The effects of network structure on the spread of disease and opinions, the functioning of the power-grid, and security of technological networks have become clearer through the past two decades, leading to the foundation of the field of network science. The **effect of these network structures on decision-making and control** is less clear, as this more granular information leads to an explosion in the number of decision variables. Decision-making becomes harder when there are complex evolving processes acting on networks (e.g., epidemics), and when the network itself evolves. Deciding when, as well as how, to act further expands the decision-space.

The amount and resolution of data available to decision-makers is growing at an astounding pace. Decision-making structures developed for the simple models of yester-year, that homogenized heterogeneities and planned for worst-case scenarios when lacking information, are not able to utilize this wealth of information. Thus, new modeling approaches and tools are needed to adapt to the rigors of our data-rich age.

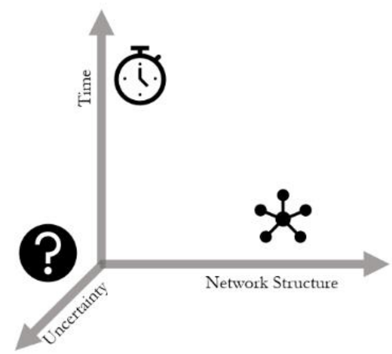


Figure 1. *Decision-making in complex systems can benefit from intelligently exploiting 3 complicating factors that are typically simplified for tractability: timing, uncertainty, and network structure.*

My fundamental goal is to understand the role of *timing*, *network structure*, and *uncertainty* in optimal decision-making in complex networked systems. As an electrical engineer by training, I characterize mathematical structures for decision-making for, and within, social, biological, and technological systems.

I principally use the mathematical theories of optimal control and dynamic programming, (nonlinear) optimization, games, and graph spectra to specify optimal decisions and to characterize the resulting evolution of networked systems. This both allows the **design of better policies** (e.g., for curbing the spread of epidemics under resource constraints) and the **design of better incentives** for autonomous decision-makers. I will continue to work with with subject matter experts in sociology, psychology, epidemiology, and power systems to define problems and to develop practical synergistic solutions, as such interdisciplinary collaboration is a key part of my research program, which can be broken down into the following 3 thrusts:

1. Developing tractable dynamic centrality, influence, and vulnerability metrics for complex systems,
2. Creating an analysis framework for incentive-driven spreading of social phenomena,
3. Understanding the trade-off between robustness, learning, and optimality in influence processes.

The metrics developed in the first thrust will provide dynamic decision-making heuristics and algorithms for real-world policy-making, while the second thrust will help anticipate decisions made by strategic actors, allowing a second-order incentive-design approach to shaping networked outcomes in such scenarios. The third thrust, which runs in parallel to the first two, is focused on understanding the effect of information limitations on the performance of both types of policies, as well as adapting their approached to be suitable to the incorporation of new information (i.e., learning).

In the next section, I will outline how my prior work has prepared me to reach these objectives.

Summary of Contributions

In my career, I have sought to illuminate decision-making structures that simplify complex dynamic decisions in biological, social, and technical contexts. The unifying theme across my work has been stressing that in dynamic processes, *when* one takes an action is sometimes more important than how one targets the action, and ignoring the temporal element of decision-making can lead to sub-optimal outcomes.

In my PhD at the Penn, supervised by Saswati Sarkar and Santosh Venkatesh, I showed how limited resources should be used to across time to shape epidemic processes [1-7]. As an intern at NEC Labs, I investigated how grid-scale batteries should be operated and how their stored power should be priced [8, 9]. As a postdoctoral associate at Cornell, working with Qing Zhao and Lang Tong, I showed how political and marketing campaigns can benefit from coordinating actions over time using simple structures [10]. In my postdoctoral work at Yale with Leandros Tassiulas, I have investigated optimal decision-making in social groups with limited information [11-16].

