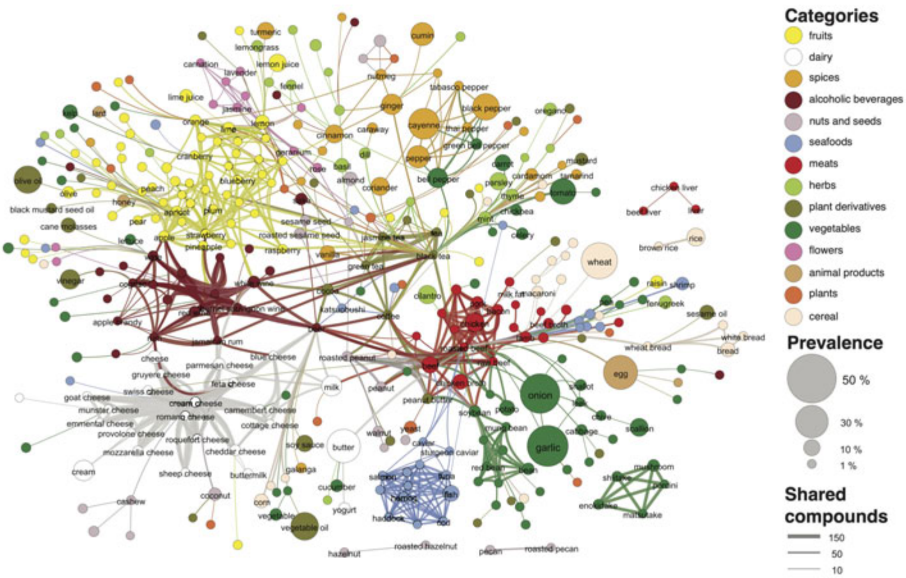

Figure 1.4 The flavor network of ingredients that shared flavor compounds. This visualization (Ch. 13) displays the structure of the *network backbone* (Ch. 10), the most prominent connections. Figure from [6].

achievement was just recently selected by *Science* as the "Breakthrough of the Year." You can probably guess what we want to say here: AlphaFold's machinery indeed uses this network perspective to represent the interaction between amino acids and an important breakthrough was their ability to accurately predict this network structure!

Here is another fun example, now at the scale of the galaxy and universe. Have you ever imagined traveling through the galaxy to reach other stars? We can formulate this problem more concretely by imagining the *maximum distance* that humanity may be able to travel and connect the stars that are reachable with this distance. Not only is this an entertaining musing on life, the universe, and everything, but it also is a curious case of the *percolation* problem that we will talk about later in the book.[7] Can we humans percolate through the galaxy like our coffee percolates through a filter?

OK, we have traveled from our society to the forest, and from our dinner plates to the universe. Still, we would argue that these are just small tips of the network iceberg. Once you fully embrace network thinking, you will start to see network structure and network data *everywhere*!

[7] Which, again, is an excellent example that supports our point that network thinking is a powerful analogical framework to translate theories and tools across domains.

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1.4 Basic terminology

Here is a brief overview of some basic network terminology. If you have already been exposed to these, it may be a useful review; if you haven't, don't worry. We will return to them in more detail as we progress through the book.

1.4.1 Basic concepts

Mathematically, a network is represented by an object called a *graph*, which we denote $G = (V, E)$. Graphs contain at least two sets: nodes (or vertices) and edges (or links). Here V is the set of nodes in the network, while E is the set of edges. Each edge connects a pair of nodes. We denote the number of nodes in G with N and the number of edges M. You've seen pictures of nodes and edges already, in Figs. 1.3 and 1.4, where nodes were drawn as circles or other shapes and edges were lines or arrows. We use the terms *edges* and *links*—as well as *nodes* and *vertices*—interchangeably throughout this book. We also use the terms *network elements* or *elements* to refer to either nodes or links or both.

A network consists of two kinds of elements:

Nodes also known as vertices.

Edges also known as links.

Understanding what the nodes represent, and what relationship(s) between the nodes are represented by the links, is critical for understanding any network data.

We illustrate some basic network concepts in Fig. 1.5.

Two nodes are connected when a link exists between them, making them *neighbors*. The set of neighbors connected to a node is its *neighborhood*. We denote the set of neighbors of a node i with N_i. The number of neighbors a node has is called its *degree* and we are often interested in the *degree distribution* $\Pr(k)$, the probability that a randomly chosen node from our network has degree k. This distribution is fundamental.

