# Exploring Peer Prestige in Academic Hiring Networks

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Dedicated to my mother, for countless reasons.

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#### CHAPTER I

## Introduction

#### 1.1 iSchools and Identity

#### 1.1.1 What is an iSchool?

Relatively young and highly interdisciplinary, iSchools have begun to exhibit characteristics of an academic community, through conferences, promotional materials, advisory boards, and institutional naming. With diverse institutional characteristics, this nascent intellectual community arises from common epistemological foundations rooted in computer science, information technology, library science, information studies, and related fields. While a group of schools of information have self-identified as iSchools in name and by conference participation, there is controversy over just what an iSchool is.

Concerns over academic legitimacy are understandably important to the faculty and administrators in the community of iSchools. It is a matter of interest the to leaders of these academic units, who are responsible for the future development of their school and discipline, and to academic administrators whose institutions consider the move to iSchool status. iSchools engage in a broad range of interdisciplinary research pursuits and offer a variety of courses that integrate studies from computer science, design, and library science, among other disciplines.

Course offerings at iSchools vary widely in accordance with the variety of de-

gree program offerings. There is consistency among schools with ALA accreditation providing instruction in information services, school media, reference, information seeking behavior, and related topics relevant to the practice of librarianship. Programs in Human-Computer Interaction show the technology face of iSchools, including courses in interface design, information architecture, and usability. Other courses of study may center around such topics as privacy, intellectual property rights, information management in organizations, information economics, telecommunications, domain-specific informatics, and ethics.

#### 1.1.2 Intellectual Identity

Growing interest in the concept of identity in iSchools inspired conference papers on this theme at the 2005 iConference. Leazer (2005) expressed concern over a perceived schism between schools focusing primarily on humans and others specializing in technical systems design. Furner (2004) noted that difficulty in defining information obstructs the development of a disciplinary identity, and further challenges arise when information studies are defined by the phenomena they examine. Epiphenomenal studies such as ethics are considered a central distinguishing characteristic for information studies, and apply to the design of information systems and services as well as the study of human information behaviors. Building an academic identity based upon these indirect characteristics will remain an ongoing challenge for schools of information; Annabi et al. (2005) identified a series of issues involved in the development of a sustainable academic community.

Among the problems discussed at the 2005 iConference, student recruitment and student placement are particularly challenging for a new academic discipline, and are critical to the success of the iSchools. Identity is a clear root factor in these challenges, as a lack of awareness of the iSchool movement hinders student recruitment efforts, and program graduates must articulate the identity and value of their interdisciplinary studies to secure employment. Further challenges identified by Annabi et al. (2005) pertain to the development of the scholarly community from the perspectives of publication, funding, and interdisciplinary research efforts.

The growing pains of a newly-minted academic discipline were familiar to the related field of information systems, which emerged in the 1970's and has grown into today's management of information systems (MIS) programs. Lyytinen and King (2004) identified a sentiment of academic inadequacy stemming from the lack of a theoretic core in information systems, and countered it with a model of disciplinary legitimacy centered on salience of the issues studied, the production of strong results, and the maintenance of plasticity. The information field differs from information systems in that iSchools typically evolve from established, respected academic disciplines such as Library and Information Science (LIS) and Computer Science (CS.) Information schools, far from lacking a theoretic core, must instead synthesize the relevant aspects of the theoretic cores of several related fields.

#### 1.1.3 Problem Statement

iSchools don't really know who they are as a community and at the same time are forming an intellectual identity as a new breed of interdisciplinary researchers. In order to remain viable within their organizational boundaries, the members of the community must establish an individual identity in alignment with the iSchool community identity.

#### 1.1.4 Research Audience

The primary audiences for this research are the students and faculty of iSchools and people interested in becoming involved with an iSchool. PhD students have expressed interest in identifying outbound edges from their school to find potential employers perceived as "friendly" to their alma mater. Faculty seeking positions in other schools may also use the network data to the same end, either seeking out positions based on their alma mater or based on their current affiliation, which would be a more strategic approach, according to the literature. The literature shows that the strongest effect of prestige on hiring is made by the most recent affiliation, so new PhD graduates are "assessed" according to their alma mater, post-docs by their post-doc institution, and active faculty by their current position.

Faculty search committees might use the information to consider possible schools from which to recruit graduates, or as a basis of comparison between job candidates. Their actions would be dependent on their strategic approach to the goals they wish to pursue in hiring, which may be to hire from the most prestigious institution's graduates, to hire from the institutions with which their neighbors have ties, to hire from the institutions to which they are already linked, or to hire so as to increase diversity of the faculty's institutional background. It is more likely that rather than such an overt reliance on the representation of prestige, this analysis might contribute one of many points of comparison between top candidates for a faculty position.

