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The Landscape of *NeuroImage*-ing Research

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Abstract

As the field of neuroimaging grows, it can be difficult for scientists within the field to gain and maintain a detailed understanding of its ever-changing landscape. While collaboration and citation networks highlight important contributions within the field, the roles of and relations among specific areas of study can remain quite opaque. Here, we apply techniques from network science to map the landscape of neuroimaging research documented in the journal *NeuroImage* over the past decade. We create a network in which nodes represent research topics, and edges give the degree to which these topics tend to be covered in tandem. The network displays small-world architecture, with communities characterized by common imaging modalities and medical applications, and with hubs that integrate these distinct subfields. Using node-level analysis, we quantify the structural roles of individual topics within the neuroimaging landscape, and find high levels of clustering within the structural MRI subfield as well as increasing participation among topics related to psychiatry. The overall prevalence of a topic is unrelated to the prevalence of its neighbors, but the degree to which a topic becomes more or less popular over time is strongly related to changes in the prevalence of its neighbors. Finally, we incorporate data from *PNAS* to investigate whether it serves as a trendsetter for topics' use within *NeuroImage*. We find that popularity trends are correlated across the two journals, and that changes in popularity tend to occur earlier within *PNAS* among growing topics. Broadly, this work presents a cohesive model for understanding the emergent relationships and dynamics of research topics within *NeuroImage*.

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Keywords

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1. Introduction

In many fields of research, scientists develop intuitive knowledge of which topics are popular, which might be on the horizon, and which tend to be studied in tandem. Yet each scientist's view of the research landscape is based on a subsampling of the full space, depending on the nature and extent of their experiences in the field. It is therefore of ten daunting for those who are new to a field to construct even a superficial picture of the research landscape. Moreover, even for those scientists that are steeped in a particular research area, it can be challenging to imagine new connections that might be drawn between topics that historically have been thought of as unrelated.

Recently, the emerging field of network science has proven useful for gaining an understanding of the broader space of scientific research [1]. Previous work on collaboration and citation networks has provided insight into authors social patterns [2,3,4], important studies and turning points in the literature[5], and the largescale structure of the scientific landscape [6,7]. When examining networks of researchers and networks of articles, the scientific landscape has generally been found to show small world properties, reflecting clustering within specialty and efficient paths between specialties [6,7]. Yet individual fields show variability in their specific network topology [8,6], opening the door for greater understanding of how any given field efficiently carries out and disseminates scientific research.

In the field of neuroimaging, these types of bibliometric approaches have recently gained popularity. In particular, recent work has studied the most impactful neuroimaging papers [9], revealed text-based subfields within functional neuroimaging and their relationships with the activation of specific brain regions [10], and created networks that characterize the relationships between research topics within cognitive neuroscience [11]. Unlike the study of co authorship and citation networks, this latter study instead uses a technique that quantifies the relationships between scientific ideas. Here, the operationalization of science as a set of interconnected ideas provides a unique opportunity to study how research topics are related within and across sub disciplines, and how these topics and their relations grow and change over time.

As neuroimaging researchers, we sought to apply this technique to literature from our field, and to use this framework to simultaneously investigate largescale and node-scale network features both overall and over time. In this work, we apply graph theoretical approaches to a network of the 100 most common topics covered in the journal *Neuro Image* over the ten-year span from 2008 to 2017. We dis cuss the largescale structure of this network, the communities of research areas that emerge from the topic relationships, the roles of individual topics in shaping the network, the ways in which these roles have changed over time, and the potential network and literary foundations of topic popularity. In sum, our study offers unique insights into the nature and use of scientific research in contemporary neuroimaging.

Methods

Data collection

For this study, we retrieved keywords and abstracts from 8,547 articles published in *Neuro Image* between 2008 and 2017. We used the keyword sections to create a list of potential topics to be searched for in the abstracts. We chose this technique over latent topic modeling for two reasons: (1) it reflected scientists' explicit opinions as to the words and phrases that constitute relevant scientific topics, and (2) it allowed for the incorporation of multiword phrases.

To develop a list of potential network nodes, we manually curated the list of topics. The specific curation procedure that we implemented was constructed so as to address potential sources of variation in the topics. First, variability in how re searchers referred to topics was manually adjudicated, and different terminology for the same idea was consolidated. For example, *functional magnetic resonance imaging* and *functional magnetic resonance images* were considered to be referring to the same topic. Second, common abbreviations were detected by linking multiword phrases to their associated parentheticals in keyword and abstract text. Moreover, all variations of the full phrase were replaced by the relevant abbreviation in the abstract and keyword text. For example, variations of the topic *functional magnetic resonance imaging* were found to be associated with the abbreviation *fMRI*, and we therefore replaced references to these terms by *fMRI* in the abstract and keyword text.

Network construction

We calculated the prevalence of each potential topic by finding the proportion of abstracts or key word sections that contained at least one reference to the given topic within the timespan of study. We used the 100 most common topics between 2008 and 2017 as nodes to construct the network. Notably, we chose this value because it represented the approximate number at which the least prevalent words occurred sufficiently often to produce a statistically reliable signal in both static and temporal analyses of the network. To ensure that our findings were not unduly dependent on this choice, we also varied the number of topics chosen to construct the network. The effects of network size on the inferred topology are shown in Table S1.

Edges were weighted by the φ coefficient for binary association [12], representing the degree to which two topics tended to be discussed in the same articles. We applied a threshold of positive significance, removing negative edges and nonsignificant edges. This step was taken to increase the interpretability of the intertopic links, leading them to signify a meaningful association between two topics within the neuroimaging literature. Nevertheless, to ensure that our findings were not unduly dependent on this choice, we also performed sensitivity analyses in which we maintained all edges. We report the effects of this choice on the community structure of the network in Figure S2, and we also discuss those results in a later section.

Network structure

To quantify the structural features of the full network, we sought to investigate the degree to which topics tended to form tightly connected clusters, as well as the overall level of integration of research topics across the network

Local topic clustering can be quantified using the **clustering coefficient**, which is defined for a node as the probability that two of its adjacent nodes are connected to one another. The version of the clustering coefficient used here is a measure of transitivity defined as follows[13]:

$$c_i^w = \frac{1}{S_i(k_i - 1)} \sum_{h, j \in N} \frac{(w_{ij} + w_{ih})}{2} a_{ij} a_{ih} a_{hj}, \quad (1)$$

where N is the set of all nodes, and s_i is the node's **strength**, or the sum of all edge weights originating at node i. The variable k_i is the node's **degree**, or the number of edges originating at node i. Finally, w_{ij} is the edge weight connecting node i and node j,and a_{ij} is 1 if $w_{ij} > 0$ and 0 otherwise. The overall clustering behavior of the network can be obtained by taking the average clustering coefficient over all nodes[14].

Integration across the network can be quantified using the **characteristic path length** of a network. Path length is defined as the average shortest path length between all node pairs[15]. A version of the path length for a weighted network can be defined as follows

$$L = \frac{1}{n(n-1)} \sum_{i \neq j} d_{ij}, \quad (2)$$

where n is the number of nodes and d_{ij} is the shortest weighted path length between nodes i and j, defined as the inverse of the edge weight w_{ij} and obtained using the algorithm given by Johnson[16].

Notably, these two measures of clustering coefficient and path length can be combined to obtain the **small-world propensity** of a network, which represents the degree to which a network shows similar clustering to that of a lattice network, and similar path length to that of a random network[17]. This metric is similar to the commonly used small-world index[15], σ, but has been shown to be unbiased even in the context of networks with varying densities[17]. Both measures broadly represent how well a network can be characterized as having both disparate clusters and strong between cluster integration. The small-world propensity of a network is defined as follows:

$$\phi = 1 - \sqrt{\frac{\Delta_c^2 + \Delta_L^2}{2}}, \quad (3)$$

where

$$\Delta_c = \frac{C_{lattice} - C_{observed}}{C_{lattice} - C_{random}} \quad (4)$$

and

$$\Delta_L = \frac{L_{observed} - L_{random}}{L_{lattice} - L_{random}}, \quad (5)$$

with C representing the network clustering coefficient, defined as the average of all node-specific c_i^W values.

In this study, lattice and random networks were constructed according to the methods described and implemented by Muldoon and colleagues [17]. Specifically, weighted lattice networks were created by distributing the observed edge weights such that the set of highest weights were assigned to lattice edges with a Euclidean distance of 1, the next set of highest edge weights were assigned to lattice edges with a Euclidean distance of 2, and so on until all observed edge weights were assigned. Random networks were created by randomly distributing edges among the nodes of the network. Importantly, the empirically observed degree distribution of the topic network was preserved for both lattice and random networks. Benchmark distributions of clustering, path length, and small-world propensity were obtained from 100 random networks with the same size, degree distribution, and strength distribution as the topic network[18].

Community detection

To determine whether and how the network clustered into subfields, we performed community detection using an iterative generalized Louvainlike locally greedy algorithm to maximize a common modularity quality function [19]. This technique implements a stochastic optimization of the quality index value Q, in which nodes are reassigned to modules one by one until no reassignment can improve Q. By iterating this optimization until convergence, one obtains a globally optimal set of community assignments, after accounting for local maxima in the Q space.

