**Saving Data Analysis:** **Epistemic Friction and Progress in Neuroimaging Research**

*Abstract*

Data must be manipulated for their evidential import to be assessed. However, data analysis is regarded as a source of inferential errors by scientists and critics of neuroscience alike. In this chapter I argue that of data analysis is epistemically challenged in part because data are causally separated from the events that they are intended to provide evidence for claims about. Experimental manipulations place researchers in epistemically advantageous positions by making contact with the objects and phenomena of interest. Data manipulations, on the other hand, are applied to material objects that are not in causal contact with the events they are used to learn about. I then propose that some of the inferential liabilities that go along with data manipulation are partly overcome through the occurrence of epistemic friction. I consider two forthcoming contributions to network neuroscience to illustrate the benefits, and risks, of the data analyst’s reliance on epistemic friction.

1. **Introduction**

Debates about progress in the sciences of the mind and brain tend to be organized around technological innovations that have changed the epistemic landscape of neuroscience. This includes debates about the promise and prospects of neuroimaging technologies (Roskies 2010a; Klein 2010), the empirical potential of brain computer interfaces and other neural augmentations (Datteri 2009; Chirimuuta 2013), and the revolutionary status of optogenetic interventions (Bickle 2016; Sullivan 2018). These technologies are rightly recognized as significant. Afterall, they push neuroscience forward by providing researchers with the ability to create new kinds of data, to perform new interventions, and to test new hypotheses and theories. Attending primarily to measurement technologies, however, has led to philosophers to overlook more common but less obviously impactful innovations in research methods. The particular innovations I have in mind are the development of tools and techniques for handling, manipulating, and analyzing data.

The importance of data analysis is hard to overstate. Consider functional magnetic resonance imaging (fMRI) research. In its early days, critics of the technology focused their attention on the subtractive method that was used to analyze fMRI data. This line of critique explicitly drew a continuity between the scientific utility of a measurement tool and the methods used to analyze data it produces (e.g., van Orden and Paap 1997; Uttal 2001). While historically used to pair cognitive processes with discrete parts of the brain, now neuroimaging technologies like fMRI are, for example, used to identify the information represented in patterns of brain activity and to articulate the relationship between network dynamics and cognitive capacities. The technology itself improved in this time, most notably with the recent approval of more powerful 7-Tesla scanners for human use. However, higher resolution measurements were not sufficient to lead neuroscientists to treat fMRI data as evidence for claims about, for instance, the representational content of brain activity. It was the development of multi-voxel pattern analysis methods, which preceded the human use of 7T scanners, that catalyzed efforts to search for neural representations with fMRI data (Haxby 2012; Horikawa and Kamitani 2017). Similarly, research into brain networks has been supported by the translation of network theory methods and principles into the context of neuroimaging research (Pessoa 2014; Thompson, Brantefors, and Fransson 2017).

Another reason for philosophers of neuroscience to put more effort into identifying epistemically relevant aspects of data analysis is that data sharing has made it possible for scientists to have productive careers that do not involve the design of experiments or collection of data. Data sharing mandates and initiatives are motivated by the recognition that data are important for advancing our understanding of the world, and that they provide greater benefits to science and society when shared and reused (Leonelli 2016). Through data repositories such as OpenNeuro (Poldrack and Gorgolewski 2015) and large scale data acquisition initiatives such as the Human Connectome Project (Van Essen et al 2012), the accessibility of imaging data has created an environment in which data are being analyzed by scientists who played no role in acquiring them. Accounting for how this division of cognitive labor and skills is influencing the trajectory of the neurosciences requires explicating the epistemic characteristics of data analysis.

The primary aim of this chapter is to advocate for data analysis by explaining how, in light of inferential risks inherent to the practice of data manipulation, data analysis protocols could possibly advance knowledge. To do this I propose that epistemic friction occurring when an analyst interacts with data helps to overcome some of the epistemic obstacles associated with data manipulation.

I proceed as follows: In the next section I provide an overview of neuroimaging experiments. Along the way I outline epistemic challenges that are associated with data analysis. In section 3 I argue that data analysis techniques assist researchers in making judgements about the evidential significance of data. In section 4, I locate the epistemic obstacles associated with data analysis in the separation of data from the causal forces that played a role in its production. Then, I draw on Jose Medina’s epistemology of resistance (2012) to ground the search for ‘epistemically frictional forces’ that may be operative in the context of data analysis and interpretation. In section 5 I examine two forthcoming contributions to methods in network neuroscience. I identify frictional interactions that occurred during the development, testing and validation of these contributions. The first is a critique of the way the participation coefficient, a derivable network measure, is applied in temporal network analyses (Thompson et al 2019a). The second is a new method for deriving network-level communities from time-series data (Thompson et al 2019b).[[1]](#footnote-1) Finally, I conclude with a forward-looking reflection on epistemic friction.

**2.     Epistemic Gaps in Neuroimaging Research**

Functional magnetic resonance imaging (fMRI) is the most widely used measurement technology in human neuroscience. It is popular because it is non-invasive and can be used to investigate the relationship between brain activity and cognition in healthy human subjects. Broadly speaking, MRI scans measure magnetic properties of chemicals in small pieces of the brain called volumetric pixels, or voxels. To do this, the scanner creates a uniform magnetic field within its bore. Then, radio pulses with specific frequencies are sent into the bore at regular intervals. By leveraging the magnetic properties of different chemicals in the body, scanning protocols can be created that are able to detect the location of different tissues within the bore. For instance, fMRI scans measure the blood oxygenation level dependent (BOLD) signal by leveraging the magnetic properties of hydrogen atoms. As neurons (and other cells in the brain) become more active, they need more energy. This causes oxygenated blood to flow in greater volume to the area and provide the cells with oxygen. This creates a local change in the ratio of oxygenated to deoxygenated blood. This change is what the BOLD signal is sensitive to (see Huettel, Song, McCarthy 2008 for an introduction to resonance imaging).

Enthusiasm for fMRI is tempered by skepticism about the utility of the BOLD signal in the study of human cognition (e.g., van Orden and Paap 1997; Uttal 2001; Roskies 2010a; Aktunc 2014). Skeptics typically draw attention to two related challenges for fMRI research. The first is that neuroimaging technologies measure phenomena that are causally distant from the targets of research, such as the use of blood oxygenation to investigate neural activity. The second is that data manipulations, which seem to be used to overcome that distance, are themselves a source of inferential error.