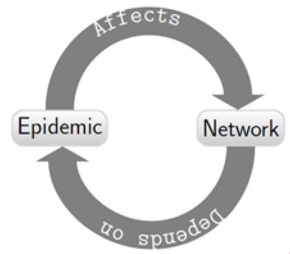


Figure 2. *Heterogeneity types: 1- Network heterogeneity, 2- Resource heterogeneity, & 3- Epidemic heterogeneity.*

Epidemics represent one of the single biggest threats to humanity. Their success at wreaking damage across a population led to the development of epidemic routing in communication systems. My work on epidemics started through work on message spreading protocols in delay-tolerant networks (DTNs), where end-to-end connectivity is rare and messages must be relayed to reach their destination. I showed, for the first time, how the remaining energy in nodes should be optimally utilized in the message forwarding decision at each instant to guarantee message delivery while maximizing the life-time of the network, leading to a simple and deployable DTN message-forwarding algorithm [1, 2]. I then studied more general heterogeneous networked epidemic models and showed that optimal coordinated curative actions involve offering vaccinations and treatments as early as possible and not waiting to take action, regardless of the topology of the network [3, 4]. I also proved this structure persists for curbing malware spread in computer networks, where the remedy (patches) can, unlike vaccines, spread immunity. I delved further into studying stealthy complex malware, like Stuxnet, that aimed to spread in order to reach a particular target while avoiding detection. I showed that the most damaging attack would be one that spread the most virulent variant of the malware first, at the risk of discovery [5, 6]. Surprisingly, this remains the most damaging attack even if the network implements various popular quarantine policies upon malware detection. In my thesis, I created an overarching taxonomy of heterogeneity for epidemics, and characterized the optimal control of epidemics in the presence of heterogeneity (Figure 2, [7]).

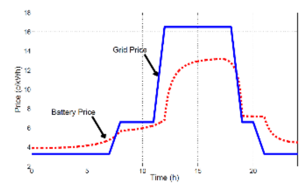


Figure 3. *Relative price of stored microgrid battery power over the span of a day*

Grid-scale batteries are a key enabling technology for the integration of unpredictable renewables into the electrical grid. I showed how the optimal use of electric batteries in a microgrid can be mapped into a problem of pricing battery power across time, and created a novel, principled way for obtaining the prices from price (using shadow prices), demand, and generation data [8] (figure 3). Our work is patent-pending [9].

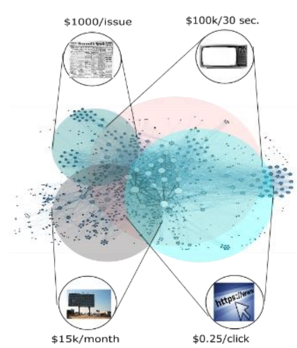


Figure 4. *Choosing advertising channels requires considering the reach of channels, their price, and the underlying social network*

Opinions are the raw material that shape purchasing decisions and voting intentions in a democratic society. In 2017, over $1 trillion will be spent on marketing globally [17], while $9.8 billion was spent on advertising in the 2016 US elections alone [18]. However, the effect of advertising over a channel is limited by its reach and the relationship of targeted individuals to that it. Furthermore, these marketing efforts are filtered through the social networks of individuals, and these secondary effects are increasingly key to marketing strategies (Figure 4). I showed how campaigns should optimally allocate their budget across time and the advertising channels at their disposal to maximize purchase decisions and votes: an optimal campaign should initially prioritize reach, and only focus on targeting likely voters/purchasers late on in the decision cycle, while taking care to use each channel in waves (i.e., cycling the use of channels) [10].

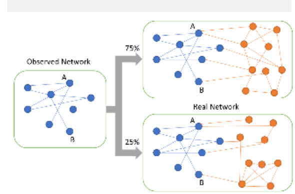


Figure 5. *The relative influence of A and B depends not just on the observed network, but on the unobserved network and the amount of uncertainty*

Many models of social influence are predicated on complete knowledge of a social network. In the real world, only parts of a social network are visible to decision-makers, possibly along with statistical knowledge of the rest of the network or its internal dynamics. I showed how limited network information can be used in scalable algorithms to choose optimal seed sets to create cascades [11-13] (Figure

5), as well as how the stability of a social group can be quantified, even without knowledge of the prevalent group norms [14-15]. In particular, I proved that possible realizations of uncertain networks should be sampled in direct proportion to their likelihood of correctness to find influence maximizing sets under realistic scenarios [13], and that fairness norms can make a group less stable [14].