A *walk* is a sequence of edges that join a sequence of nodes; a *trail* is a walk where all edges are distinct; a *path* is a trail where all nodes are distinct. For instance, the edges (i, j), (j, u) and (u, v) form a path (assuming $i \neq j \neq u \neq v$) i–j–u–v that goes from node i to node v through nodes j and u. A path that begins and ends at the same node is called a *cycle*. Although there are other types of walks and paths, we are often interested in *shortest paths*, the paths connecting nodes using as few links as possible. The lengths of shortest paths are often used to define *distances* over a network. Information spreads over paths. These paths are fundamental.

If a path exists from every node to every other node, then we say the network is *connected*; otherwise, it is *disconnected*. A disconnected network will consist of two or more *connected components* (sometimes just called *components*). A connected component is a subset of nodes where paths exist between every pair of nodes in that subset. The connected component containing the largest number of nodes is called the *giant connected component* (GCC) or *giant component*. Often, a network is disconnected but the giant component contains the large majority of nodes.

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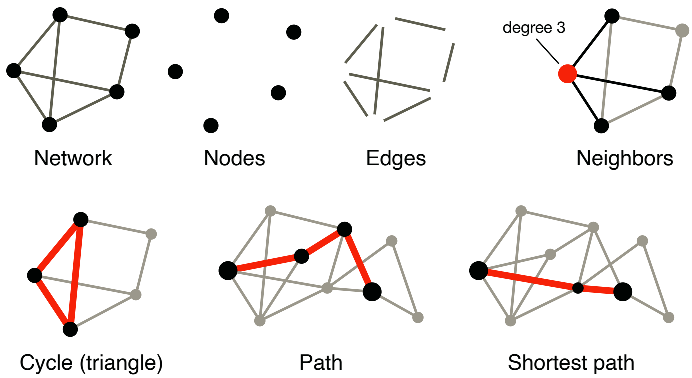

Figure 1.5 Nodes and edges form the basic elements of networks. Neighborhoods, cycles, paths, and shortest paths are some of the structures we examine in network data.

For a connected network, the *eccentricity* of a node is the length of the *longest* shortest path beginning at that node. The longest shortest path between any two nodes in the network is the *diameter* of the network.[8]

1.4.2 Operationalizing a network

The key decision we need to make when working with network data is determining what the elements should represent (to *operationalize* the network). ***What are the nodes?*** Is it a social network where each node represents a person? Or perhaps each node represents a group of people? Along those lines, ***what are the links***? If nodes are people, do links exist between two people when they are friends on a first-name basis? Or is it based on when they have exchanged messages through a website? If nodes are groups of people, what are the links? Perhaps links exist when groups overlap, sharing one or more people? Or perhaps instead two groups are linked if they share a common context, perhaps they are teams that work in the same branch of an organization? Often these questions are not made explicit. Yet, appropriately defining nodes and links between nodes is the key to extracting the right network—or networks!—from data.

1.4.3 Basic types of networks

The "zoo" of networks contains many network animals, depending on what properties they have or definitions they meet (Fig. 1.6). An *undirected* network is one where links are symmetric and have no direction. In an undirected network, if node i is connected to node j then node j is also connected to i. A *directed* network, on the other hand, is one where links are not necessarily symmetric. The link $i \to j$ may exist without the corresponding link $j \to i$.[9]

[8] If the network is not connected, we usually treat it as having a diameter of infinity.

[9] Directionality brings with it some complexity. Instead of node degree, we now need to consider *in-degree* and *out-degree*. Links point from a *source node* to a *target node*. Likewise, shortest paths that exist between