The indirectness of measurements certainly presents investigators with a challenge, but it is not one that stops fMRI research from making progress. Afterall, measurements that are indirectly related to the targets of investigation are typical of neuroimaging. Diffusion tensor imaging (DTI) is another example. A DTI scan uses a dual echo protocol to ‘tag’ and ‘track’ the motion of water molecules. The first echo sends a magnetic pulse that adds spin to a subset of water molecules in the brain. Then, a second echo leverages the added spin factor to identify which of the tagged water molecules have remained stationary since the first echo. Information about water diffusion is not what researchers are interested in. Instead, it is used to infer the presence of long-distance neural projections in the brain. Long distance connections between neurons are made via axons sheathed in a fatty tissue called myelin. The inference from DTI scans to claims about bundles of axonal projections is based, in part, on the fact that it is easier for water to flow down the length of a myelinated axon than it is for the water to flow across the myelin (Assaf and Pasternak 2008).

Experimental design plays an important role in improving the epistemic circumstances of imaging research. For example, carefully designed and monitored tasks are used to ensure, as much as possible, that the cognitive and neural processes of interest are part of the nexus of causal factors that gave rise to the acquired data. Scientists interested in memory may have participants perform tasks in the scanner that require them to identify images as familiar or novel (Martin et al 2018), while researchers interested in our ability to exert control over our actions might have subject’s perform a variant of the stop signal task (Bissett and Logan 2011). Controlling the circumstances of data production and using indirect measures with known causal links to the targets of inference furnishes data with the potential to be used as evidence. However, even the best designed experiment in cognitive neuroscience doesn’t result in data that can be immediately situated as evidence against or in support of theory. The realization of data’s epistemic potential requires researchers to extract information relevant to their research questions from data. This is what data analysis is used to do, and why perceived flaws with analysis protocols are at the heart of most skeptical attacks on neuroimaging research (see Wright 2017 for a discussion).

Determining the extent to which information about a particular event or phenomena can be obtained from the available evidence is to evaluate what Currie calls the ‘epistemic retrievability’ of that event (2018). The more difficult it is to identify and exploit causal links between an event of interest and available data the lower its retrievability is (p. 125). Currie focuses on the historical sciences, drawing attention to challenges associated with linking ‘traces’ of the past, such as fossils, with the events from which such artifacts originate. The biggest challenging historical scientists face is that the causal factors responsible for the formation of a fossil, and the causal forces that acted on the specimen over the millions of years between its creation and the present, are not fully known. This is where explanations of and theories about the causal processes that lead to the formation of specific artifacts enter the picture. The richer and more sophisticated these theories are the better scientists are able to (a) identify causal links between the events of interest and data at hand, and (b) exploit those links to extract from information about those events from data. Using data to learn about the events involved in its production requires, at least to some degree, exploiting known and hypothesized causal links between events of interest and data.

The causal chain of events linking observations of blood oxygenation to underlying neural activity creates a dependency relationship between the intensity of the BOLD signal in a particular part of the brain and the intensity of the cellular activity that is a partial cause of the changes in local hemodynamics. This gives the BOLD signal the potential to be used as evidence for claims about neural activity.

What is known about the dependency relationship linking changes in neural activity to changes in the BOLD signal informs what can and cannot be inferred about neural activity from imaging data. For example, the  BOLD signal is known to show the same change in magnitude if neural activity increases or decreases, making it unable to “...easily differentiate between function-specific processing and neuromodulation, between bottom-up and top-down signals, and it may potentially confuse excitation with inhibition” (Logothetis, 2008, p. 877). Even though neural excitation may have been causally involved in an observed BOLD signal, that the BOLD signal is insensitive to the difference between excitation and inhibition renders it unable to provide evidence for claims about those kinds of fine-grained neural actions. In addition to placing limits on the claims that data can be used as evidence for, what is and is not known about the causal connections between the target of research and data at hand informs data are analyzed.

Data manipulations are used to exploit the known and hypothesized features of the relationship between the BOLD signal and underlying neural activity to bring fMRI experiments to bear as evidence on claims about cognitive and neural processes (Buckner 2003). To transformation the BOLD signal into patterns that reflect neural activity, a hemodynamic response function (HRF) is constructed. An HRF is a mathematical formula, or model, that relates observed changes in hemodynamics — the BOLD signal — to underlying metabolic activity associated with changes in neural activity. Decisions about the parameters and shape of the HRF are partly informed by the current state of knowledge about the causal relations linking the BOLD signal to neural activity (see Poldrack, Mumford, Nichols 2011 for an introduction to fMRI data analysis). The full causal story that links the BOLD signal to neural activity is not known, and sometimes known details are not relevant to a particular analysis. Additional considerations including the specific hypotheses under test, how conservative researchers want their analysis results to be, and the quality of the data that they are analyzing play a role in HRF modelling (i.e., Lindquist et al 2009).

Data analysis techniques, like modelling the HRF, are flexible and require researchers to make a substantial number of decisions to implement them. This flexibility is valuable because it allows analysis methods to be adapted to different experimental circumstances, allows models to be fit to different kinds of data, allows researchers to soften assumptions about the causal forces and entities of interest in the face of uncertainty about them, and enables exploratory research to be conducted efficiently. On the other hand, that there are many valid and defensible choices that can be made. It for this reason that analysis is regarded as a source of epistemic liabilities.

The rapid increase in the sophistication and variety of analysis methods available to researchers has prompted critical reflections on the negative impact of ‘analytic flexibility’, or the freedom to make choices during data analysis. As a matter of research pragmatics, researchers can’t apply every possible method and parameter setting to their data and report all findings. They must make choices about what methods to use, and when to stop analyzing their data and write up a paper. As the number of decisions researchers make in the course of analysis goes up the probability that they will find a data pattern that supports a given hypothesis also goes up (Carp 2012). This implies that increases in the degrees of freedom researchers have during analysis correspond with increases to the frequency of false positive findings appearing in the literature. This concern has been reinforced by recent work showing that using different software tools to conduct the same fMRI data analysis procedures produce significantly different results (Bowring, Maumet and Nichols 2018*;* see Taylor et al 2018 for a response).