The **modularity** value, Q, of a network represents the degree of separation between nodes in different groups[20,21]. Intuitively, it quantifies how well the network can be separated into non-overlapping communities with many, strong withingroup connections and few, weak between-group connections. For a weighted network, the modularity can be defined as follows:

$$Q^W = \frac{1}{l^W} \sum_{i,j \in N} \left[W_{ij} - \frac{s_i s_j}{l^W} \right] \delta_{m_i m_j}, \quad (6)$$

where I^W is the sum of all edge weights in the network, and fiδ_{mimj} is 1 if $i = j$ and 0 otherwise. Importantly, it is well known that the modularity landscape suffers from a near degeneracy of optimal solutions[22]. We addressed this issue by using 100 iterations of the Louvain-like algorithm[19]. From the set of partitions obtained across these many iterations, we build an agreement matrix from which we subsequently extract a consensus partition[23].

Nodelevel structure

We examined several additional structural features at the level of network nodes. In addition to the previously mentioned measures of node degree and node strength, we sought to understand the ways in which nodes served as bridges between distant topics, and the degree to which they maintained connections to topics outside of their own cluster.

Bridging behavior can be measured using the **between ness centrality**, which is the proportion of all shortest paths within the network that pass through a given node[24]. It is defined as follows:

$$b_i = \frac{1}{(n-1)(n-2)} \sum_{h, j \in N; h \neq j, h \neq i, j \neq i} \frac{\rho_{hj}^{(i)}}{\rho_{hj}}, \quad (7)$$

where p_{hj} is the number of shortest weighted paths between node h and node j, $\rho_{hj}^{(i)}$ is the number of shortest weighted paths between node h and node j that pass through node i, and weighted paths are calculated using the inverse of the edge weights.

The diversity of a topic's connections can be measured by the **participation coefficient**, which quantifies the degree to which the node's connections are evenly distributed across all modules (or clusters) in a network[25]. The participation coefficient tends towards 1 as connections bridge modules, and tend towards 0 as connections remain largely intra modular. This metric is defined as follows:

$$P_i^W = 1 - \sum_{m \in M} \left(\frac{\mathrm{s}_i(m)}{\mathrm{s}_i} \right)^2, \quad (8)$$

where M is the set of modules, and $s_i(m)$ is the sum of edge weights from node i to other nodes within module m.

Temporal node structure

To examine changes in topic contributions over time, we created a dynamic network using a sliding window of ±6 months from a central month. Central months ranged from July, 2008 to June, 2017 and data from January, 2008 to December, 2017 were included in the analyses. This dynamic network was comprised of 109 individual networks with overlapping time windows, each with the same 100 topics examined in the full static network.

To understand the relationships between changing structural roles, we obtained the **temporal slopes** of each network measure described previously. These slopes were calculated using linear regression on a `month' variable, and were standardized by the magnitude of the measure over the full 10 year time window. As opposed to quantifying higher order trends, linear relationships were used so measures of temporal changes could be incorporated into correlation and regression analyses in a wellpowered and interpretable manner. The formula is given below, for an example measure, θ:

$$\theta_{j,t} = \alpha + \beta t + \in, \quad (9)$$

$$\Delta_j^{\theta} = \frac{\hat{\beta}}{\theta_j}, \quad (10)$$

where $\theta_{j;t}$ is the θ value for node j in the network at time t,Δ_j^{θ} represents the slope of measure Ω for node j, and θ_j represents the value of θ for node j within the context of the full network.

Topic prevalence

To understand how these measures of a node's topological role within the network might relate to the topic's usage in the literature, we examined the prevalence of each topic. We defined the prevalence of a topic as the proportion of article abstracts and keyword sections in which that topic appeared. To further understand how one topic's popularity in the literature might be related to the popularity of topics to which it was closely related, we defined a new measure, ξ, that quantified the prevalence of a topic's neighbors. This measure was defined as:

$$\xi_i = \frac{1}{s_i} \sum_{j \neq i} W_{ij} p_j, \quad (11)$$

where pj is the overall prevalence of node j, given by the proportion of articles in which topic j appears within the time window covered by the given network.

We additionally introduced a measure, Ω, that quantifiedΩ the degree to which a node is connected to topics that are increasingly used in the literature. This measure is given by the weighted average of the prevalence slope values of a node's neighbors, and can be de fined as follows:

$$\Omega_i = \frac{1}{s_i} \sum_{j \neq i} W_{ij} \Delta_j^{p},$$

where Δ_j^p is the prevalence slope of node *j*, given by the percent change per month in the proportion of articles in which topic *j* appears, according to the same algorithm given above for calculating slope measures.

Results

We collated data from 8,547 articles published in *NeuroImage* between January, 2008 and December, 2017. Using phrases in the keyword sections and their appearance within abstracts, we created a network of research topics. Nodes in the network represented the 100 most common topics over this time span. Edges in the network represented the co-occurrence of topics within articles, quantified by the φ coefficient of association for binary variables12. We removed negative and nonsignificant correlations, comprising roughly 63% of possible edges; these edges had notably lower magnitude and less variability (range: [0.23,0.02], interquartile range: 0.02) than the edges that remained (range: [0.02,0.59], interquartile range: 0.06). Twenty-seven percent of possible edges remained, yielding a network with 100 nodes and 969 edges (Figure 1).

Structure of the topic network

To understand the overall structure of the neuroimaging landscape, we calculated the average node clustering and characteristic path length for the topic network. Relative to null networks, the topic network had high levels of clustering ($p < 0:01$), with a clustering coefficient 2.24 times the average value found in the null networks. Addition ally, the network had a higher characteristic path length than the random networks ($p < 0:01$), with a path length [1.31] times the average value of the null networks. High values of the clustering coefficient and middling values of the characteristic path length can be indicative of small-world architecture in a network. We therefore tested for the presence of small world ness in the topic network using the small-world propensity score, which combines clustering and path length scores[17]. The small-world propensity value of the topic network was 0.72, which was significantly higher than would be expected from a random network ($p < 0:01$). These results indicate that research topics in neuroimaging have small-world properties, with high local clustering within distinct subfields as well as some bridges between these subfields. This structure may suggest a pathway for innovation, in which tight clusters advance and refine existing relationships and ideas, and links between clusters facilitate the creation of new connections and future research opportunities[27].

Topic communities

We next sought to characterize neuroimaging subfields as defined in a datadriven manner from the architecture of the topic network. We performed community detection using a Louvainlike locally greedy algorithm to maximize a common modularity quality function[19]. The modularity value of a network intuitively represents the degree of separation between nodes in different groups[20,21]. It quantities how well the network can be separated into non overlapping communities, with many withingroup connections and few betweengroup connections. Using this technique, we identified five communities, characterized by topics related to structural magnetic resonance imaging (MRI), functional MRI, brain structures, Alzheimer's disease, and electroencephalography (EEG), respectively (Figure 1, **SI Interactive**).

From the community structure of this network, we were able to identify familiar subfields. Specifically, broad divisions appeared based on imaging modality, with structural MRI, functional MRI,and EEG forming the bases of three separate communities. Additionally, data collection and analysis techniques that are commonly utilized within specific modalities tended to cluster within the modality's community. This was true of the terms *segmentation, tractography*, and *voxel-based morphometry* (VBM) within the structural community. Similarly, it was true of the terms *resting state, motion*, and *independent component analysis* with in the functional community. Finally, it was also true of the terms *oscillations, event-related potential*, and *synchronization* within the EEG community. Intuitively, papers that bridge these communities might combine imaging modalities[28], or address topics typically associated with one modality using another[29].

While these three communities separated from one another along boundaries of the imaging modality used, the other two communities were more characterized by the content of the neuroscientific question being asked and answered. For exampleΩthe largest community, instead of being clustered around a modality, was instead focused on physical structures and associated research topics. This community contained various brain regions, including the *cortex, insula, cerebellum, thalamus*, and *amygdala*, as well as topics that tend to be considered alongside specific regions, such as *emotion, depression, reward*, and *pain*. Interestingly, the remaining community appeared to be heavily focused on research related to Alzheimer's disease, including topics like cognition, hippocampus, aging, atrophy, and mild cognitive impairment. Perhaps unsurprisingly, the closest neighbors of this community were the structural MRI community and the brain structures community (Figure 2).

Differences in the makeup of these communities can be seen in Figure 1C, in which topics were categorized as being either an analysis method, a medical application, an imaging modality, or a physical structure. In this figure, communities characterized as structural MRI, functional MRI, and EEG & MEG can be seen to have more topics related to imaging modalities, while the brain structures community has a high proportion of topics related to anatomy and the Alzheimer's community has a high proportion of topics related to medical applications. Given this broad division along imaging modalities, it is also of interest to ask whether finer scale structure exists in the community architecture that is unexplained by modality boundaries. To address this question, we performed a secondary community detection analysis after removing topics classified as "imaging modalities". The results of this partition, including the topic type make up of these new communities can be seen in FigureS1. Broadly, after removing modalities the topics from the Alzheimer's disease community join with structural MRI topics, and topics from the functional MRI community are split between new communities made up of functional MRI/EEG & MEG topics, and functional MRI/brain structures topics, respectively.

We also carried out additional supplemental analyses to determine the effect of maintaining negative and nonsignificant edges on the network partition. These results, shown in Figure S2, reveal that the inclusion of all edges yields a courser partition with only three communities. These communities roughly represent a structural MRI and Alzheimer's community, a functional MRI and brain structures community, and an EEG & MEG community.