It is of some concern that once such a ranking analysis as presented by this study is known, people have difficulty ignoring it as an input to decision making. Both on an individual basis and in groups, improving one's prestige is a common and primary goal. It is only natural to desire prestige, which brings accumulative advantages in the academic settings. Instead of focusing entirely on prestige, this research focuses on understanding the unique roles by which iSchools contribute to the greater intellectual community.

#### CHAPTER II

# Literature Review

#### 2.1 Prior Work

The literature was consulted in several disciplines to ground this research in the complex contexts of social networks and academic hiring. An interdisciplinary approach is both appropriate to the study of the interdisciplinary iSchools and necessary to the study of the iSchool movement, as there have been no formal studies of this emergent academic community and the most directly related writings generally pertain specifically to the subset of schools that have ALA accreditation. The dearth of published literature related to the formation of the iSchool community is a result of the recency of the formal self-identification of the member schools as part of the I-Schools Caucus.

While there are few resources specific to the iSchool community, the sociology literature supports the investigation of identity, academic hiring, and the social aspects of networks. Papers in physics and statistical mechanics provide a network science context for understanding community structures and prestige. These literatures infrequently cite across disciplines, indicating a need for interdisciplinary research that synthesizes the perspectives of physical and social science with respect to networks.

#### 2.2 Identity and Academic Emergence

#### 2.2.1 Emergent iSchool Community Identity

The emergence of iSchools appears to be a direct result of a sea change in LIS programs in the 1980's, when several long-standing American Library Association (ALA) programs closed or ceased to maintain their accreditation. Hildreth and Koenig (2002) documented the prevalent survival strategies for LIS schools: merger with a larger partner or expansion into IT-related fields. It comes as little surprise that over half of the iSchools are represented as mergers or realignments in this analysis. Two iSchools have been successful mergers; Rutgers incorporated LIS with communications and journalism, and UCLA's information studies program partnered with education. Further, a number of hale LIS programs have been organizationally realigned and aggressively expanded their studies related to information technology; these include Syracuse, Pittsburgh, Drexel, Florida State, Michigan, Washington, Illinois and Indiana.

The survival of an academic discipline depends on a complex set of variables. Small (1999) found that an academic survival strategy to achieve organizational legitimacy and stability underlies the way an emergent intellectual enterprise develops its identity. According to Tyworth and Sawyer (2005), several issues of identity were highly ranked as priorities for iSchools; while the emerging field's target identity is established, it is not yet realized. In defining identity, iSchools face a challenge discussed by Soofi (1994): the definition of "information" is variable and contextually specific. As our understanding and needs have changed with the development of new information technologies, schools previously devoted to the traditional library science alone are changing academic focus and identity to meet the evolving needs of the information age. Wenger (1998) emphasized the dynamic nature of identity due to the social contexts of its construction. While long-term effects of reputation still underpin institutional identity, more recent changes in the names and focus of the iSchools reflect a shift in academic identity to support organizational survival in a changing social context.

#### 2.2.2 Adaptation in Academia

As Gioia and Thomas (1996) observed, academic institutions undergoing strategic change tend to use projected image goals, often in the form of prestige rankings, to indirectly influence identity. They found that the changes of identity often required for survival in today's academic world generate a conflict between the definition of identity as reliant on durability and the practical necessity of a more malleable identity. Lyytinen and King (2004) found that in the information systems field, flexibility and social relevance may be more important to academic legitimacy than a traditional theoretical core.

The identity adaptation of iSchools has resulted in the generation of an interdisciplinary field that is at once based on a traditional theoretical core as well as flexible, socially-relevant studies and practice. The practice of interdisciplinary academic study is a challenge, particularly when the field's identity is still evolving and involves a number of complementary research areas. In an interdisciplinary department or school, diversity of expertise brings strength, and iSchool faculty come from many fields. Weick (1976) proposed several potential benefits of such a flexible, adaptable approach in the context of building links between institutions. An adaptively coupled organization, highly interpretive and proactive, was characterized by Brown and Duguid (1991) as an enacting organization. While the recent changes in identity that lead to the development of iSchools may have originated in academic survival strategies, they exemplify the idea of the enacting organization, responding to meet new information needs in changing social contexts.

#### 2.3 Prestige in Academic Hiring Networks

#### 2.3.1 Prestige in the Academy

In the academic arena, prestige is considered an important reflection of identity. Burt (1976) and Burt (1977) outlined a general framework of stratification and prestige in a social network and provided a conceptual foundation for subsequent exploration of academic hiring networks. Bair (2003) examined the role of faculty hiring practices with respect to prestige for finance doctoral programs, where the majority of new hires in the top ten programs were graduates of those same top ten programs, suggesting academic inbreeding. Burris (2004) found that for three social science disciplines, departmental prestige was an effect of a department's position within PhD hiring networks.