The epistemic status of data analysis is further complicated by the line of attack often adopted by skeptics about neuroimaging. Uttal was concerned that positive results in neuroimaging may primarily rest on decisions made about signal thresholding (2001), van Orden and Paap famously critiqued the logic of subtractive analysis (1997), and more recently Ritchie, Kaplan and Klein have challenged assumptions implicit in common uses of pattern classification analysis (2017). Each of these critiques identifies an inferentially undermining assumption that goes hand in hand with a specific approach to data analysis.

Even optimists about the potential of neuroimaging research recognize that epistemic obstacles are integrated into the processes of data manipulation. Consider Roskies discussion of inferential distance in neuroimaging research (2010a). She characterizes the inferential distance between evidence and claims that it purports to be about as the number and certainty of the inferential steps one needs to take in order to move from evidence to claim. As the numbers of steps increase, or their relativity certainty decreases, the inference becomes less reliable. She argues that data manipulations increase inferential distance because of the assumptions that go along with choices made about which methods to use and how to implement them. As Roskies puts it, the problem is that “... the same raw data can produce different results depending on reasonable choices about data processing…” (2010a, p. 203).

Data patterns may not only fail to be sensitive to the causal factors they are used to make inferences about, but they may even falsely appear to be explanatorily relevant because of a difficult to detect sensitivity to decisions made during the analysis process. Put succinctly: there is no guarantee that a difference between data patterns corresponds with differences in the causal factors that played a role in creating the data. This leaves us with a philosophical puzzle: how can data analysis play an essential role in neuroimaging research without corrupting the quality of the resulting inferences?

In the next section I take the first step towards addressing this puzzle: examining the epistemic status of data patterns. I propose that their primary role is to assist in evaluating the evidential import of data.

**3.     The Status of Data Patterns**

The hemodynamic response function is an estimate of the neural activity underlying the observed BOLD signal. To create an HRF model from fMRI data is to transform it into data patterns – HRF parameter values – that correspond with the underlying neural activity. Thus, one possible explanation for the utility of data manipulations is that data analysis facilitates the use of data as evidence by transforming it into an approximation of the results of an ideal experiment. That is, the greater the similarity between the product of a data analysis procedure and what the data would have looked like had it been acquired in an ideal experiment, the more information it provides about the target of investigation. Philosophical treatments of data analysis that have this flavor can be found in Mayo’s error statistical philosophy (1995), Woodward’s account of data interpretation (2000), and McAllister’s treatment of data patterns as phenomena (1997).

If the epistemic significance of data patterns, which are the product of data analysis, are evaluated by their similarity to the hypothetical products of ideal experiments, then the sources of error outlined in the previous section are serious threats to the utility of neuroimaging research. Indeed, arguments that infer from epistemic problems with data analysis to skepticism about neuroimaging technology tend to rely on the assumption that the proper role of data manipulations is estimating the products of an ideal experiment (e.g., van Orden and Paap 1997; Aktunc 2014). Counter-arguments notice that, by looking at how data are evaluated in practice, this treatment of data analysis (Wright 2017), and style of criticism (Roskies 2010b), artificially restricts the epistemic roles that data and data analysis techniques can play. While some data manipulations are directed towards correcting for measurement error, or otherwise overcoming inferential distance by approximating the results of ideal experiments, this account does not generally capture what most analysis techniques do.

Modelling the HRF as well as many of the transformations automatically performed by an MRI scanner at the time of data acquisition (see Israel-Jost 2016) are examples of data transformations that find approximations of an ideal experiment within data. Techniques that eliminate artifacts arising from head motion and inhomogeneities in the scanner’s magnetic field, as well data manipulations that conform data from different subjects onto the same ‘brain template’ so that different brains can be compared, are done to emphasize the signal in data. Most of these data transformations are classified as pre-processing. The aim of automatic processing done by the scanner, modelling steps like constructing an HRF, and pre-processing in general is to transform data such that they become similar to what the data would have looked like had the experimental circumstances been more ideal. That is, had the subject not moved, had the scanner’s field been homogenous, were it the case that all brains have the same shape, or had it been possible to directly measure neural activity.

However, pre-processing data does not mark the end of data analysis. Most of the manipulations applied to data after preprocessing are not intended to create something that could have been obtained in an experimental setting or would even be created were ideal experiments possible. Instead, analysis methods are used to isolate patterns that are informative about the evidential import of data with respect to the targets of research. Patterns that are useful for assessing data’s evidential significance need not, and often do not correspond with what would be measured if researchers had better experimental tools. As an example, consider functional connectivity analysis.

To show that two regions of the brain are functionally connected is to show that the time course of neural activity in those regions covaries (Friston 1994, p. 57). A functional connectivity analysis involves three steps. In the first, the brain is divided into ‘parcels’, or regions of interest. Parcellating the brain involves drawing lines along the cortical surface that mark the boundary between two distinct regions, or parcels. Once the brain is parcellated, researchers compute an activation time-series for each parcel. One way to do so would be to take the BOLD signal in each voxel within a parcel and average them into a composite BOLD measurement for each parcel. The BOLD signal time series from each parcel can then be compared. Parcels that have strongly correlated average BOLD signals are said to be ‘functionally connected’ or ‘co-activated’.

Functional connectivity does not provide evidence of actual interactions occurring between the functionally connected parts of the brain. It only shows that activity in spatially distinct parts of the brain are, in some way, synchronized. To show that two parts of the brain are interacting is to identify an instance of effective connectivity (Friston 1994, p. 57). Effective connectivity is very difficult to establish in neuroimaging research. Under ideal measurement circumstances, such as if investigators had access to real-time information about when and how different parts of the brain were communicating with each other, there would be no need to calculate functional connectivity. Effective connectivity would be directly, or more directly, observable.

Not only does it not correspond with effective connectivity, which most cognitive neuroscientists would prefer to gather evidence about, but like many widely used analysis methods it is not fully understood what causal factors it is actually sensitive to. In particular, it is unclear what links there are, if any, between functional connectivity and the neural substrates that underlie the isolated data patterns (Horowitz 2003). Complicating the picture is suggestive evidence linking functional connectivity analysis to movement (van Dikj et al 2012), to noise in the global signal (Murphy and Fox 2017), and even research showing that subject’s with split brains in which no physical connection exists between their two hemispheres display strong correlations in activity between the segregated regions (Uddin et al 2008). These challenges to functional connectivity analyses have spurred investigations into the underspecified links between the isolated data patterns and neural functions. It has since been shown that functional connectivity is sensitive to some changes in neural responses (Schölvinck et al 2010; Chang et al 2013). Even with all of this uncertainty, it’s still a popular method for analyzing neuroimaging data.