Structural roles of individual topics

Overall structural roles—To investigate the roles of individual topics in shaping the overall structure of the network, we examined the topics' general connectivity (degree and strength), their role in creating efficient pathways between clusters (between ness centrality), their level of local clustering (clustering coefficient), and the degree to which they have relationships with topics outside of their own community (participation). See **SI Interactive** to explore the values of these metrics for each node.

Topics' between ness centrality was significantly related to both their degree ($p = 0{:}36$, p < 0:001) and strength ($p = 0{:}52$, $p < 0{:}001$), with partial correlations revealing that this effect was driven predominantly by strength. These relationships suggest that topics that serve as bridges connecting disparate communities tended to have many relatively strong connections, properties indicative of“hub” nodes. Many of the topics with high strength and high between ness centrality were brain structures, such as cortex, white matter, and amygdala(Figure 3). The imaging modalities *fMRI* and *MRI* also had high between ness centrality. Yet a few specific topics related to structural imaging, *DTI* and fractional anisotropy (FA), had high strength and low betweenness centrality, possibly indicating high clustering in the structural MRI community.

To better understand the trade-off between tight connections within a subfield and broad connections across neuroimaging, we investigated the relationship between topics' clustering coefficient and participation coefficient. Somewhat un surprisingly we observed a significant negative relationship between clustering coefficient and participation coefficient ($p = 0{:}66$, p < 0:001), suggesting that topics with highly related neighbors tend not to have many intercommunity connections. Highly clustered topics included *multiple sclerosis, corpus collosum*, and *white matter*, while highly participatory topics included *learning, hippo campus*, and *schizophrenia* (Table 1). The high clustering coefficient throughout the structural MRI community possibly reflects relative isolation of these modalities, methods, and neuroscientific applications within the field.

Temporal changes in structural roles

Though the contributions of individual nodes to the topic network demonstrate the manner in which topics relate to the field as a whole, these metrics only capture a static snapshot of highly dynamic relationships. As such, it was of interest to investigate the dynamic properties of the topic features described in the previous section, in order to better understand how changes in the field may emerge over time. To do so, we created a dynamic network using a ±6month sliding window that captured the network structure at each central month between July, 2008 and June, 2017. With the fi6 month window, data between January, 2008 and December, 2017 were incorporated into the network. Dynamic properties of topics were examined by obtaining the slope of each graph metric, and then standardizing by the overall metric obtained in the previous section. This calculation yields an estimate of a topic's percent increase or decrease in each measure monthovermonth, and can reveal whether topics' roles within the field have been changing over time.

The term *connectome* was removed for the following analyses because it was not mentioned in *NeuroImage* abstracts or keyword sections until 2010,making its trajectories strong outliers for some measures. Yet the appearance of a new topic in this data, especially one that has rapidly grown in popularity, presents a unique opportunity to better understand the manner in which topics' various roles within the network grow and change in tandem. As might be expected, the term connectome experiences drastic changes in its structural properties during its entrance into the literature (FigureS3). Its degree and its between ness centrality both grow gradually starting in 2010, before beginning to drop off around 2015. Its clustering coefficient and participation take inverse trajectories, with clustering dropping and participation rising dramatically over the first 1.5 years, before they both leveled off to values that have been maintained for the duration of the study. These within-topic relationships resemble the between-topic relationships presented in the previous section, yet it is unknown whether these effects are specific to new topics experiencing drastic change.

In analyzing the remaining 99 topics that were present in the literature for the duration of the study, we indeed found that topics' temporal slopes of between ness centrality were significantly related to slopes of both degree (p= 0:23, p = 0:02) and strength (p= 0:37, p < 0:001). This behavior suggests that not only is a topic's overall strength related to its between ness centrality, but as topics strengthen their connections, they serve to more efficiently connect disparate regions of the network. Topics showing increases in between ness centrality, degree, and strength over time included *plasticity, reading,* and *stroke*. Topics showing decreases in between ness centrality, degree, and strength included *visual cortex, working memory,* and *voxel-based morphometry* (Table 2).

While the trade-off between the static clustering coefficient and participation coefficient reflects overall isolation or integration in the past ten years, the changes in these measures over time may better reflect how a topic will relate to the field going forward. Here, the slopes of the clustering coefficient and participation coefficient were negatively related (p = 0:64, p < 0:001), suggesting that as topics become more integrated into a sub field, the strength of their relationships with topics outside of that sub field tends to fade. Topics that have shown increasing clustering over time included plasticity, development, and multiple sclerosis, while topics that have shown increasing participation over time included DTI, emotion, and depression (Table 2). For this measure, structural MRI topics, while generally high in overall clustering, were found to be moving in a variety of directions. Specifically, topics related to tractography (e.g., DTI, myelin) showed increasing participation, suggesting increasing integration into the field, while other structural topics(e.g., segmentation, multiple sclerosis) showed increasing clustering, suggesting further isolation.

Foundations of topic prevalence

Overall topic prevalence—Of particular interest was the relationship between graph measures and topics' popularity in the literature, operationalized by the proportion of articles in which they appeared. In addition to considering the structural features described in the previous section, for this analysis we defined a new variable, fi, which measured the degree to which a topic was a member of a “rich club” of commonly discussed topics. As opposed to the typical rich club coefficient that measures the edge strengths of each node’s neighbors, this metric measured the prevalence of each node’s neighbors. We then regressed the log of topic prevalence on between ness centrality, degree, strength per edge, clustering coefficient, participation coefficient, and fi. We found that degree ($t93 = 5:29$, p < 0:001), strength per edge ($t93 = 4:27$, p < 0:001), and clustering coefficient ($t93 = 3:45$, $p < 0:001$) were associated with topic prevalence. These relationships suggest that, accounting for the other variables, topic prevalence tends to be associated with having more, stronger, and more diverse connections. Interestingly, of was not associated with prevalence ($t = 0:72$, p = 0:47), indicating that topics do not tend to be preferably connected to similarly popular topics.

Temporal changes in topic prevalence

While topics’ overall prevalence in the literature appears to reflect the broad relevance of a topic within the field (see Table 1, changes in topics’ prevalence over time yields more insight into the ways in which neuroimaging literature has evolved over the past decade. By examining the trajectories of topic prevalence, and estimating the linear increases or decreases in prevalence over time, we aimed to shed light on these trends. No communities tended to show greater increases or decreases in prevalence overall (F1;97 = 0:21, p = 0:65), with all containing some topics that gained popularity and some that lost popularity in the literature. The largest increases were seen in functional connectivity, resting state, default mode network, diffusionweighted imaging, brain development, transcranial magnetic stimulation (TMS), and oscillations, generally reecting a shift towards the study of connectivity in the brain. The largest decreases were seen in voxelbased morphometry (VBM), cerebral cortex, hemodynamic response, positron emission tomography (PET), epilepsy, atrophy, Alzheimer’s disease, and mild cognitive impairment (MCI), potentially signifying a modest transition away from methods and applications generally associated with structural imaging (Figure 4). Trajectories of individual topics can be explored in more detail in the **SI Interactive**.

We next sought to investigate whether changes in topics’ structural roles were associated with changes in their prevalence in the literature. Similar to the “prevalence-rich club” measure just described, for this analysis we de fined a new variable,Ω that measured the degree to which a topic tended to be related to topics with increasing or decreasing prevalence in the literature. We then regressed the slope of topic prevalence on and the slopes of between ness centrality, degree, strength per edge, clustering coefficient, and participation coefficient. We found that slopes of degree ($t92 = 3:10$, p <0:01) and participation coefficient ($t93 = 2:20$,$p = 0:03$) were significantly associated with the slope of topic prevalence. These relationships suggest that topics tend to gain more connections as they become more commonly discussed in the literature, but these connections tend to be limited to the topic’s own sub field.

Interestingly, was strongly associated with changes in topic prevalence ($t93 = 7:54$, p < 0:001),indicating that although a topic’s overall prevalence is not related to the prevalence of its neighbors, changes in a topic’s prevalence are highly related to changes in the prevalence of its neighbors (Figure 5). This pattern is best exemplified by the trio of topics, *functional* *connectivity, resting state*, and *default mode network*. Certain topics' deviance from the model fit may also suggest that based on their role in the network – they are currently undervalued in the literature. Three such topics that did not increase in prevalence but were expected to show moderate to strong increases are independent component analysis, effective connectivity, and semantic (Figure 6). The fact that the predicted growth of these topics differed from their observed growth could potentially indicate that there is room for further use of these methods or investigation into these topics.

Potential 'trendsetting' role of PNAS

In addition to looking at topics' changing structural roles as a mechanism for understanding popularity, it is of interest to determine whether topics' use in multidisciplinary journals may help to predict trends, or possibly set trends in motion, will later become apparent in more specialized journals like *NeuroImage*. To provide a preliminary assessment of this possibility within the neuroimaging literature, we apply the same temporal techniques to articles published in PNAS over the same time span. Here, we investigate whether the slopes of prevalence within PNAS are associated with the slopes of prevalence within *NeuroImage*. Moreover, we also determine whether shifts in trajectories within one journal tend to occur before or after shifts in trajectories of the other journal.

In this analysis, connectome again represents an interesting case study, in that its use in the *NeuroImage* literature did not begin until 2010. Figure 7 displays the prevalence trajectories of connectome within PNAS and *NeuroImage* articles. This results visualized in this figure suggest that this topic has increased in popularity in both journals over the time span, although its usage and its rise in prevalence appear to occur earlier within PNAS than within *NeuroImage*. These trends suggest that for emerging topics in a field, prevalence may track similarly within broad journals and more specified journals, with broad journals potentially taking on a `trendsetting' role.