The same dynamics for hiring patterns in economics were implied by Cawley (2003), who explicitly acknowledged the common understanding that most initial jobs for economics PhDs are in lower-ranked departments than the department from which the new faculty have received their degree. Bedeian and Feild (1980) found evidence of extensive cross-hiring among the top management graduate programs and a preference among hiring departments to choose graduates from departments with similar prestige rankings as their own. In the sociology field, Baldi (1995) concluded that the prestige of the PhD-granting department was the strongest determinant of the prestige of initial job placements. This confirmed the results from Long et al. (1979) in the field of biochemistry, where preemployment productivity was found to confer no significant advantage in job placement.

#### 2.3.2 Productivity and Prestige

The academics conducting these studies voiced concern that hiring be universalistic rather than particularistic, based on some less important criteria than academic performance and potential. Several studies have looked into the relationship between hiring and productivity; Long (1978) determined that the employing department had a strong effect on individual faculty productivity, but the effect of productivity on job allocations was weak. Further study by Long and McGinnis (1981) concluded that the culture of the academic departments effects faculty productivity such that individuals perform to the standards of their current cultural contexts, irrespective of prior and later productivity. This indicates that as a hiring criterion, productivity may not be all that valuable as an indicator of success.

When hiring is not based on productivity but on some other particularistic criteria such as prestige, potentially detrimental effects to the field may result in the form of academic inbreeding, which seems to generate greater stratification of departmental prestige over time. Hunt and Blair (1987) discussed several problems associated with the Matthew Effect as a result of particularistic hiring among management academics. Particularistic hiring was also identified by Bedeian and Feild (1980) as a factor in the relationship between the prestige of individual placements of faculty department and graduate department. The Matthew Effect is better known in network science as preferential attachment, or the "rich get richer" phenomenon, and is also known to sociology as accumulative advantage. In each nomenclature, researchers fear stratification of prestige unrelated to merit.

In the iSchools, evaluating faculty productivity proves difficult, particularly for comparison to prestige. Adkins and Budd (2006) measured LIS research faculty productivity through publication and citation rates, but Meho and Spurgin (2005) warned that increasing departmental interdisciplinarity and incompleteness of databases poses significant threats to the validity of LIS faculty productivity studies. Additionally, evaluating LIS schools alone would exclude several iSchools which are not accredited by the ALA, and evaluating the iSchools based only on their LIS programs would not appropriately represent the breadth of the relevant faculty expertise at such institutions as Rutgers and UCLA. Accounting for the variations across iSchools that is introduced by their interdisciplinarity will remain a challenge in any attempt to rank these schools based on scholarly productivity.

In studying academic hiring networks, the time scale of personnel changes, as a reflection of changing identity, may be seen as problematic to analysis. While Braha and Bar-Yam (2006) showed that individual roles may change dramatically over the short term in dynamic networks, studies of academic hiring have taken an aggregate perspective. The long-term aggregation of hiring choices is appropriate in the academic context, as established disciplines show little variation in prestige rankings over time. This may be an effect of the contingencies of initial positions in social hierarchies, noted by Lin (1999), or another factor such as a halo effect of the reputation of the larger institution within which a school or department operates.

#### 2.4 Networks

#### 2.4.1 General Networks Literature

Despite the cross-cutting interdisciplinary applicability of network science techniques and theories, the fields of sociology and physics are the primary contributors to the general networks literature. Newman (2003) provided a thorough review of the accomplishments of network science to date across several fields. Two topics that are continually relevant to social networks are small world networks and the strength of ties. Travers and Milgram (1969) tested the now-famous theory of small worlds in social networks experimentally to verify that the chain of social acquaintances between two individuals can be remarkably short. Kleinberg (2000) documented the searchability of these small world networks, in which short chains are ubiquitous and local information is sufficient for the network to find short routes; Kleinberg (2001) then generalized the features of small world networks that are conducive to search. Watts et al. (2002) concluded that most social networks are searchable and defined a social network model in which group membership is a property of individual identity and also a primary basis for interaction.

Granovetter (1973) studied the strength of weak ties, a theory based on the idea that the degree of overlap between the friendship networks of two people is determined by the strength of their tie so that individuals are more likely to be friends with their friends' friends. Petróczi et al. (2006) generated a scale for a continuous, quantitative measure of tie strength in social networks, focused on online communities. Direction is also an important characteristic of network ties; Garlaschelli and Loffredo (2004) elaborated on prior measures of link reciprocity to propose a new definition using the correlation coefficient between the entries of the adjacency matrix of a directed graph.

#### 2.4.2 Algorithmic Rankings and Growth in Networks

Prestige is usually communicated in the form of rankings, and a number of algorithms are available to rank the nodes of a network. Adapting the concept of peer review to the structure of web links, Page et al. (1999) described PageRank, which efficiently computes objective rankings for large numbers of web pages based on network topology. Farahat et al. (2006) evaluated three ranking algorithms that assign weights to nodes using a dominant eigenvector that describes the network's link structure; they also proved the existence of these eigenvectors and the uniqueness of the PageRank eigenvector, which is a desirable quality in a ranking algorithm.