The uncertainties inherent in data patterns, such as incomplete information about what causal factors an analysis method is sensitive to, is not a unique problem for interpreting the outputs of data analysis.  Uncertainties are present in all stages of research, and accounting for that is an important task for the philosopher of science. Feest, for instance, construes the process of research as “... one of simultaneously exploring a specific subject domain and of applying, revising, and extending existing concepts” (2017, p. 1168). She locates uncertainty in research by arguing that the explanatory targets of psychology, such as ‘working memory’ or ‘response inhibition’, are best understood as ‘epistemically blurry’ insofar as “... the very question that empirical data are even descriptively relevant to the object in question is part of the investigative project” (p. 1167). Data analysis techniques are also epistemically blurry as the significance of a derived data pattern is itself something that must be determined in the course of research. The realities of day to day neuroscientific research are that investigators are applying epistemically blurry tools to advance their understanding of epistemically blurry targets of research.

The interpretation of a data pattern is not only determined by facts about how that pattern was arrived at, but also by auxiliary facts about data acquisition, and by comparison with other patterns derived via other methods. For instance, confidence that functional connectivity analysis may be indicative of coordination in information processing or some form of communication between spatially separated parts of the brain is partly based on graph-theoretic analyses. The relevant results show that networks identified with functional connectivity have an efficient ‘small world topology’ that allows for the effective integration and processing of information across distinct sub-systems of a network (see van de Heuval and Hulshoff Pol 2010). Consistent with Roskies’ response to criticisms of subtraction, multiple data patterns, often derived from multiple data sets are used to triangulate on explanations (Roskies 2010b). Together, multiple patterns provide researchers with a more complete picture of the causal forces involved in data’s production than a single pattern could.

Data patterns are the result of processes that selectively distort data, exemplifying some features and suppressing others. Theses transformations can introduce assumptions, suppress information relevant for evaluating the claims of interest, and may not even be the result of reliable processes since analysis outcomes can depend significantly on decisions made during their implementation (see Wright 2018). While the results of functional connectivity analysis may be epistemically blurry, clarity is not established prior to the application of the method, but instead is achieved as a consequence of its use. Interpretations are challenged and the analysis method itself is refined in subsequent empirical research. The epistemic drawbacks of analysis methods that stem from the uncertainties inherent in their application are, at least to some degree, addressed over time through community-level interactions with patterns the method isolates.

Like manipulations of experimental systems, data analysis involves intervening on an object of interest with the aim of revealing features that are meaningful to the analyst (Boem and Ratti 2016). At the same time, decisions involved in the selection and implementation of a data manipulation provide an opportunity for biases, implicit assumptions, and other source of inferential error to enter into the research process. In the next section I argue that data manipulations have inferior epistemic status when compared to experimental manipulations because of the separation between data and the causal factors that created them. Thus, the problem with data analysis isn’t that it’s flexible, it’s that the manipulations are not appropriately constrained by the causal factors of interest. I then propose that data analysis may be better off than it appears if other epistemically frictional forces are at work when analysts are interpreting data.

**4.     Introducing Epistemic Friction**

Controlled experimental manipulations are effective tools for confirming hypotheses and theories (Currie and Levy forthcoming). Data manipulations — as discussed at length above — are constitutive of the error-prone process of data analysis. The differences between the targets of these manipulations forms the basis for differences in their epistemic status. Experimental manipulations alter the circumstances of data production, while data manipulations alter data.

The causal proximity of the targets of experimental interventions to the events they are used to learn about is appealed to in arguments that experiments have epistemic priority over computer simulations (Guala 2002; Roush 2018). It is this material correspondence between the objects and the targets of investigation that is often recognized as “... responsible for experiments’ advantage over simulations in terms of inferential power” (Parke 2014, p. 519). Currie and Levy expand on this view, arguing that control and correspondence work together to grant experiments their confirmatory power. Control is important because it provides insight into the materials under investigation (forthcoming,p. 5). On their view, the correspondence between the objects manipulated and the target of inference does not have to be material. Instead, the manipulated objects just need to be a representative member of a broader class by virtue of “… sharing focal properties with the target” (p. 7). The sharing of focal properties, they argue, is what enables researchers to generalize what is learned about the targets of investigation in the lab to similar phenomena that occur under less controlled circumstances.

Data manipulations are applied to the products of experimental manipulations. If data manipulations are epistemically inferior, then something beneficial must be lost in the transition from experimentation to data interpretation. Morgan’s distinction between surprising and confounding results is useful here (2005). Surprising observations are unexpected. Confounding observations are unexplainable with the theoretical and conceptual resources available to investigators, and so provoke further inquiry.

Unexpected experimental observations can be confounding because explaining them may require discovering new causal aspects of the experiment. By confounding researchers, experiments lead to learning more about the circumstances of the experiment. Unexpected data patterns typically lead to learning more about the data manipulation that produced them because the unexpected results can often be explained by appealing to the decisions that went into creating those patterns.

When experimental manipulations are found to be flawed, such as when an experiment fails to replicate or when observations are incongruent with theoretical predictions, divergent results can often be explained by appealing to the circumstances of data production. This is one reason offered for publishing and investigating replication failures. Failures, if explanations for them are sought, can lead to discoveries (Crandall and Sherman 2015, p. 98). Discovering flaws in an experimental manipulation often reveal something about the causal factors involved in producing the data or the backgrounding theory that was used to devise an experiment. Alternatively, in domains like psychology, where individuating the phenomena of interest is a primary task of research, incongruent experimental findings are useful for exploring the boundaries of conceptual and theoretical constructs (Feest *forthcoming*).

Differences between data patterns, on the other hand, can be explained by a variety of factors that have nothing to do with the circumstances of data production, such as method selection, model parameter choices, programming errors, and oversensitivity to noise in data. Discovering that a manipulation of fMRI data is sensitive to head motion advances knowledge about the method itself but does not provide additional insight into the neural or cognitive phenomena it is being used to study.