When considering the full set of topics, the similarity between temporal trends in the two journals holds. Specifically, topics' prevalence slopes within PNAS articles showed a moderate, significant correlation with their prevalence slopes within *NeuroImage* articles (r = 0:29, p < 0:01). Thus, topics that showed a greater linear increase in popularity over time within *NeuroImage* tended to also increase in popularity within PNAS over the same time span. Yet because these values represent a simple summary of the trend, it is unknown whetheructuations in topics' popularity over time tend to occur in one journal before they occur in the other (Figure 8).

To address this question, with in topic correlations were calculated between the two journals' trajectories. For each topic, correlations were calculated for a range of possible temporal offsets – 24 months in each direction – and the optimal offsets was taken as the value at which the highest correlation between the two slopes was obtained. Attest of the optimal o fisets was performed using the 94 topics with nonzero prevalence within PNAS for at least 50% of the time windows. We failed to reject the null hypothesis of mean 0($t93$ = 0:34, 95%CI = [3:98; 2:91], p = 0:73).While this finding suggests that, across all topics, popularity changes in PNAS do not tend to precede popularity changes in *NeuroImage*, it is potentially of greater interest to determine whether PNAS serves as a trendsetter specifically for up and coming “hot topics.”

To examine this possibility, we conducted a weighted *t*-test using only the topics for which popularity in *NeuroImage* was increasing over the course of the study. Topics were weighted by the magnitude of their prevalence increase, in order to better capture the contributions of such “hot topics.” In this analysis, optimal offsets tended to be significantly less than zero (p = 5:79, 95%CI = [7:83;3:75], t_{52} = 2:84, p < 0:01), with *PNAS* trajectories preceding *NeuroImage* trajectories by roughly 6 months on average. This effect was not found for topics that decreased in prevalence over the course of the study (p = 0:06, 95%CI = [2:77; 2:88], t_{52} = 0:02, p = 0:98), suggesting that PNAS’s trendsetting role may be limited to topics that are growing in popularity.

Discussion

Neuroimaging is an exciting, broad, and rapidly changing field. These features make it a rich territory for new ideas and innovative connections between existing topics, but also contribute to a complex and dynamic landscape of research. Over the years, network analysis has proven to be a useful tool for modeling and understanding similarly complex systems, including social structures[30], psychiatric symptoms[31], and the brain[32]. More recently, these techniques have revealed previously unknown features of scientific research and collaboration within and across fields [1,8,6,5]. Building on this body of work, we set out to examine the network structure of neuroimaging research over the last ten years, and to describe the changing roles and relationships of specific areas of study.

Structure of the topic network

A network of research topics was constructed using ten years of *NeuroImage* articles, and was found to have features uncharacteristic of a random network. Specifically, the network had higher levels of clustering and higher path length than a random network. As a result of the large increase in clustering and moderate increase in path length compared to a random network, the neuroimaging landscape was found to show a high degree of small world ness. This feature signifies local clustering within distinct sub fields, potentially facilitating iteration and advancement within existing topic relationships, and sparse connections between sub fields, potentially facilitating innovation and the creation of new connections[8,33,27].

This small world structure is consistent with then networks described in studies of coauthor ship and citation[6,7] within broader cross sections of scientific research. Interestingly, this structure also resembles the structure found in many brain networks[34]. Additionally, while prior research has not directly engaged with the largescale structure of neuroimaging literature, a previous study on the semantic network of cognitive neuroscience described the presence of “islands” that were bridged by terms with high between ness centrality[10]. These characteristics are potentially consistent with the small-world structure found in the current study.

Topic communities

While examinations of the network structure of scientific research at a larger scale have revealed inter disciplinary communities of research scientists[35] and topics[27], it remains of interest to gain a better understanding of topic communities at the scale of individual fields. At the smaller scale of the neuroimaging topic network, communities appear to largely agree with the sub fields that might be expected by a scientist, in that they are divided along the major lines of structural MRI, functional MRI, and EEG/MEG research (Figure 1, SI Interactive). Yet while potentially unsurprising, the strong divisions across imaging modalities suggest that there might be opportunities for further insight and innovation through the joint investigation of several modalities within studies. Indeed, researchers in the field have recently argued that while some specialization is beneficial, experience across modalities is important both professionally and scientifically[36]. In some ways, this trade of reflects a small scale version of the debate surrounding inter disciplinarity across scientific fields[37,38,] in which some believe better science arises from specialization[39] and others believe cross disciplinary work is vital for innovation[40].

One additional and perhaps surprising finding was the presence of a community that was almost exclusively related to research on Alzheimer's disease. The existence of this community is potentially a reaction of the growing burden of Alzheimer's disease[41], which has been met with increases in research e fiorts[42] and neuroimaging resources[43].While the prevalence of these topics within neuroimaging appears to indicate a strong response within the field to the pressing need for research in this area, future work could investigate how the characteristics of this sub field influence the translation of neuroimaging findings to clinical research and practice. This question could potentially be pursued by quantifying the ways in which topic relationships relate to future citation patterns.

Structural roles of individual topics

In addition to quantifying the overall landscape of neuroimaging, we sought to gain a better understanding of how individual topics contributed to its structure. The degree to which topics bridged gaps between distinct clusters (between ness centrality) was significantly associated with the number of connections they had to other topics (degree) and the strength of those connections. This pattern of relations is consistent with the presence of"hub nodes," which have many diverse connections across the network and facilitate information transfer across disparate regions of a network. This finding is broadly consistent with a previous study of the cognitive neuroscience literature that also found high between ness, high degree hub nodes[10]. Topics that fit this pattern tended to be very broad, and were often either related to imaging modalities or brain structures, such as fMRI and cortex. Yet some more specific topics also served to connect seemingly distant sub fields, like memory and amygdala (Figure 3; Table 1). While patterns in overall between ness centrality seem to be strongly related to the breadth or specialization of topics, similar relationships between degree, between ness centrality, and strength held when examining their percent change over time within nodes. For these measures, both change in degree and change in strength were positively associated with change in between ness centrality, suggesting that the associations observed between the overall measures may not be strictly reflective of the inherent nature of the topics, but may additionally be tapping into the way topics' structural roles develop and change over time. Additionally, topics that followed this pattern of increasing betweenness centrality and degree over time did not show much overlap with the broad topics that had high overall levels in these measures, and were instead more related to specific applications like plasticity and reading (Table 2).

In terms of the relationships that topics formed with other topics, there appeared to be a trade-off between strong integration in a specific sub field (clustering) and having diverse connections across communities (participation), as evidenced by a significant negative association between the two measures. Topics related to structural MRI tended to be highly clustered, relating very strongly to other topics in that area and rarely forming associations with topics from other sub fields. In fact, seven of the ten most clustered topics were directly related to white matter tracts or diffusion imaging. Topics that had diverse connections across sub fields were more variable, but tended to be related to research applications, as opposed to modalities, regions, or methods. Highly participatory topics included schizophrenia, learning, stroke, epilepsy, and memory (Table 1).

The negative association between the clustering and participation coefficients held for topics’ changes in clustering and changes in participation, again suggesting that the overall associations might tap into the manner in which structural roles change alongside topics’ changing roles in the literature. Interestingly, although topics related to structural MRI were some of the most highly clustered overall, different topics within this sub field seem to be moving in different directions over time. Multiple sclerosis and segmentation, for example, showed increasing clustering, while myelin and DTI showed increasing participation. Applications related to psychiatry also seem to be developing more diverse associations across the neuroimaging landscape, with emotion, depression, and anxiety all showing relative increases in participation (Table2).

Foundations of topic prevalence

Although the structural roles of topics within the network can provide valuable information about how ideas and sub fields interact and change, the aspect that is potentially the most relevant to researchers in the field is the frequency with which topics are discussed in the literature. As such, we sought to understand how a topic’s structural features in the neuroimaging network might be associated with its overall prevalence in the literature, and how changes in those features might correspond to changes in its prevalence.

Over the past ten years, we found that a topic’s overall prevalence in the literature, de fined as the proportion of keyword sections and abstracts in which it was mentioned, was positively associated with its total number of connections and the average strength of its connections, and negatively associated with the degree of local clustering within its neighboring topics. These results suggest that common topics tend to have many relatively strong connections to other topics, and that these neigh boring topics tend not to be highly related to each other. Interestingly, highly prevalent topics were not more likely to be connected to other prevalent topics, and therefore little evidence was found for a prevalence based rich club.

Potentially more interesting than the structural foundations of overall prevalence are the structural foundations of changes in topic prevalence. In other words, we were curious to know what changes in network features might be associated with changes in how commonly a topic was discussed in the literature. Here, we again found that degree was relevant, with changes in degree showing a positive association with changes in prevalence. Importantly, this finding demonstrates that not only are popular topics also well connected, but that becoming more well connected is associated with becoming more popular. Additionally, changes in participation were negatively associated with changes in prevalence, suggesting that as a topic becomes more prevalent, its connections tend to become more localized to the topic's own community. Interestingly, the degree to which a topic's neighbors increased or decreased in prevalence was strongly associated with the degree to which that topic itself increased or decreased in prevalence. This pattern of relations is perhaps unsurprising, as one might expect the fortunes of related topics to be linked.