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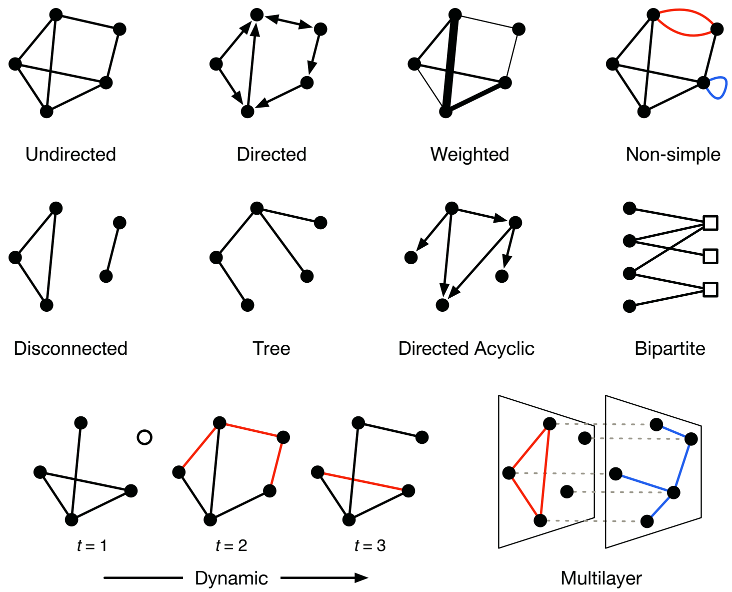

Figure 1.6 A sample of the network "zoo."

Networks can also be considered *weighted* or *unweighted*. A weighted network is one where each link, denoted i, j has an associated edge weight w_{ij}, typically a scalar, that captures how "strong" the link is. Usually, larger weights denote stronger links. And of course, a network can be both (un)directed and (un)weighted.

A network may, or may not, contain *multi-edges* and *self-loops*. A multi-edge is one where multiple edges occur between the same two nodes while a self-loop is an edge between a node and itself. When these are forbidden the network is called *simple* because it can be represented by a simple graph. When multi-edges are present, the network is represented by a *multigraph*. Likewise, when self-loops are present, the network is represented by a *graph with loops* or a *loopy graph*.[10]

Trees are networks where no cycles exist. Between any two nodes there is at most one path connecting them. A disconnected tree is sometimes called a *forest*. More complicated than a tree, in directed networks, a *directed acyclic graph* (DAG) is one where cycles exist but no directed cycles are present. One cannot leave a node and, following directed edges, follow a path back to the start.

Bipartite networks are networks that have two distinct sets of nodes, where each link (usually) lands only between nodes of different sets. Surprisingly, many network datasets contain bipartite networks or are derived from a bipartite network via a projection. A *bipartite projection* is a network derived from one of the two node sets in a bipartite

nodes ignoring link direction may no longer exist if we only consider paths that follow the directions of links. So we distinguish between *weakly connected* and *strongly connected* networks, where the former ignores direction when considering connectedness while the latter does not.

[10] Not to be confused with cycles.

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network by adding edges between nodes who had neighbors in common in the original bipartite network; the bipartite edges are "projected" onto one of the sets.

Dynamic networks, often called *temporal networks* are networks that change over time. The links, or nodes and links, are functions of time. (Occasionally, for weighted temporal networks, it is the link weights that vary in time.)

Multilayer networks are networks where nodes can be arranged into multiple categories or layers, and edges can connect between nodes in different layers or in the same layer. A *multiplex network* is a special case of a multilayer network where edges between layers can only connect nodes that represent the same entity. It may be easier to think of a multiplex network as a network without layers but where edges fall into categories that convey the same information as the multiplex layers.

Hypernetworks, also known as hypergraphs, are networks where edges are not limited to being between pairs of nodes. Hyperedges can contain two or more nodes.[11]

The zoology of networks. Here are a few of the basic kinds of networks we tend to encounter in data.

Undirected If a link i, j exists then i is a neighbor of j and j is a neighbor of i.

Directed If $i \to j$ then j is a neighbor of i but i is not a neighbor of j unless the link $j \to i$ is also present.

Weighted Associated with each link i, j is a weight w_{ij}, usually a non-negative scalar, representing how "strong" or "important" the link is. Weighted networks can be directed or undirected.

Simple A network where each link can exist at most once and where self-loops (links beginning and ending with the same node) are not allowed.

Bipartite A network whose nodes fall into two disjoint sets and links only exist between nodes of different sets. While it may sound esoteric, bipartite networks are surprisingly common in data and have many real-world applications.

Trees Networks without loops. At most one path exists between any pair of nodes.

Dynamic also known as temporal networks. The links and possibly nodes are functions of time.

Multilayer Links and possibly nodes fall into difference categories called layers.

Hypernetworks also called hypergraphs or higher-order networks, are networks where edges may contain more than two nodes.

And networks are often combinations of these categories, such as a weighted directed network or a dynamic multilayer network.