Experimental manipulations are valued for their potential to confirm hypotheses and uncover new facts about the world. They are able to play both of these roles because experimental interventions change objects of interest or change the conditions under which those objects are observed. That is, good experimental manipulations interfere with causal processes in a detectable way (Woodward 2003). Data manipulations, on the other hand, interfere with the data produced by an experiment. Data are, once produced, separated from the causal forces that generated them. This causal separation underwrites the epistemic inferiority of data manipulations. When researchers experimentally intervene on a system there is, to speak metaphorically, friction created between the target of investigation and the means of measurement.

Friction is important for knowledge production in general. Sher argues that epistemic friction places constraints on how we obtain and formulate knowledge claims, which helps to avoid developing ‘idly hovering theories’ that do not accurately describe the world (2010). She recognizes that friction can arise from a variety of places, including our standards for theorizing, rational or pragmatic desiderata, and from physical constraints set by the world itself.

Sher’s wide view of friction provides some hope for the data analyst. While an analyst cannot rely on data manipulations coming into contact with neural and cognitive causes for epistemic friction, there may be other resistive forces present during the process of data interpretation that can provide some epistemic assurances. If this is the case, then concerns about the efficacy of data analysis could be addressed by fine tuning research practices to ensure that an appropriately corrective friction is present.

Concerns about the epistemic obstacles inherent in data analysis such as analytic flexibility are not directed at community level practices. They are concerns about how data analysis is implemented and executed by individuals. Thus, relevant sources of resistance that might improve the circumstances of data analysis are those that affect scientists as they make decisions about parameters, models, software and ultimately determine the significance of the data patterns they discover. Medina’s epistemology of resistance draws attention to the epistemic forces that derive from the “… social positionality and rationality of embodied agents…” (2012, p. 27). As a result, Medina’s work provides a useful lens for examining how an agent’s beliefs encounter resistance through interaction with both externally and internally originating beliefs and perspectives.

Epistemic resistance, or friction, is valuable because it cultivates epistemic virtues of openness, curiosity/diligence, and humility (Medina 2012, chapter 1). An agent exhibits openness when they are attentive to and take seriously the perspectives of others, curiosity/diligence when they meet epistemic challenges head on and actively seek new information, and humility when they recognize that their own knowledge has gaps and limitations. When an agent encounters too much or too little friction epistemic vices such as closed mindedness, laziness, and overconfidence are cultivated instead. It is noteworthy that these virtues involve engaging with beliefs and points of view that are external to the agent in question. The vices push agents to disregard, via overconfident, or avoid through laziness, external sources that conflict with their beliefs. The epistemic value of diversity is a common feature of socio-epistemic accounts of progress in science (e.g., Borgerson 2011; Longino 2012), and is visible in frictional interactions at the community-level.

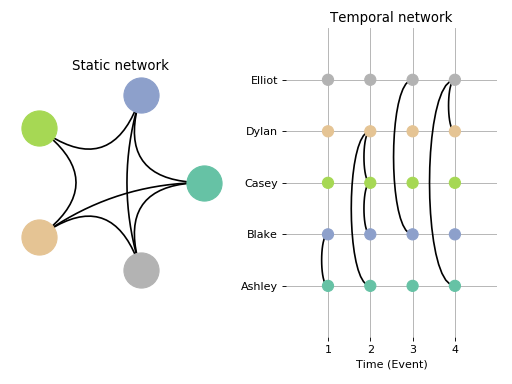
Debates about the efficacy of a method like functional connectivity advance knowledge because they involve different researchers with different points of view. Criticisms of functional connectivity cast doubt on its capacity to provide evidence of communication between regions. This lead to investigations into the causal dependencies between neural actions and functional connectivity. The participants in this debate have different stakes and interests in functional connectivity, and so are able to productively resist each other’s points of view. This suggests that ameliorating the obstacles inherent to data analysis may require conflicts with the analyst’s internal beliefs, desires, or expectations to arise during the interpretation of data.

In the next section I elaborate upon this notion of epistemic friction by considering examples of friction that arise during analysis method development and critique.

**5. Friction in Network Neuroscience**

The most recent trend in network neuroscience has been to use tools concurrently developed in temporal network theory (Holme & Saramärki 2012) to examine how brain networks change from moment to moment (Lurie et al *pre-print*).

A network consists of nodes related to one another via edges. Creating a network requires dividing data into nodes, determining which nodes should be connected by edges, and quantifying the strength of each connection. Nodes are the members of a network, such as people or organizations in a social network. Edges represent relationships between nodes. In a friendship network, for example, edges may connect nodes if the people they represent are friends (Fig 1).



***Fig X.1*** *Static and Temporal Networks****Caption:*** *The left image shows a static social network. Each circle is a node that represents an individual, and each black line is an edge connecting two individuals. The right image shows a temporal network with the same nodes. The horizontal lines correspond to the nodes of the network and each vertical slice is a temporal snapshot. Along the vertical slices black lines indicate which nodes are connected during that snapshot. At time 1 only Blake and Ashley are connected, and at time 3 only Blake and Elliot are. The temporal network representations are also ordered in time, and so the network shown at time 1 occurred prior to the network shown at time 4. Source:* [*https://teneto.readthedocs.io*](https://teneto.readthedocs.io)

A temporal network often consists of a collection of sequentially ordered static networks. The static networks that make up a temporal network are snapshots. Since snapshots are static researchers have to make all of the decisions and perform all of the transformations necessary to conduct static network analyses. This includes deciding how to divide the brain into nodes such as by anatomically individuating regions, and providing criteria that define which nodes are connected by edges and the strength of those connections such as by using functional connectivity analysis. In addition to this, to create a temporal series of networks researchers must also decide how to individuate snapshots in time which involves choosing or devising an analytic procedure that extracts a ‘moment’ or window of time from the data over which to calculate a static network.

Once a network representation of data has been created its properties and features can be derived. With a static network a researcher can identify properties of specific nodes, such as their participation coefficient, or examine how nodes within the network group together into communities. Communities are collections of nodes that have stronger connections with each other than they do with nodes outside the community. Identifying community structure requires assigning a community identity to each node within a network. With a temporal network a researcher can further investigate how properties of nodes and the structure of the network change from snapshot to snapshot.