In general, these associations between structural factors and topic prevalence are potentially quite useful, as they provide a method for determining when a topic's popularity in the literature deviates from what would be expected based on its position within the network. In this context, topics that have seen unchanging prevalence despite an expected increase might represent areas on the cusp of further growth in popularity. Two examples of this phenomenon are independent component analysis and effective connectivity. Additionally, topics that have seen sharper declines than would be expected based on their relationships, like atrophy and voxel based morphometry, might have become less popular to a degree that does not accurately represent their remaining value (Figure 6)

In addition to determining how topics' structural features within *NeuroImage* may relate to their changing prevalence over time, we sought to investigate whether topics' prevalence trajectories within a high impact multidisciplinary journal – in this case, PNAS – were predictive of their trajectories within *NeuroImage*. Though topics' prevalence trends were correlated across the two journals, neither journal tended to show consistent temporal priority among all topics. However, among only topics that showed growing popularity, temporal trends in PNAS tended to precede those in *NeuroImage* by approximately 6 months. These results therefore suggest that PNAS is not generally predictive of topics' fluctuations within *NeuroImage*, but it potentially contains valuable information about which topics may be on the rise.

Limitations and future directions

The findings presented in this paper have several important limitations. First, prior work has demonstrated that scientific fields often differ in the structure of their co-authorship and citation networks[8,6]. Therefore it is possible that journals within specific fields may also differ in the structure of their topic networks. If this is the case for neuroimaging, using *NeuroImage* specific data may limit the degree to which the findings in this paper can be generalized to the field as a whole. Future work could include other journals that cover similar areas, like Neuron, Brain, and Human Brain Mapping, and could investigate whether and how these networks differ from the network obtained from *NeuroImage*.

Second, the restriction of the dataset to topics that appeared in keyword sections and abstracts may ignore information contained in introduction and discussion sections. While this approach was taken in order to obtain a clearer picture of the topics covered in depth within a given article, future work could engage with topic modeling techniques applied to full articles. Similarly, the measure of topic co-occurrence used for edge construction represents only one potential strategy for quantifying topic relationships, and alternative methods might yield different network structures.

Third, the methods used in this paper are only a small subset of the available methods for analyzing networks, and do not cover many of the more complex techniques that have been developed in recent years. Though this is partially due to this study's focus on the roles of individual topics, there is still much to be gained from applying such techniques to this type of data, and future work could more thoroughly engage with these methods.

Fourth, the presence of brain regions and tissue types in the data presents an opportunity for quantifying how topics' network features relate to their positions within established functional or structural brain networks. Previous research[10] has begun the task of linking semantic features of neuroimaging studies with relevant brain regions, but examination of the coherence or deviance between topic and brain networks could provide additional insight into the organization of neuroimaging literature.

Finally, topic networks represent only one of several types of networks that can be used to quantify the structure of scientific research. Specifically, co authorship, citation, and article similarity network shave the potential to reveal a great deal about neuroimaging research, and a thorough integration of these networks with the topic network represents important future work. Using multilayer network methods, the integration of these networks could al low for a better understanding of the role of highly productive researchers and highly cited papers in shaping and responding to the dynamic topic network.

Conclusion

As science advances, collaboration grows, and the boundaries between research areas blur, it will be increasingly difficult to form and maintain a complete picture of the landscape of any given field. As these changes occur, formal quantitative studies of scientific research officer an opportunity to better synthesize and understand relationships between existing and new domains of inquiry. Here, we used network science to gain insight into the landscape of neuroimaging research in a ten year span between 2008 and 2017, and we revealed previously unknown structural features that emerge from published literature. We found the network to have small-world properties, with communities centered largely around distinct imaging modalities, and bridges between them made up of broadly relevant applications and methods.

We additionally quantified the structural contributions of individual nodes, finding high clustering among topics related to structural MRI and increasing participation among topics related to psychiatry. We discovered that the degree to which topics see increasing or decreasing prevalence in the literature can be well predicted by their position within the network – a relationship that may help reveal topics that are currently undervalued. Finally, we found no evidence that broad, high impact journals set popularity trends within neuroimaging, showing that topics' prevalence changes in *PNAS* and *NeuroImage* are correlated but not separated in time. Overall, this work sought to characterize the landscape of neuroimaging research at the current moment, and to inform researchers of the structural and literary trends that form the foundations of the field.

Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

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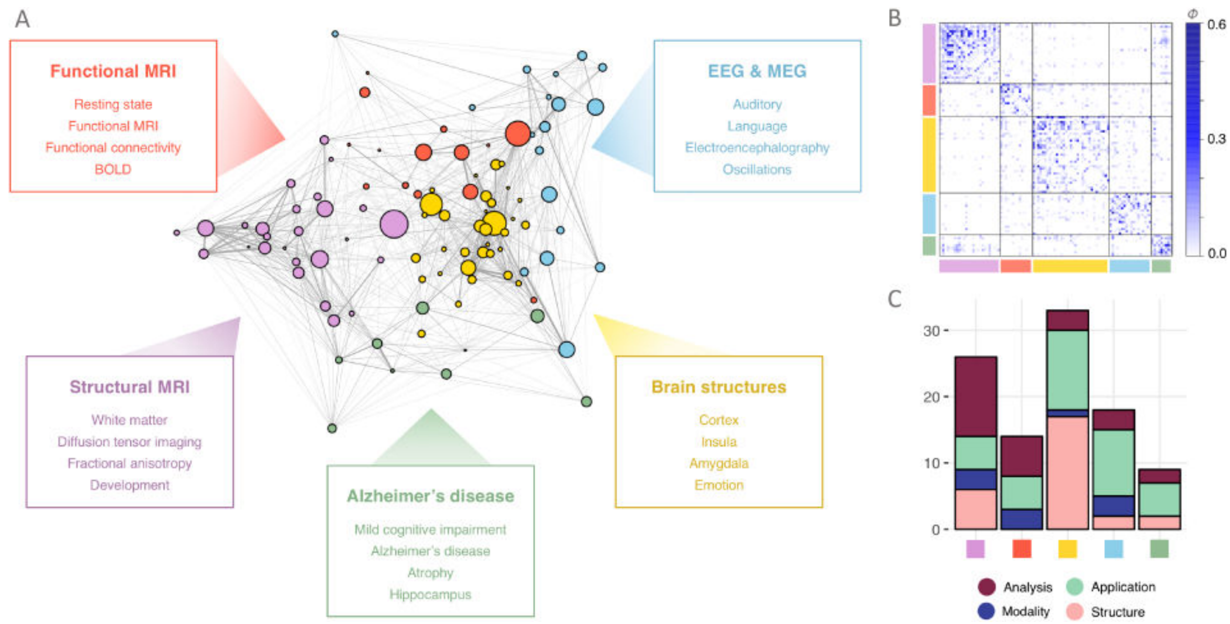

Figure 1: Architecture of the topic network.

Nodes ($N = 100$) reflect research topics and edges ($E = 969$) reflect the degree of co-occurrence in abstracts and keyword sections. *(A)* Visualization of the topic network using the layout proposed by Davidson and Harel[26], in which color represents community a filiation and size represents prevalence in the literature. Broad titles and four characteristic topics are displayed alongside each community. *(B)* The adjacency matrix sorted by topics' community affiliations. *(C)* Topic makeup of each community, based on the relative share of analysis methods, scientific applications, imaging modalities, and brain structures.