The rankings that a node in a network can achieve are affected by the way in which the network was formed. There is a significant literature on preferential attachment, a model of network growth commonly referred to as the "rich get richer" phenomenon which has many variations. Newman (2005) reviewed the empirical evidence for power-law networks, and saw the strongest potential for describing power-law phenomena in the generative models of Yule's process (another name for preferential attachment) and self-organized criticality. Boguna et al. (2004) and Jackson and Rogers (2006) proposed network growth models that show greater similarity to social processes based on social distance and on link generation strategies. In a study of the evolution of a dynamic email network, Kossinets and Watts (2006) identified the need to address the interactions of cyclic closure bias and focal closure bias in dynamic network models. Plerou et al. (1999) and Matia et al. (Jul 2005) examined network growth dynamics in research publications.

#### 2.5 Community Structure in Complex Networks

#### 2.5.1 Status, Roles and Topology

Identity in a social network is dependent upon the roles each actor plays in the network. Burt (1976) sought to provide a structural foundation upon which to base later analysis of multiple dimensions of network prestige, specifically investigating ways to measure the degree of topological equivalence for actors in a network. Burt (1977) built on the concept of social distance to create a general theoretical framework of stratification and prestige in a network, which provides a method for identifying community structure based on network topology. The idea that structural equivalence or near equivalence can identify the network roles that nodes play, based on

their patterns of ties in the network, has been readily adopted as a basis for research on community structures in the physical sciences as well as in social science.

The concept of social distance generated from the theoretical foundation of structural equivalence has informed several studies on status and topology in social networks. McPherson et al. (1992) used social distance concepts to develop and test a theory of the dynamic behavior of voluntary groups by combining network topology and evolutionary theory. Akerlof (1997) considered the network interactions between agents with inherited positions in social space, for which an expected interaction value between any dyadic pair is dependent upon their social distance.

### 2.5.2 Modularity and Community-Finding Algorithms

In the physical sciences, networks with community structures are considered to exhibit modularity. Nodes' membership in communities within a network are often identified through a computationally-intensive process of simulated annealing, and developing new community-finding algorithms is a current research topic of interest in physics and statistical mechanics. Newman (2003) reported that the traditional method for identifying community structures in a network is through hierarchical clustering, wherein strength of ties between dyadic pairs in a network determines group membership of the nodes. While Guimera et al. (2004) showed that under certain conditions, stochastic network models of random graph and scale-free networks can have high modularity, Newman (2006a) acknowledged this potential problem and specified modularity as the number of edges falling within groups minus the expected number in an equivalent random network. He formulated modularity in terms of eigenvectors of a modularity matrix for the network, which enabled the use of spectral analysis techniques. Newman (2006b) favored the modularity matrix approach because the magnitudes of an eigenvector could be considered indicative of "strength" of a node's membership in a group.

In the context of functional modules in metabolic networks, Guimera et al. (2005) proposed a method to maximize modularity in networks based on undirected links which did not require an *a priori* specification of the number of modules. In the same month, Guimera and Amaral (2005) demonstrated this method for identifying functional modules in complex networks of metabolic interactions by identifying modules with simulated annealing and classifying nodes by their intra- and inter-module connections. An open issue identified in the study was the question of how to adapt current module-detection algorithms to networks with a hierarchical structure, which are common to complex adaptive systems in many contexts. Ravasz et al. (2002) suggested that hierarchical organization may be a strategy by which metabolic networks achieve the high clustering coefficients that indicate modular organization.

With a slightly different perspective, Palla et al. (2005) introduced a technique for exploring overlapping communities in large scale networks, based on the assumption that a typical community consists of several complete subgraphs that tend to share many of their nodes. While most studies of community structure in networks focuses on identifying the communities, Ethiraj and Levinthal (2006) studied the dynamics of innovation and performance in complex systems. The study found that too little modularity slows the pace of adaptation and can lead to lock-in at local maxima, while too much modularity can stymie any possible adaptive change due to greater interdependencies.

#### CHAPTER III

## Hypotheses

#### 3.1 Identity and Hiring in iSchools

#### 3.1.1 Prestige Rankings and Identity

Why do we care about rankings? What does this preoccupation say about our implicit understanding of prestige as a function of image and identity? The sociology literature studies hiring networks to understand how prestige influences hiring, looking for evidence of an academic caste system and stratification of elite schools due to inbreeding in hiring. Prestige rankings are a common operationalization of image and identity; for a community in which identity is a matter of concern, developing an appropriate measure of prestige could ameliorate this concern. Providing prestige scores to iSchools allows each school to be understood within a community context, which may play a significant role in developing community identity. In the case of existing rankings, the community context is incomplete.