In the rest of this section I consider two forthcoming contributions to network neuroscience methods. The first is a critique of how the participation coefficient, a static network measure, is commonly used in temporal network analyses (Thompson et al *pre-print a*). This case shows how the absence of epistemic friction can lead to the misuse of analysis methods. The second case examines the development of the temporal community by trajectory clustering (TCTC) method for inferring community structure directly from time series data (Thompson et al *pre-print b*). I use this case to highlight how anticipating and reducing epistemic friction facilitates the development and uptake of new methods. I will highlight other instances of epistemic friction along the way.

**5.1 Participation in Time: Looking for Friction**

Identifying parts of a network that may be particularly sensitive to damage, or otherwise play an important role in facilitating communication between and the coordination of disparate parts of the brain is a valuable use of network analyses. A node that has these properties is classified as a hub. One way to identify a hub is to calculate the ‘degree’ of a node, which, conceptually, involves counting how many edges it has. While its degree gives a sense of how strongly connected a node is, it doesn’t account for the diversity of those connections. Power and colleagues noticed this and showed that node degree is more impacted by the overall size of the network than it is the communicative role a node plays within that network (Power et al 2013). They proposed that the participation coefficient should be used instead of node degree to identify hubs, in part because it is sensitive to the diversity of the connections that a node has (see also van de Heuval and Sporns 2013). This work establishes the participation coefficient as a good measure for identifying hubs and estimating the degree to which a network is integrated.

The participation coefficient is one property of nodes within a network that has proven to be particularly insightful for cognitive neuroscientists. The participation coefficient of a node can be calculated if the network has been subdivided into communities. The participation of a node is measured by contrasting how many of its edges connect it to nodes that are part of communities outside of its own (Guiàmerà and Nunes Amaral 2005). A node with a zero-participation coefficient has no edges that connect to nodes outside of its community. That is to say, it is only interacting with nodes that are within its own community. A node with a participation coefficient of 1 has at least one edge connecting to every other community in the network.

If the participation coefficient provides some evidence that a given node or region is a hub, then evaluating how participation coefficients change over time could help zero in on more specific functional attributions for regions of the brain. Indeed, several influential articles have used the participation coefficient in temporal networks to address questions about the role of network-level integration and segregation in task performance (e.g. Betzel et al 2015; Shine et al 2016; Pedersen et al 2017; Fukushima et al 2018).

Consider Shine and colleagues work examining how the dynamics of network-level activity relates to the successful performance of cognitive tasks (2016). The broad theoretical aim of their investigation is to provide evidence that global network integration is important for effective cognitive performance (p. 544). A network is more integrated when there are more connections between its parts and segregated when parts of the network are relatively isolated from one another. To estimate how network integration changes over time they needed a network measure that reflects the strength of between region connectivity. Citing the work of Power and colleagues as justification for the decision, they choose to use the participation coefficient for this. This decision is an example of the community acceptance of a measure reducing friction during analysis.

This is not to say that the decision to use the participation coefficient in this way was made lightly by Shine and colleagues. I am merely noting that the existence of evidence than an analysis method tracks properties of interest, such as results showing that node participation corresponds with the hub-status of the node, helps researchers to choose a method or parameter value more rapidly than if there were no empirical results to appeal to or consider.

Shine and colleagues compared how the participation coefficients of nodes changed over time and found that they tended to increase during tasks. From this they inferred that “... that the brain transitions into a state of higher global integration in order to meet extrinsic task demands” (p. 546). A forthcoming critique of the participation coefficient as used in temporal network analysis raises a subtle problem for this interpretation (Thompson et al *preprint a*).

To conclude from a change in participation coefficient between network snapshots that the network is more integrated it must be assumed that differences in participation between network snapshots are comparable. However, different network snapshots are typically allowed to have different community structure. That is, from one snapshot to the next the overall number and distribution of communities can change. This is a problem because the participation coefficient of a node depends on the community identity of it and its neighbors. In other words, when the community structure of a network is allowed to vary over time, then the participation coefficient of a node becomes sensitive to its own connectivity and to the overall community structure of the network. In the paper critical of how participation is measured in temporal networks (Thompson et al *preprint a*), the authors estimate, using fMRI data, that if community structure was held fixed across snapshots, then 66% of nodes change their participation in the opposite direction compared to when community structure is allowed to vary. The problem, put simply, is that the participation coefficient applied to a temporal network is sensitive to more properties of the data than its interpretation as evidence of network integration allows.

The participation coefficient is a well-established measure of network integration. In fact, it is one of the more well established and widely used analysis techniques amongst those that were used in the paper summarized above (Shine et al 2016). It is not surprising that comparisons of participation coefficients through time have not yet been explicitly tested to verify that the measure was sensitive to only between community connectivity. There is no salient, *a priori* reason to doubt the efficacy of the participation coefficient in a network analysis context, especially given that there is consensus amongst network neuroscientists that the participation coefficient is a good indicator of network integration. What is more surprising is that it was closely examined at all.

While identifying a low friction decision can explain how the participation coefficient has been systematically misapplied in temporal analyses, a moment of high epistemic friction was the occasion for this critique being conceived.[[2]](#footnote-2)

In 2017 an article outlining temporal extensions for measures from static network theory for fMRI researchers was published by the lead author of the participation coefficient critique (Thompson, Brantefors, Fransson). Two of the measures presented in that paper were criticized during the author’s dissertation defense for being classified as ‘temporal’ while failing to leverage temporal information in the data. There was nothing inherently wrong with the measures, only that they were mislabeled as ‘temporal’, and that this mislabeling may lead to misuse of the measures. The problem with calling them ‘temporal’ is that events are ordered in time, and neither of the two measures criticized are sensitive to that ordering.

When the network neuroscience community began to use the participation coefficient as part of temporal network analysis, the researcher decided to add the ability to calculate the participation coefficient into a software package they created and maintain. They had, due to that comment made during their defense, formed a habit of checking measures and algorithms more carefully before incorporating them into the package or using them in their research. In checking into the participation coefficient, they noticed that differences between temporal networks might make differences in participation difficult to interpret. The end result of this investigation was the critique partly summarized above, and the creation of a method for calculating node participation that is less sensitive to changes in community structure over time (Thompson et al *pre-print a*).