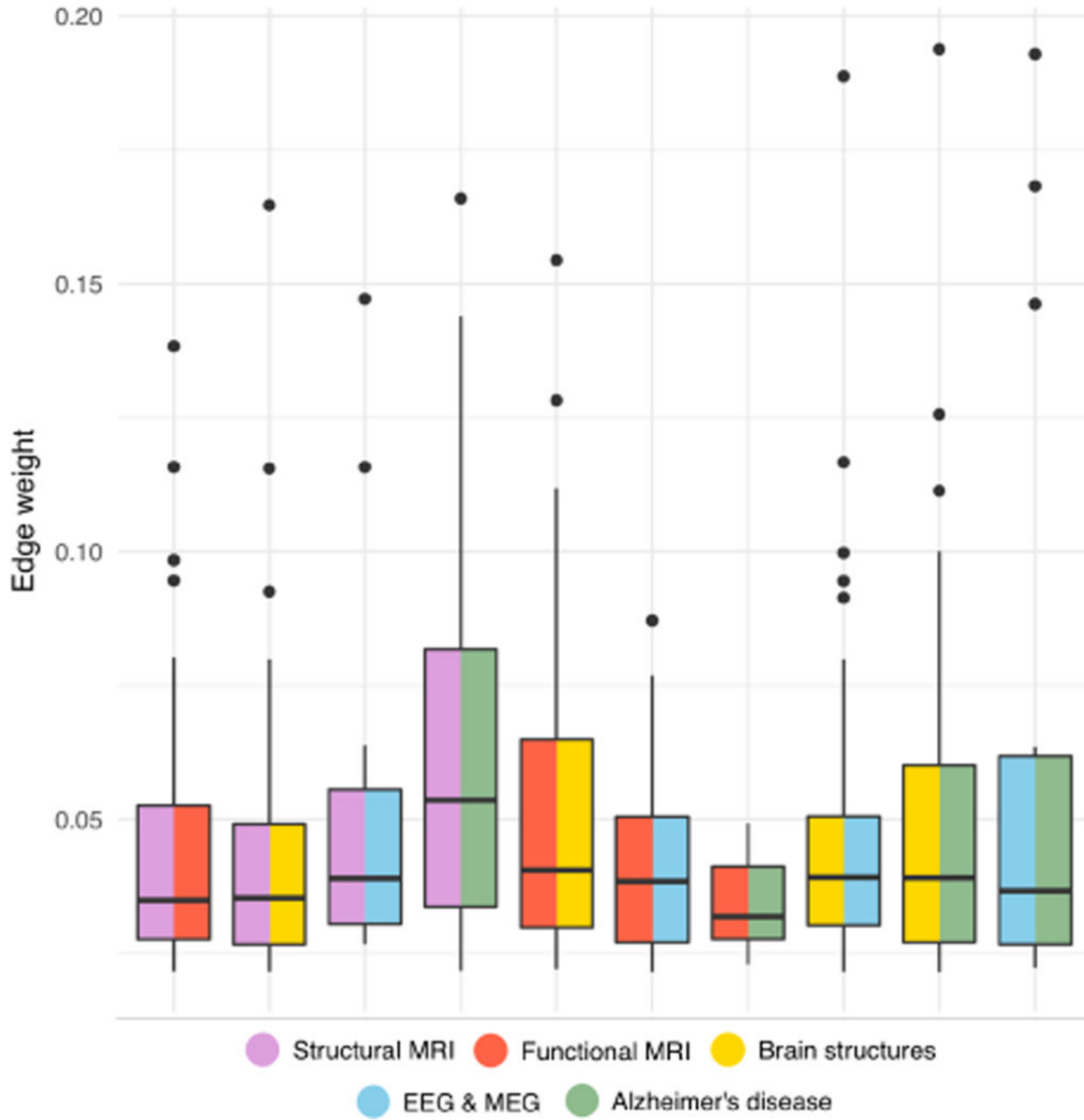

Figure 2: Strength of crosscommunity connections.

The distributions of nonzero edge weights for every pair of topic communities. The colors of each boxplot show the pair of communities being represented.

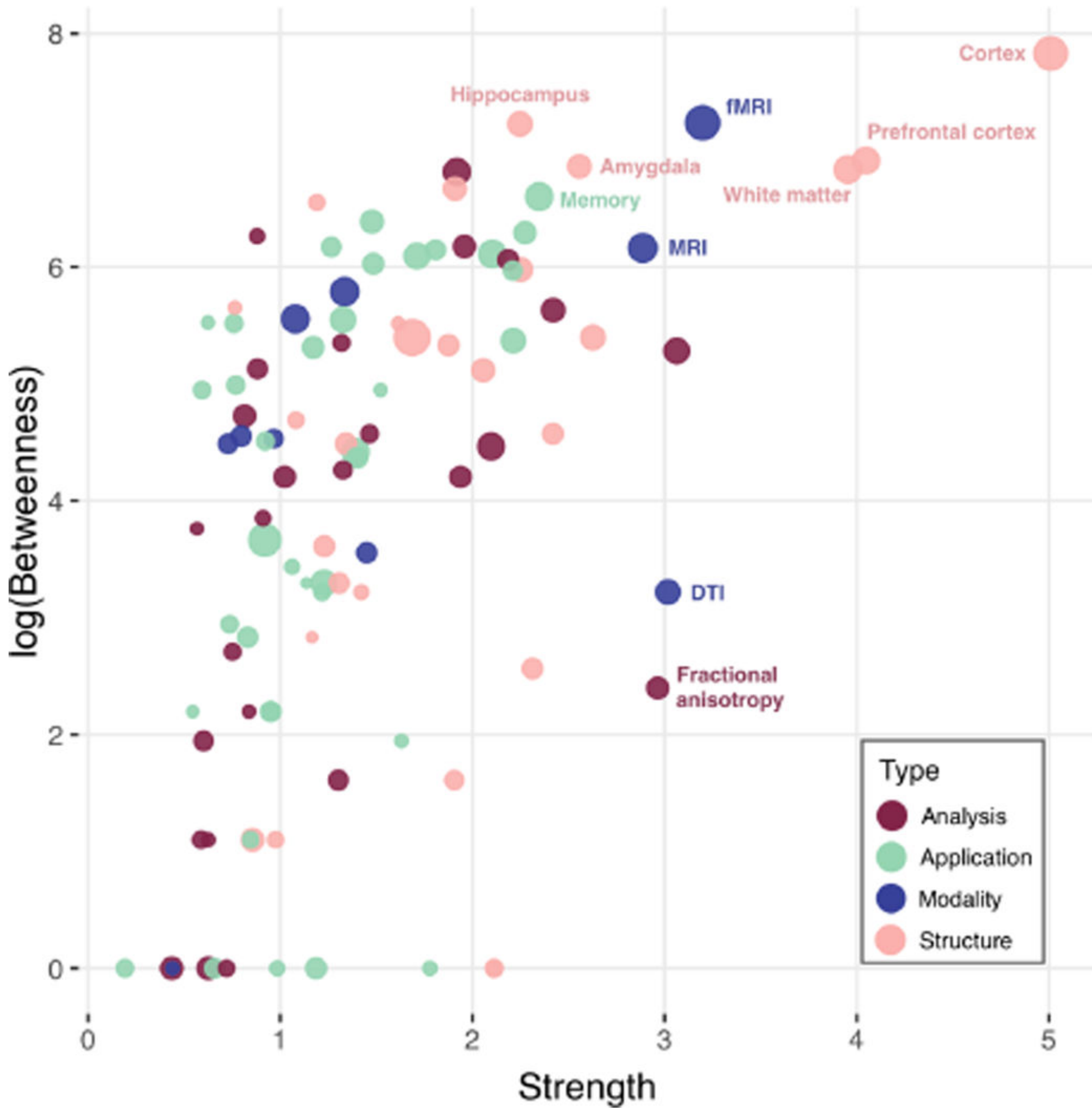

Figure 3: Relationship between topics' strength and betweenness centrality.

Points represent individual topics. Points are scaled by topic prevalence, and are colored by the topic type.

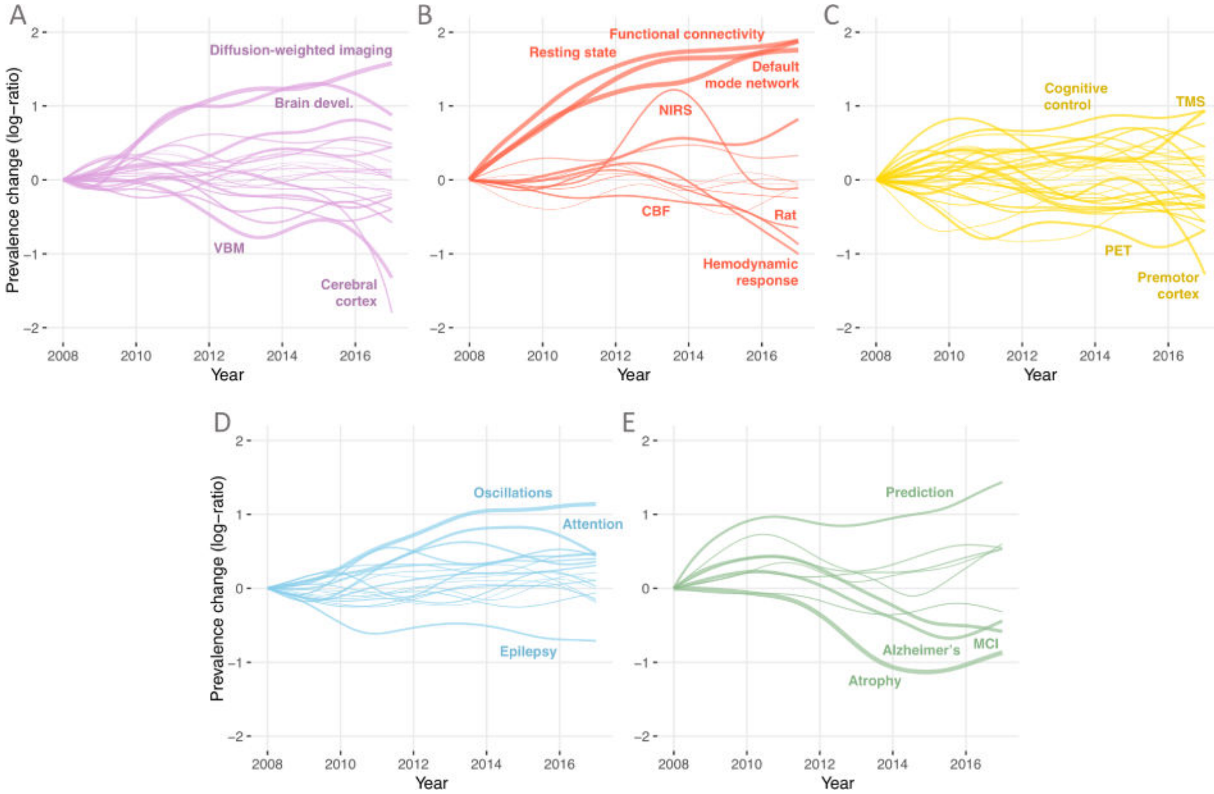

Figure 4: Changing prevalence of neuroimaging topics.