The information school movement alters the value of the USNWR rankings for LIS schools as currently formulated for two reasons. First and foremost, a number of schools are not included in the published rankings. Notably, those schools who do not have ALA accreditation are summarily excluded from consideration in the traditional rankings, which focus on the library science aspect of information and library science programs as a primary sample selection criterion. This is an understandable choice, as there are few other guidelines by which to select the sample of schools for ranking.

Second, the rankings assess the schools on an incomplete set of criteria that favors some program structures, such as a traditional library science curriculum, over other information school programs that focus on the broader research agendas that reflect the true diversity of interdisciplinary study. The epistemic shift from libraryspecific studies toward the information-centric iSchool paradigm creates a challenge in identifying appropriate rankings by which to compare the iSchools; ratings from the National Research Council, which are often used for sociology studies and other research around hiring in academia, reflect neither the diversity of studies at today's iSchools nor the full range of the community membership. Until these national ratings encompass the entire iSchool community, the identity information conveyed by prestige rankings offer a potentially misleading partial representation of this emergent academic community.

#### 3.1.2 Hiring and Prestige in Academia

Why look at hiring networks? In prior studies of hiring networks, researches have consistently found a relationship between hiring network topology and prestige; PhD program prestige is repeatedly shown to be much more relevant to post-PhD placement prestige than scholarly productivity at the time of graduation. While scholarly productivity has little influence on hiring, hiring has a strong effect on scholarly productivity (Long 1978).

Studying hiring instead of productivity for indicators of prestige requires the implicit assumption that these findings are generalizable to other fields. Assuming that where you work influences how much you produce, if scholarly productivity measures predict prestige accurately, the measures should correlate strongly with hiring prestige measures. Unfortunately, due to problems with the source data for scholarly productivity measures, particularly for the iSchools, we cannot expect that scholarly productivity data would support this outcome under analysis. The incompleteness of the scholarly productivity data and the inherent complexity of its measures make the more concise and complete data of a hiring network preferable for this study from an analytic standpoint.

#### 3.2 Research Hypotheses

Prestige ratings based on peer survey responses, published by such groups as USNWR and the NRC, imply a hierarchy of quality in the institutions reviewed. One target audience for the ratings are college-bound students, and as such the ratings project an important aspect of identity with respect to student recruitment; for this reason, it is important to question the value of the survey responses as indicators of academic program quality. The null hypotheses evaluate whether network measures of centrality can predict the peer survey prestige ratings that are a part of the community context of identity in an academic discipline.

#### 3.2.1 Network Measures for Regression

The network measures selected for regression analysis to explain the variance in USNWR ratings included the number of graduates in the network from each department, indegree, outdegree, total degree, weighted PageRank, and betweenness; for the CS network, the NRC rating was included as well. Each of these measures was included in analysis because each represents a different perspective on prestige and centrality in a social network, as discussed in section 5.5. In addition, information entropy measures were included to examine the potential roles of diversity in hiring practices and areas of faculty subject specialization.

Null Hypothesis 1. In the iSchool hiring network, there is no correlation between

a node's LIS USNWR rating and its network measures; specifically, the number of graduates in the network from each department, indegree, outdegree, total degree, weighted PageRank, betweenness, hiring diversity, and subject diversity.

Null Hypothesis 2. In the CS hiring network, there is no correlation between a node's CS USNWR rating and its network measures; specifically, the number of graduates in the network from each department, indegree, outdegree, total degree, weighted PageRank, betweenness, hiring diversity, and subject diversity.

#### 3.2.2 Plan of Research

Exploring indicators of prestige in hiring networks as related to the measure of prestige presented in peer rankings such as US News & World Report rankings provides a social networks perspective on hiring and identity in the iSchools. This research collected a hiring network of iSchools, compared it to a similar hiring network for Computer Science departments, and analyzed the ratings of the schools by utilizing existing USNWR ratings and prestige measures for the hiring network. The research used linear regression to project inclusive prestige ratings for the full CS and iSchool communities.

#### 3.2.3 Expected Outcomes

The expected outcomes of the research are only partially defined; I expect that there will be evidence of structural similarity between the two hiring networks, but that there will also be marked differences. I also expect that the network context will have a strong effect on the statistical strength that would support the rejection of the null hypotheses. In a full ego network context, the definition of the ego-alter relationship will prevent alters from receiving anything more than a minimal value in centrality measures. In the network composed only of egos, sample size is significantly reduced. In this case, the sample size is reduced to 18 actors in the iSchools network, only 11 of which have a USNWR rating, and this presents challenges to statistical significance.

Regardless of whether statistical tests support rejection of the null hypotheses, this study is itself a sociotechnical artifact, as defined by Trist (1981) of the formation of the intellectual community of the iSchools. As such, it provides documentation of the search for identity in an emergent academic community, a phenomenon of regular interest to the evolving academy.

#### CHAPTER IV

### Methods

#### 4.1 Research Design

A network data set representing faculty hiring in iSchools was generated for this study through manual data collection. Historically, this data would have been collected through a survey or from a directory that aggregated survey data of faculty by department for an academic field; in this study, the faculty of iSchools are the population of interest.