Friction appears throughout this discussion. Low epistemic friction during analysis decisions partially explains why a method was misapplied, and higher friction in a different circumstance led to research revealing those interpretive errors. The critique itself will, if it has an impact once it is published, become a source of friction for researchers interested in node participation in temporal networks.

While reducing epistemic friction by appealing to literature exploring the utility of the participation coefficient contributed to the misuse of the method, pursuing the goal of reducing friction can, in different circumstances, be productive. This is the focus of the next case.

**5.2. Dynamic Communities: Reducing Friction in Practice**

Each discrete analysis step distorts data. The more steps there are in an analysis procedure, the more opportunities there are for noise to compound and interfere with the final results. Creating temporal network representations from BOLD signal data and assigning a community identity to each node has three steps. The first is to define the nodes of the network, such as by dividing the brain into anatomically differentiated regions. Then, edges between those nodes need to be determined. The BOLD signal is time series data and is what might be called ‘node collected’ because it is a continuous measure of changes in voxels, and groups of voxels correspond with nodes in brain networks. The alternative is ‘edge collected’ data, which describes a situation in which measurements directly pertain to the edges that exist between nodes. Counting interactions between friends in a social network is edge-collected data since the observations are about the connections between friends. When dealing with node collected data researchers have to use data manipulations like functional connectivity analysis to infer edges and their weights. Once edges are inferred, the third step is to assign the nodes to communities.

Temporal Communities through Trajectory Clustering (TCTC) is a new method for identifying how community structure changes in time that performs the last two steps of this process in a single transformation (Thompson et al *pre-print* b).TCTC groups nodes together into communities when their corresponding time series’ fall within the same trajectory. For a group of nodes to be part of the considered part of the same trajectory the correlations between their BOLD signals must meet four criteria set which correspond with the algorithm’s parameters. Two parameters, the tolerance rule and distance rule, control how much error is allowed. The size-rule determines the smallest community size, and the time rule determines how long a community-like arrangement of nodes has to be in synchrony to count as a community.

As described, it seems like TCTC is poised to make the epistemic situation of network neuroscience worse.[[3]](#footnote-3) Afterall, while the method may eliminate a step from the analysis process and so eliminate a source of error, there are four parameters that researchers have to specify in order to apply TCTC. This has the potential to increase the number of decisions researchers have to make during analysis. Furthermore, TCTC is not a wholly new method, but an alternative approach for performing analyses that network researchers already have protocols for. Creating it increases analytic flexibility as it is another method a researcher may choose to use.

If this method is to improve the epistemic situation of network neuroscience then it must be shown that the it has advantages over existing methods, and it needs to offer some epistemic benefits to compensate for worsening the problems that follow from analytic flexibility. Epistemic friction provides useful handles for evaluating the epistemic potential of new methods like TCTC. Method development can be framed as a process of anticipating and reducing epistemic resistance. Furthermore, one of the advantages TCTC has over a competitor method is that it can reduce a particular source of epistemic friction in analysis. I consider each of these in turn.

TCTC is designed to identify temporal dynamics in community structure. If the results of TCTC are averaged over time it should produce patterns similar to those generated by static community detection methods. To show that TCTC produces minimally reliable patterns it was applied to time-averaged open-access neuroimaging data. The analysis recovered time-averaged differences between sessions of resting state scans that were expected to be found in that data. Furthermore, the community structure differed when different tasks were compared. This shows that TCTC produces the expected when it is used to perform a time-averaged network analysis of an openly accessible fMRI dataset. A dataset that has been analyzed in hundreds, if not thousands, of studies. That is, TCTC produced results that are consistent with the currently accepted findings within the field.

This kind of demonstration provides a baseline level of confidence for a new method. Philosophers of science have identified similar bootstrapping practices in the development of new measurement technologies (Hacking 1981; Bechtel and Stufflebeam 1997), and so it is not surprising to find it playing a role in the development of new analysis methods. While it provides some confidence in the method’s reliability, it is not itself sufficient to show that the method has epistemic advantages over alternatives. Afterall, the primary use for TCTC is to reveal temporal dynamics in community structure. Applying it to time-averaged data will not show that it can do this.

Recall that data patterns are informative about events underlying data to the degree that they are sensitive to causal dependencies that connect those events to the data they are derived from. Showing that a pattern in fMRI data is sensitive in this way can be done directly by conducting a multimodal study, such as using direct neural recordings in conjunction with fMRI. This is not common, especially for a new method, as it requires having access to appropriate materials and measurement technologies.

Another way to evaluate the sensitivity of an analysis method is through simulation. In a simulation data are fabricated with known internal structure or ‘ground truth’. The method is applied to the fabricated data and ideally recovers the structure that was placed there. In the original draft of the TCTC paper simulations were not included in part because they do not accurately correspond with the epistemic circumstances of research. In a simulation the ground truth is known, while in most circumstances of research it is unknown. On one hand, simulating analyses can be useful for determining what kinds of patterns a method is sensitive to. On the other, it is difficult to generalize from successful simulation results to actual experimental conditions because of the lack of correspondence between the epistemic stances researchers have in each context. However, the first round of reviewers requested simulations and so they have since been included in the paper. In this case, the need to reduce friction between prospective users and the method outweighed the desire to avoid reducing friction in hypothetical scenarios of method misuse.

The primary case made for TCTC’s results being informative and offering an advantage over currently used community detection methods is an argument that TCTC has less inherent friction than alternatives. The criteria TCTC uses for community detection, by design, refers to low level features of the network. To illustrate how this is an argument for pattern interpretability, consider the temporal extension of the Louvain algorithm for community detection, which is an alternative to TCTC (Mucha et al 2010). This method has two parameters. The resolution parameter determines how communities are identified, and the coupling parameter determines how adjacent snapshots influence one another. When setting the optimization parameter for Louvain community clustering researchers are deciding how strong the overall network modularity should be (Meunier et al 2009). The coupling parameter, on the other hand, does not have a concrete interpretation. It tells the algorithm how to use information from temporally nearby network snapshots in the determination of communities.