(A-E) Topics' prevalence trajectories over the course of the study, by community. The yaxis gives the logratio of prevalence at each time point compared to baseline. Plots represent the structural MRI, functional MRI, brain structures, EEG & MEG, and Alzheimer's disease communities, respectively. Curves are smoothed using a cubic spline with 6 degrees of freedom.

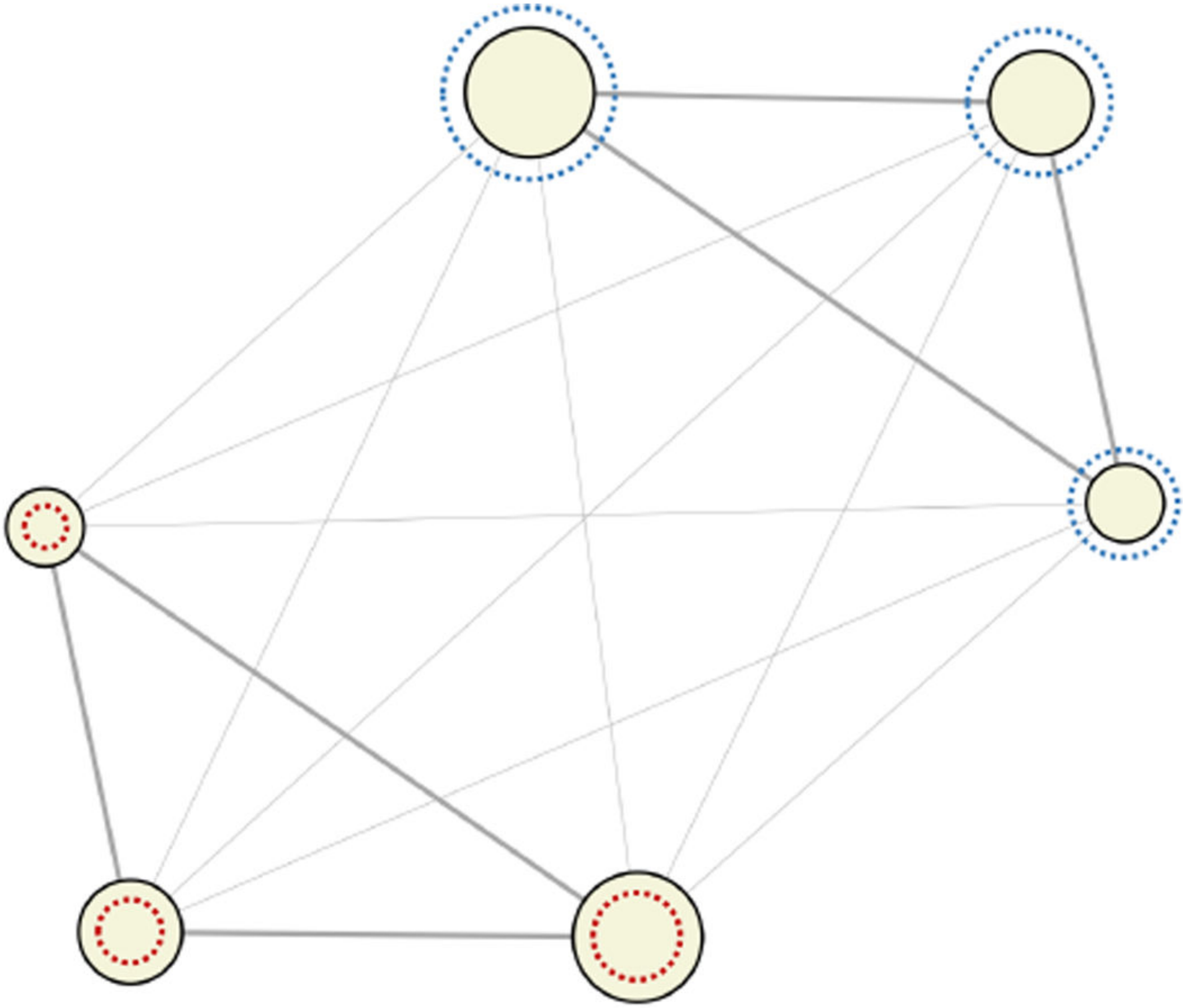

Figure 5: Illustration of the relationship between a topic's prevalence and the prevalence of its neighbors.

Node size represents prevalence, reflecting the finding that topics do not tend to be more strongly connected to topics with similar overall prevalence. Dotted lines represent changes in prevalence over time, reflecting the finding that topics tend to be more strongly connected to topics with similar prevalence change.

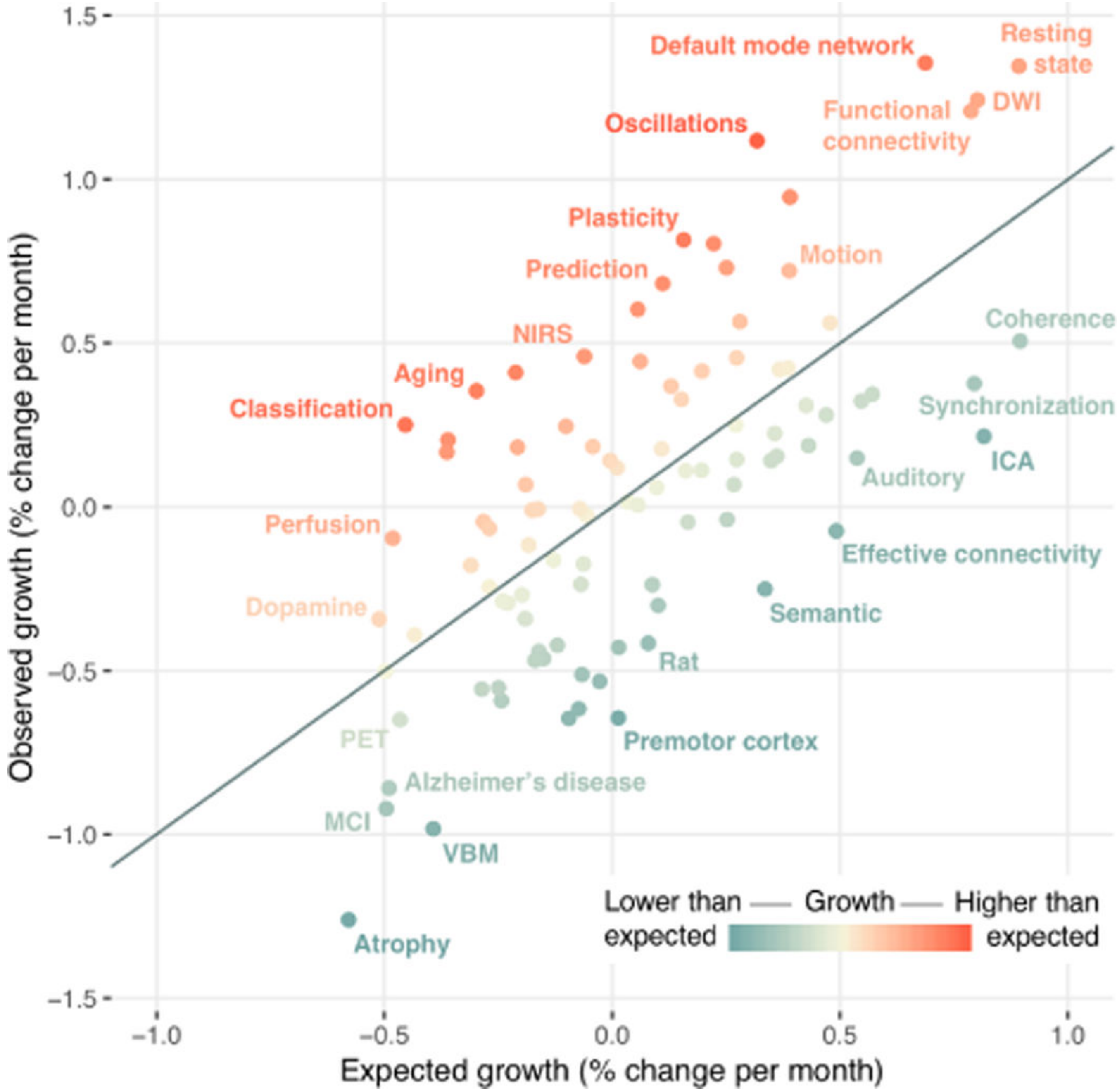

Figure 6: Relationship between topics' expected and observed prevalence changes.

The x-axis represents the expected growth of a topic's prevalence, given by the fitted value of the linear model based on network features. The y-axis represents the observed growth, given by the linear slope of prevalence over time. Color indicates the direction and magnitude of the deviance between the two measures.