Future Research Directions

In the next 5 years, I plan to investigate 3 research thrusts that will propel my long-term research goal: understanding the role of time, agent autonomy, and model uncertainty in designing effective interventions.

Thrust 1 - *Tractable dynamic centrality, influence, and vulnerability metrics for complex systems*

An important insight of complex systems models has been that limited outside action can be amplified by a system's internal dynamics to cause an outsize effect on its behavior. For example, much work has gone into optimal selection of individuals to immunize to stop the spread of an epidemic, or optimal targeting of individuals with public health interventions to spread beneficial behaviors in society.

The bulk of research has focused on defining *ad hoc* centralities and constructing heuristic algorithms to find the best targeting action to take, among many, at a specific point in time. This approach is sub-optimal in two ways: 1- it frequently substitutes notions of centrality to the structure of a graph for importance in terms of influencing decision-making, an assumption that has failed miserably in practice [19], 2- it artificially assumes that one is constrained to interact with the network at a specific point in time, whereas one can interact with real-world systems at varying times, and can indeed plan contingent courses of action that rely upon coordinated efforts across time. This is especially the case in non-linear processes, such as epidemics, where the result of an intervention can depend very critically on the timing of actions.

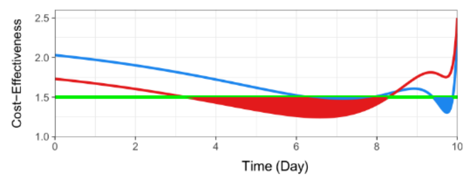


Figure 6. *Dynamic cost-effectiveness (centrality) metric derived to quantify the relative usefulness of a channel over time. The green line represents a greedy algorithm that only uses the channel when the metric is above the line.*

The introduction of time into decision-making further complicates computational processes, and can make even tractable problems intractable through an explosion of the decision-space. Thus, there is a need for principled ways of understanding structures of optimal decisions in complex networks across time that limits this decision-space explosion and identifies critical targets. It is also necessary to adapt notions of influence and centrality to these more realistic dynamic settings to aid practical decision-making.

I plan to investigate centrality metrics derived from dynamic notions of duality (i.e., shadow-prices) resulting from optimal control formulations of influence problems (see Figure 6, [10]). These centralities will have a direct mapping to influence (e.g., as opposed to degree centrality) and can vary across time. Furthermore, their direct relationship to the optimal decision-making structure means that they can be used directly to make resource allocation decisions. While ideas presented in [10] rely upon knowledge of global network structure, constructing approximations dependent on local data will be a major step in this thrust. In addition, many studies have shown that a multiplicity of networks (e.g., online social networks, friendship networks) can affect spreading phenomena simultaneously, so I plan to investigate generalizations of these centralities to multi-layer networks. Finally, the direct mapping of the centralities to the models of resource allocation means that they can be adapted to varying goals, and can be validated in field studies and online experiments, the long-term goal of this thrust.

Thrust 2- *Analysis framework for incentive-driven spreading of social phenomena*

While mechanistic epidemic models are adequate to explain the spread of some pathogens and behaviors, they perform less well in describing spreading processes that are due to complex human decisions. While simple economic models have been created to show how cascades can form and fads can be created [20, 21], the decision-making mechanisms of individuals have to be simplified beyond recognition to obtain tractable, though surprising, results. The theories of network games and

Figure 7. *Modeling social group decisions requires understanding psychological, inter-personal, and networked phenomena.*

evolutionary games offer more promising approaches to understanding the spread of behaviors in real-world decision-makers [22, 23], by focusing on the externalities of actions by networked individuals, and their effect on the spread of choices the learning of successful strategies in a population, leading to a mapping between these spreads and properties of graph spectra.