TCTCs parameters are grounded on facts about the relationships between the nodes themselves, not a meta-property of the communities or network such as modularity, or an abstract property such as temporal coupling. The size and time rules, for example, are parameters that explicitly place limits on how small a community can be and how long a group of nodes need to be coordinated to count as a community. Additionally, because the parameters refer to low level properties of the network, if the investigators have a sufficiently large collection of data to do so robustly, a machine-learning inspired training protocol can be used to determine the optimal settings for those parameters empirically.

Revisiting the concerns raised above about analytic flexibility, TCTC, in addition to eliminating some sources of error by skipping the edge determination step and all of the parameter decisions that might go into that, offers researchers parameters that can be computationally optimized and concretely interpreted. While, from one point of view, these are additional degrees of freedom, they also, by being computationally optimized and directly interpretable, make it easier for researchers to reduce friction with the method when applying it. In a way this means that TCTC has lower epistemic friction for analysts than the Louvain algorithm because the parameters are easier to conceptually grasp and empirically determine values for. This is an epistemic advantage not because there is less resistance, but because the resistance analysts experience when being forced to decide parameter values has easier to traverse avenues for resolution. This suggests that, in addition to considering instances and sources of friction, it is important to evaluate how friction can be and is overcome in practice.

A new method like TCTC is unlikely to be more than a curiosity if it doesn’t offer something above and beyond interpretability. To receive uptake, it needs to create new opportunities for examining data. In terms of friction, it must reveal data patterns that can provoke frictional interactions with existing theories and judgements of data’s evidential import. That is, it needs to transform data in a way that is meaningfully different from the available methods.

The most straightforward opportunity for friction that TCTC offers is that, unlike other methods for community assignment, it allows nodes to belong to multiple communities at once, or to belong to no community at all. This means that the algorithm isn’t forced to ‘make a decision’ about the community identity assigned to nodes that, according to its criteria, have ambiguous community membership. Thus, TCTC could be applied to data that has been analyzed with less flexible community assignment criteria to identify nodes that may have indeterminate community identities. This may, depending on how such an analysis turns out, raise challenges for currently accepted theories and network-level explanations fMRI data.

Another potential source of friction that arises from TCTC is that the community dynamics it reveals correlate with trial-by-trial behavior. As a demonstration of this, TCTC was used to identify five community configurations that best explain the variance in BOLD signal data collected concurrently with the performance of a 2-back task. A 2-back task requires subjects to press a button if the stimuli they are presented with matches the one presented two trials earlier. It was found that each of the five community configurations were reliably associated with different behaviors. For example, in trials where there are more communities associated with visual networks appearing in the TCTC analysis (*component 2 in pre-print version 2*) prior to the stimulus presentation participant responses tended to be more accurate. When the same communities appeared later in a trial, the network configuration was instead associated with slower reaction times.

These results show that TCTC has the potential to create friction in the field for two reasons. Firstly, it shows that TCTC can access information at the scale of trial-by-trial behavior. This alone is remarkable for neuroimaging research where the standard practice is to average data across hundreds of trials to overcome the poor signal to noise ratio of the measurements. Secondly, these preliminary TCTC results introduce a new variable into the standard brain mapping formula.

Early fMRI research was characterized by spatial mappings in which the question to be answer was “where does this cognitive process occur?” More recently, techniques like temporal network analysis have allowed cognitive scientists to use fMRI to ask, “when does this cognitive process occur?”, a question previously reserved for imaging methods with higher temporal resolution such as EEG. Through TCTC, it may become possible to examine the brain’s role in cognition in terms of its parts, their internal temporal dynamics, and their overall network configuration. That is, to investigate when, where and what networks in the brain are doing with fMRI.

Just as data do not emerge from an experiment ready to use as evidence, data analysis methods rarely produce patterns that clearly indicate what causal factors played a role in shaping the data. As was the case with functional connectivity, these early demonstrations of TCTC will not be the last word on its epistemic utility. It will take a community of researchers trying to use the method and challenging it for the full scope of its assumptions and error characteristics to be determined. Whether or not that work is and can be done is contingent on the friction that the method induces as results using it are published, and the friction investigators encounter when trying to apply it.

**6. Conclusion**

The evidential import of data are assessed through their manipulation. The process of data analysis is epistemically challenging in part because data are causally separated from the events that they are intended to provide evidence for claims about. Experimental manipulations place researchers in epistemically advantageous positions by making contact with the objects and phenomena of interest. Data manipulations, on the other hand, are applied to material objects that are not in causal contact with the events they are used to learn about. I have argued that some of the inferential liabilities that go along with data manipulation are partly overcome through the occurrence of epistemic friction. Each of the instances of friction identified above included a reexamination of the epistemic circumstances of research. It is in this moment of reexamination that an analyst evaluates and reconsiders parameter choices, recognizes the importance of decisions already made and thought to be innocuous, and takes steps to eliminate the frictional interaction and continue with their work.

While the participation coefficient case suggested that low friction can lead to inferential errors, such as the misuse of an analysis method, the TCTC case showed how reducing friction is one way for a method to help move a field forward. By providing parameters that can be optimized to fit data and are more readily interpretable, TCTC makes it both easier to examine temporal dynamics in brain networks and easier to evaluate the significance of the patterns it isolates. Whether or not a data analysis procedure is epistemically advantageous is not a matter of abstract facts about the decision’s researchers had to make, but a matter of how much friction was involved in each of those decisions, and how the investigators dealt with that friction.

I hope to have inspired interest in examining the circumstances of data analysis and discussing the positive epistemic roles played by data manipulations in neuroscience. Because, whether or not philosophers of neuroscience attend to them, data analysis methods will continue to have a substantial impact on the trajectory of research, especially as data become more accessible and analysis software becomes easier to use. How data are manipulated is a significant driver of progress in modern science. If philosophical analyses are to remain relevant and sensitive to current trends, we ought to attend as much to the epistemic characteristics of data analysis as we do to data production, measurement, and theory.

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1. 1At the time this chapter was written the cases examined were pre-prints. Pre-print material was chosen because I had the ability to observe as these contributions were conceived, developed, and written up. It was through observing and collaborating on these projects that the philosophical arguments in this chapter were developed. [↑](#footnote-ref-1)
2. The remainder of this section is partially autobiographical in content. The information reported here was obtained through conversations and collaborations with the scientist discussed. [↑](#footnote-ref-2)
3. I owe thanks to an anonymous reviewer for raising this challenge. [↑](#footnote-ref-3)