[11] There is a one-to-one correspondence between a hypernetwork and a bipartite node–hyperedge graph.

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1.5 Common properties of real networks

As network science progresses, our view of real networks and their features has sharpened. Networks are complex, with many fascinating and important properties. (We'll encounter many of these properties in this book.) Numerous research tools, both new and found, have been leveraged to describe these properties. Here are a few of the major properties scientists have uncovered.

Sparsity Most real networks are sparse, most pairs of nodes are not connected by an edge. The average degree is much less than the number of nodes.

Small world Many real networks are small in terms of distances, meaning that it only takes a few hops along links to navigate between any pair of nodes, even in a network with a massive number of nodes [309, 486]. This is the source of the famous "six degrees of separation" aphorism in social networks [235].

Transitivity, homophily, and mixing patterns Links are often transitive, meaning that if two nodes have a common neighbor they are likely to be neighbors themselves. The process forming such links, *triadic closure*, has fascinating effects and is often driven by *homophily*, the idea that similar nodes are more likely to be connected. More generally, different kinds of networks can exhibit different mixing patterns, where edges fall not at random but between related nodes.

Hubs and heterogeneity The number of neighbors that a node has can vary wildly across nodes in many real networks. Most nodes have only a modest neighborhood, while a few, called hubs, have absolutely massive numbers of connections. Strong degree heterogeneity and the unexpected existence of these hubs in many networks was one of the early surprises of network science.

Density variation Many real networks exhibit regions that have relatively more connections and other regions that are empty of links. Community structure, where networks have densely connected groups with bottlenecks between them, is one example of such density variation. Core–periphery structure, nestedness, the "rich club," structural holes [85], and more, are all organizing principles connected to variation in density.

Many of these properties interrelate. For example, transitivity can drive the dense communities of a network, and mixing patterns can lead to hubs and degree heterogeneity. These diverse properties, often all at play simultaneously, make networks both exciting and challenging to study. We will focus on many of these issues throughout this book.

1.6 Summary

As our view of nature developed and more data became available, we began to appreciate complexity and interconnectedness all around us. System thinking flourished. In the century since, researchers have codified a field of study dedicated to networks, with

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its associated language and interesting problems. This field, which came to be called network science, has blossomed due to the ubiquity of networks across science and technology, from the social networks of Jacob Moreno and the neurons of Ramón y Cajal to the Internet and World Wide Web of the late twentieth century. We can no longer imagine the world without evoking networks. And network data is at the heart of it.

Bibliographic remarks

Jacob L. Moreno's pioneering work on social groups, including what are likely the first drawings of a network (Fig. 1.3), is documented in his work, *Who Shall Survive* [317]. His daughter, Regina Moreno, recently published a memoir on her life and family, *Words of the Daughter* [319], including bringing to light the sadly overlooked, critical contributions her mother, Florence Bridge Moreno, an accomplished counselor and teacher, made to Jacob's groundbreaking work.

Santiago Ramón y Cajal, a Nobel laureate who elucidated the shape and structure of neurons and neuronal networks, has been the subject of much interest. Most recently, *The Brain in Search of Itself*, by Benjamin Ehrlich [143] is a fascinating read. Readers interested in more direct sources are encouraged to read Ramón y Cajal's own memoir, *Recollections of my Life* [388] as well as his inspiring guide *Advice for a Young Investigator* [387]. You can also enjoy his mesmerizing drawings of neurons from a beautifully compiled book *The Beautiful Brain* [330].

Readers eager for more on networks and history should consider *The Square and the Tower* by Niall Ferguson [157], a fascinating general audience book on the role of networks throughout world history.

A number of general texts on network science are worth the reader's attention including Newman [342], Barabási [35], and Menczer et al. [305].

Exercises

1.1 Can you find an interesting network that was not mentioned in this chapter? Describe what the nodes and edges represent, and then identify the type of your network. Is it a directed network? Or a bipartite network? Finally, identify a couple of concrete scientific questions and uses for the network.

1.2 Can you find a specific example where a network method or theory crossed a disciplinary boundary? For instance, a model that was originally developed to describe social systems was later applied to explain the dynamics of brain.

1.3 Let's say we want to model the social network in our classroom. How would you operationalize the network? What would be your nodes and edges? Would you introduce edge weights or directions? Why or why not? Please describe the type of your network, your operationalization choices, and rationales behind your operationalization.