A network data set for this population generated through either of these traditional methods would contain an unacceptable level of bias due to inaccuracies. In the first case of data collection through a standard survey, the response rate would have to be very high in order for the network data to be representative. Given the relatively small sample size (detailed in Section 4.2) a more realistic survey response rate would be inadequate.

Similarly, a comprehensive directory is not available for the iSchool community, and the accuracy of the nearest proxies suffers from changes to faculty rosters in the time between publication dates. The ALISE directory is often referenced for studies that evaluate faculty or performance of LIS schools but if a school chooses not to renew its ALISE membership, it is excluded from the directory, as noted by Adkins and Budd (2006). For this reason, Matia et al. (Jul 2005) recommends compiling faculty lists from institutional web sites; in addition, such online data is updated more frequently than published directories due to its value in student and faculty recruitment as well as establishing online credibility (Fogg 2003). To obtain the most recent and authoritative information, data were mined from publicly available web pages.

#### 4.2 Sampling Strategy

The population for this study is the faculty of the 19 members of the I-School Caucus as of January, 2007 (I-schools Caucus 2007). Constructing a hiring network for an academic community necessarily requires purposeful sampling in order to represent the phenomenon of interest. While there is a bias to this method of ego network construction, which represents the schools as a community whether or not such community is perceived to exist, this is ameliorated by the fact that the schools from which the sample is drawn have self-identified as members of the iSchool community. This population selection excludes those schools which are self-identified as information schools in name or mission, but which have not yet aligned their identities with the iSchool movement.

Faculty roles are variously defined among different schools, and roles such as *lecturer* or *associate in information studies* are not necessarily representative of the long-term intellectual investment in academic identity that the hiring network seeks to represent. *Professors emeritae* are more representative of the prior identity states of a school than its current state. For these reasons, only full-time professorial faculty were included in the sample; these were identified by their standard academic titles of *professor, associate professor, associate professor, associate professor, associate professor, associate dean* and *dean*.

#### 4.2.1 Sampling Frame

The sampling frame was drawn from faculty listings on the web sites of the 19 iSchools, which are considered the most authoritative public source for this information according to Matia et al. (Jul 2005) and Adkins and Budd (2006). Some schools had not updated their faculty listings as recently as others at the time of data collection, and there is some resultant level of systematic lack of accuracy which is consistent within each school sampled. While these schools were potentially underrepresented or slightly misrepresented, the entire data set is subject to this sampling bias due to the inevitable delay between hires and web page updates. These considerations aside, the quality of the sampling frame is still improved over previously available methods. The size of the sample was determined by the number of full-time professorial faculty employed by the 19 iSchools, which came to 687.

#### 4.3 iSchools Data Collection

Data were collected manually during the month of January of 2007; an automated retrieval mechanism would have been ineffective due to the varying structures of the iSchool web sites. The institutions were coded in the data using their web site URLs to assure unique identifiers. While most of the data came from the web sites of the iSchools, this did not provide the full data set, particularly as different schools offer varying levels of detail about their faculty's credentials. Additional data was collected for each faculty member, beyond their graduate institution, which provides the minimum requisite information in order to construct the hiring network. This additional information gathered were title, the year of their PhD, and the department or school from which they received their PhD. This provided data for exploratory analysis and additional investigation into factors that may influence iSchool identity. A summary of network and other characteristics by iSchool is provided in Appendix A.

#### 4.3.1 Data Sources

In addition to the iSchools' web sites, the Proquest UMI Dissertation Abstracts database, faculty web pages, and faculty vitae were consulted to complete the full data set. In cases where the dissertation abstracts provided the source of the department or school, the data was collected directly from the dissertation title page where available, and alternately from the subject listings recorded in the electronic record for the dissertation. Because the subject listings are not necessarily congruent to the literal naming of the department or school in question, some of the data about the department from which faculty graduated are biased toward generalization; however, most analysis involving this data also requires that similar areas of study are grouped together. In this regard, the subject listings are an appropriate proxy for the exact department name when the more specific data is unavailable.

An additional challenge in collecting the graduate department data point was the common tendency for curricula vitae to list the PhD program of study, as opposed to the specific degree-granting academic unit; in these cases there was usually no indication as to whether the program of study or the department was the entity listed. This affects an unknown portion of the sample, and introduces a bias toward greater specificity of degree subject area. Again, as the departments and areas of study were coded for analysis, program name made a reasonable proxy for department name.

#### 4.3.2 Response Rate and Exception Cases

A 100% response rate was achieved, with a total of 693 terminal degrees recorded for the 687 faculty; raw data are included in Appendix D. The data are complete for all full-time faculty with PhD degrees. In a few cases, faculty did not hold a PhD degree and it was not possible to identify the years their terminal degrees were granted. For these 17 academics, outstanding professional qualifications or appropriate terminal degrees in a field such as law or medicine are appropriate qualification for their posts. These cases were noted with the final degree achieved, and removed from the data set prior to analysis to maintain consistency in the units of analysis.