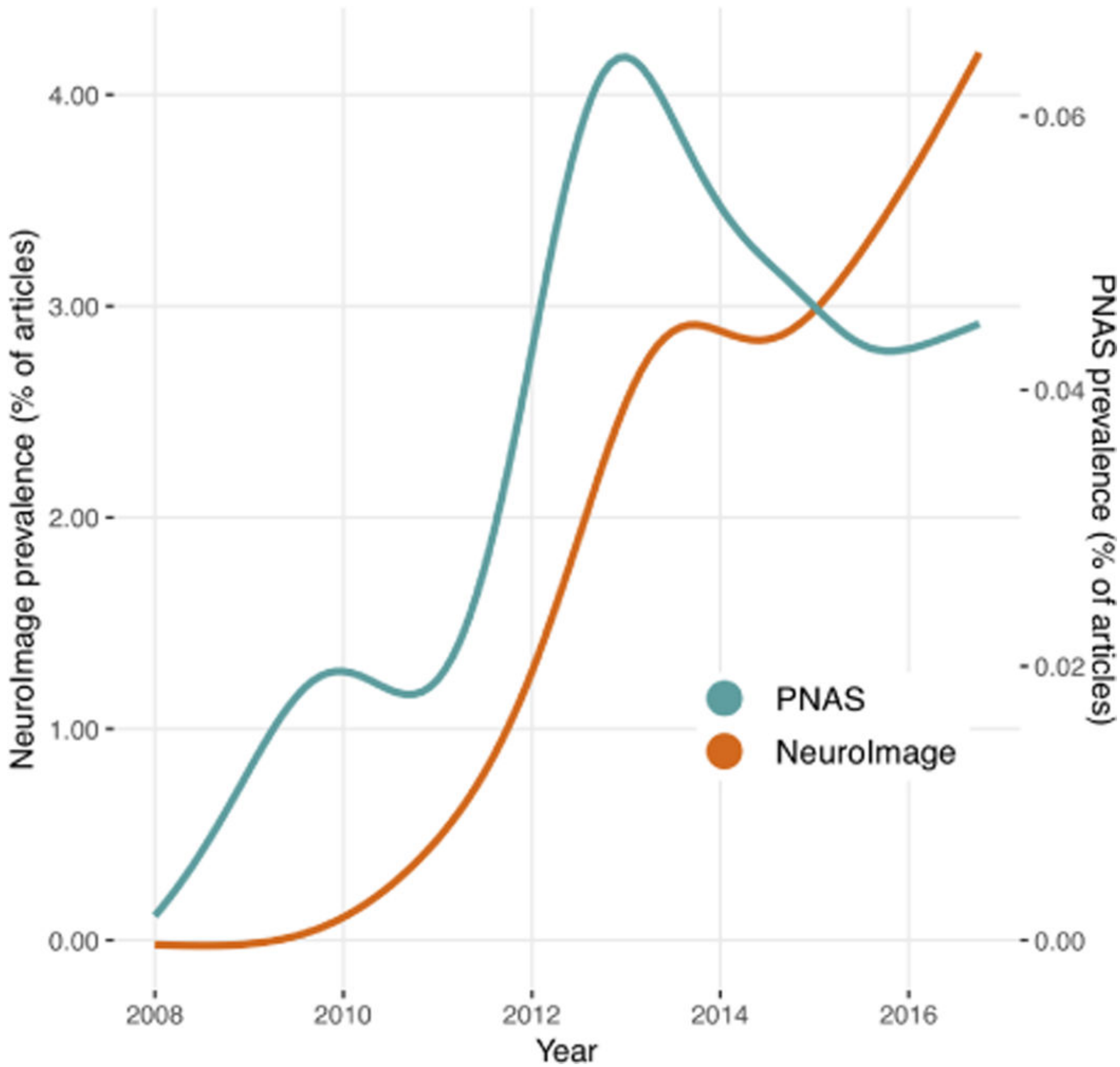

Figure 7: Increasing popularity of *connectome* within PNAS and *NeuroImage* articles.
Blue and red curves represent the prevalence trajectories of the topic connectome within the journals *PNAS* and *NeuroImage*, respectively. Both curves are smoothed using a cubic spline with 6 degrees of freedom.

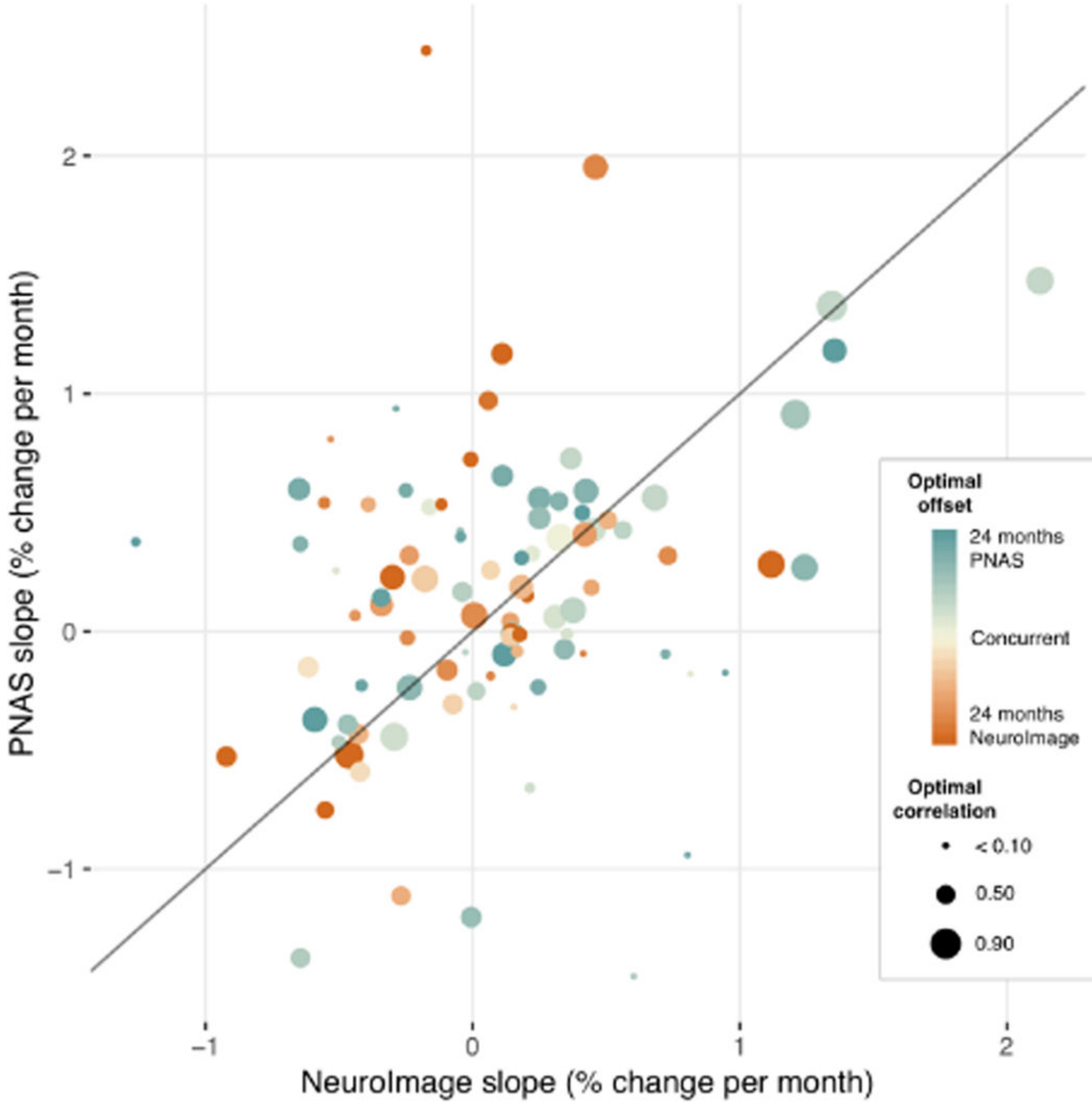

Figure 8: Relationship between topics' changing prevalence in *PNAS* and *NeuroImage*.

The x-axis shows prevalence changes in *NeuroImage*, and the y-axis shows the prevalence changes in *PNAS*. Topics are colored by the optimal lag between PNAS and *NeuroImage* trajectories, and scaled by the optimal correlation between the trajectories.

Table 1:

Rankings of topics' overall structural measures

Rank	Prevalence	Degree	Betweenness	Clustering	Participation
1	Brain	Cortex	Cortex	DTI	Schizophrenia
2	fMRI	fMRI	fMRI	Multiple sclerosis	Learning
3	Cortex	Prefrontal cortex	Hippocampus	Corpus callosum	Hippocampus
4	Human	MRI	Prefrontal cortex	White matter	Rat
5	MRI	Brain	Amygdala	Frac.anisotropy	Stroke
6	BOLD	Hippocampus	White matter	Myelin	Plasticity
7	EEG	Gray matter	Resting state	Diffusion	Epilepsy
8	Development	Thalamus	Motor cortex	DWI	Medial temp. lobe
9	White matter	Dorso. pf cortex	Memory	Emotion	Memory
10	Memory	Insula	Auditory cortex	Brain development	DM network

Table 2:

Rankings of topics' increases in the value of various structural measures over time.

Rank	Δ Prevalence	Δ Degree	Δ Betweenness	Δ Clustering	Δ Participation
1	DM network	Dyn. caus. modeling	Reading	Plasticity	DTI
2	Resting state	Basal ganglia	Myelin	Cerebral cortex	Myelin
3	DWI	Speech	Registration	Somato. cortex	Emotion
4	Func. connec.	Inf. front. gyrus	Coherence	CBF	Depression
5	Oscillations	Reading	Plasticity	Children	Pain
6	Brain development	Reliability	Basal ganglia	DWI	Orbito. cortex
7	Plasticity	Brain development	Depression	Development	Anxiety
8	TMS	Cerebellum	Stroke	Auditory	Ant. cing. cortex
9	Auditory cortex	Anxiety	Inhibition	Multiple sclerosis	Amygdala
10	Motion	Alzheimer's disease	Med. temp. lobe	Segmentation	Hemo.response