Much work has focused on simple models of rationality in such networked settings, an assumption whose relevance to real-world outcomes has increasingly been questioned, e.g., by the behavioral economics tradition. In my previous work, I have investigated social comparison and social norms [14-15], and emotional reasoning [16] and their effect on social choices and behaviors. Aggregating these effects, that manifest at differing scales (Figure 7) requires the creation of more complex network games to model, for example, the spread of cheating behavior within a company.

I plan to use the methodology of complex network games to study the spread of behaviors among complex decision-makers, incorporating biases relevant to the context (from literature in sociology and psychology), and to investigate the effects of network structure on the spread of behaviors under these scenarios. Furthermore, I will investigate the design of incentives and interventions to help spread beneficial actions. Of particular interest is the case where both the network and the incentives can be designed or altered simultaneously to optimize outcomes, a trade-off that, despite its complexity, has been investigated in detail for simple epidemics [26]. However, in a world with a proliferation of data-sources and experimentation platforms, complicated theory based on many "reasonable" assumptions is not enough anymore; therefore, I intend to validate my models of decision-making, as well as the usefulness of my interventions, through simple experiments on real subjects, as enabled through platforms such as Breadboard [27].

Thrust 3 – *Analysis of trade-off between robustness, learning, and optimality in influence processes*

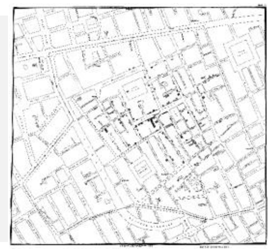
Most insights on the effect of networks and targeted interventions in networked systems depend on a complete characterization of network structure, assuming what is observed is either the whole existing network, or is a representative sample (Figure 8). However, what is not known can affect decision-making just as much as, if not more so, than what is known. Interactions between the known network and the unknown network can complicate decision-making, rendering many efficient algorithms useless in practical settings. Furthermore, systematic biases in the way information is gathered and represented is a significant factor in the decision-making process that is often neglected.

Figure 8. *Integrating methods of reasoning about unobserved network phenomena and integrating learning into decision-making is key to practical decision-making*

Surprisingly, the effects of information limitations in such systems on decision-making have been less studied. What work has been done focuses primarily on the robust maximization paradigm, which optimizes against a worst-case realization of uncertainty. This, however, can lead to glaringly wrong predictions of the evolution of networked processes (such as the initial estimates on the spread of Ebola in West Africa, which were wrong by a factor of 65! [27]), and therefore a very suboptimal allocation of resources. On the other hand, reasoning based on *a priori* expectations is not the answer, as guarantees about the mean are rarely enough evidence to convince policymakers. Finally, with the increasing amounts of data and processing power available to decision-makers, it is necessary for decision-makers to offer decision-making algorithms and heuristics that can adapt and learn from incoming data with more diverse sets of guarantees.

I aim to create a framework to span the continuum between robust and expectation-maximizing optimization for complex network contexts, such as epidemics, with objectives designed in conjunction with subject matter experts. In particular, I am interested in control approaches that focus on optimizing the trajectory of a spreading process while at the same time minimizing the uncertainty cone of possible realizations resulting from the interventions, using approaches from dynamical systems and stochastic processes. The ultimate goal of this thrust is to incorporate incoming data into a simultaneous modeling and decision-making ecosystem using the reinforcement learning framework, allowing decision-makers to tune the trade-off between robustness and optimality according to their domain knowledge and policy goals, with the certainty that the model will itself adapt its model and decisions to incoming data.

Figure 9. *Historic example: The epidemiologist John Snow curbed a cholera epidemic in 1854 by identifying its source, a water-pump in Soho, London, by plotting deaths on a dot map. He exploited geographic information and reduced uncertainty through interviews that showed drinking at the pump was the common denominator among the deceased. While we have more data and better decision-making tools, the fundamentally similar challenge of* ***deciding when and where to act to maximize societal benefits with possibly limited information*** *are the subjects of my study.*



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