Additionally, four faculty <sup>1</sup> hold two doctoral degrees each, and two faculty <sup>2</sup> serve for both schools at Indiana University. In preparing the data for analysis, the data for the two schools at Indiana were merged to maintain the university as the unit of analysis represented by the nodes of the network. After merging Indiana's schools, allowing multiple instances for faculty with two PhDs, and removing faculty without a PhD degree, the total number of faculty data points is 674. The comparison data set of faculty hiring for computer science departments was collected by similar methods in 2005 by Dr. Dragomir Radev and his associates; further details about this data are found in Section 5.1.1.

<sup>&</sup>lt;sup>1</sup>The faculty with two PhD degrees were Gerry Stahl, Drexel University; Dennis Gannon, Indiana University; Patricia Galloway, University of Texas Austin; and Juris Dilevko, University of Toronto.

 $<sup>^{2}</sup>$ The faculty who serve for both of Indiana University's Graduate School of Library and Information Science, and School of Informatics, are John Paolillo and Javed Mostafa.

#### CHAPTER V

### Analysis and Results

#### 5.1 Network Data

Since both the iSchools and CS networks are constructed by merging ego networks, they are composed in each case of a set of "inside" nodes for which we have incoming links (information on which other departments they hired from) and the remainder of the nodes for which there are no inbound edges. Those "outside" nodes have only outbound edges, and are included in the dataset if a graduate of the department was hired by one of the departments sampled. In the iSchool network, the inside nodes, or egos, are the iSchools and the outside nodes, or alters, are other institutions that do not have information schools affiliated with the I-School Caucus. In the computer science network, the inside nodes are the most highly ranked departments. This methodology produces a network with many leaf nodes, an outside node that did not provide faculty to more than one inside node, and for which we did not gather information on current faculty.

Both the iSchools and CS departments are portions of the larger academic sphere from which we draw relational information. As ego networks, there is an inherent bias in these data; while the network of alters can be considered a "social support" structure, the multiple egos are the primary actors of interest in this analysis (Wasserman and Faust 1994). To compare measures of social and network prestige in these networks, hiring the graduate of an institution is considered an endorsement in which patterns of association indicate social exchange.

#### 5.1.1 Computer Science Network Data

A comparison data set collected in 2005 by Dr. Dragomir Radev and Sam Pollack at the University of Michigan, and Cristian Estan at the University of Wisconsin-Madison, provides the sources of PhD degrees granted to the faculty of 29 computer science and electrical engineering departments, summarizing 1121 faculty PhDs in 527 edges between 123 schools. The departments selected as egos for data collection in this network were the top-ranked 26 programs in the United States and three top Canadian institutions. Reputation survey ratings from USNWR and the National Research Council (NRC) were also applied to the CS network data set for analysis of correlations between USNWR ratings and network statistics (Morse and Flanigan 2006, Maher et al. 1995).

#### 5.2 Analysis Tools and Procedures

The raw iSchool data were processed using Perl scripts to write the faculty degree information into a one-mode hiring network data file. The process additionally computed the number of graduates from each school who are iSchool faculty, and the network indegree and outdegree, which are the number of inbound and outbound edges for each school. A separate script was written to strip out all non-iSchools from the network, in order to produce a network data set that includes only the egos of the networks and the edges between them.

The data for each network were analyzed with the social network analysis software packages Pajek and GUESS, with network visualizations generated in GUESS

Network Characteristic	CS Network	iSchools Network		
Nodes	123	152		
Egos	29	18		
Alters	94	134		
Ratio of Alters to Egos	3.2	7.4		
Edges	572	429		
Average Degree	4.7	2.8		
Loops	26	17		
Total PhD Degrees	1121	674		
Average Edge Weight	1.96	1.57		
Density	0.038	0.019		
Clustering Coefficient	0.23	0.15		
Average Distance	2.2	2.3		
Diameter	5 (random = 7)	4 (random = 11)		
Betweenness Centralization	$0.21 \ (random = 0.05)$	$0.19 \ (random = 0.08)$		

Table 5.1: Network Properties for the CS and iSchool Hiring Networks

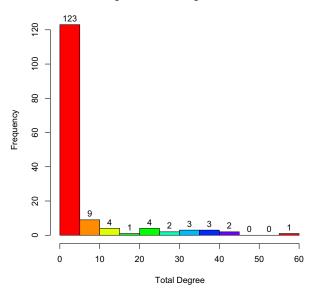
(Batagelj and Mrvar 2006, Adar 2006). Network statistics for each node were generated in GUESS and Pajek, and exported for further analysis in R (R Development Core Team 2005).

# 5.3 Network Properties

Several global network properties contribute to understanding the context of the interactions that each hiring network represents. The size of the network can be evaluated in several ways; the most apparent measures are the number of nodes and edges, and the ratio of edges to nodes, which gives the average degree of the nodes in the network. The number of nodes in each network must be considered with respect to the proportion of egos to alters, and many node statistics can only be compared appropriately when the points of comparison are all egos or all alters. For example, Table 5.1 shows that the CS network has 29 egos out of 123 nodes in its network, whereas the iSchool network has 18 egos among the 152 nodes in its network.

Only egos can have both inbound and outbound links to other nodes, so the

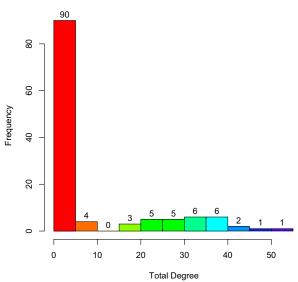
average degree of the egos differs from the average degree for the full network. This is clearly visible in the degree distributions of both networks, shown in Figures 5.1 and 5.2. In each case, most nodes have 5 or fewer links, while a few nodes, including the egos, have significantly greater numbers of links.



Histogram of Total Degree in iSchools

Figure 5.1: Degree Distribution for the iSchools

Both the number of egos and the average node degree contribute to the difference in link density for the networks; the CS network represents 1121 doctoral degrees with more egos and fewer nodes than the iSchool network, which represents 674 faculty PhDs. The number of edges into which these degrees are summarized provides another point for comparison, shown in Table 5.1 as the average edge weight for the network, which indicates how strongly the schools in the network are linked on average. It is interesting to note that despite these differences between the networks, the average distance between any reachable pair of nodes is nearly the same, meaning that although the iSchools network is more loosely connected than the CS network,



Histogram of Total Degree in CS Departments

Figure 5.2: Degree Distribution for the CS Departments

it is nearly as efficient in terms of minimizing distances between the schools.

The diameter of the network is a measure that represents the average shortest distance between any pair of nodes in the network; we find that both networks exhibit a low diameter and high betweenness, shown in comparison to the statistics for comparable random Erdös-Rényi graphs in Table 5.1. High betweenness and low diameter are key characteristics, present in both samples, of small world networks (Watts et al. 2002). Betweenness is also only comparable among the egos of the networks; in a directed network such as these hiring networks, a node must have both inbound and outbound edges in order to have a nonzero betweenness score. This is the source of the left skew of the distributions of betweenness in the iSchool network, shown in Figure 5.3, and the CS network, shown in Figure 5.4.

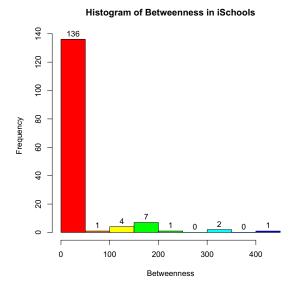


Figure 5.3: Betweenness Distribution for the iSchools

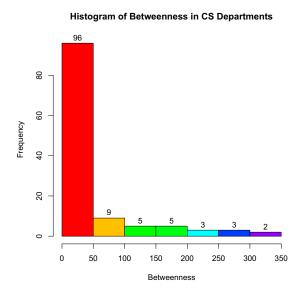


Figure 5.4: Betweenness Distribution for the CS Departments

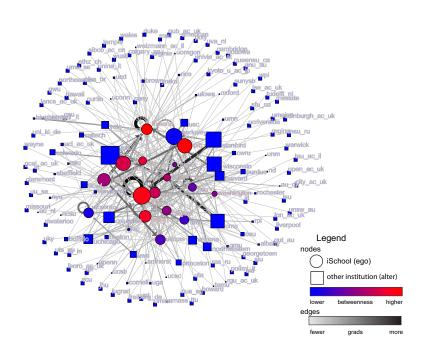


Figure 5.5: Network Visualization of Hiring in the iSchools

# 5.3.1 iSchool Network Properties

Visual inspection of the iSchool hiring patterns in Figure 5.5 quickly reveals some notable patterns. While most iSchools engage in some self-hiring, Indiana University and UCLA stand out, with heavy black self-loops for these nodes. It is also apparent that UCLA favors Stanford graduates, and Georgia Tech has a history of hiring graduates of Carnegie Mellon and MIT.

The node sizes and colors in Figure 5.5 represent two key variables; the size of each node shows the number of graduates of that institution who are currently employed by other egos in the network. Larger nodes like MIT and Stanford have many graduates on the faculty of iSchools; smaller nodes are hardly visible, and only have one graduate employed at an iSchool. Node color represents betweenness, a measure of network centrality discussed in Section 5.5.1, with blue nodes having low betweenness and red nodes having very high betweenness.

# 5.3.2 Computer Science Network Properties

In the visualization of Computer Science hiring patterns shown in Figure 5.6, we can immediately notice some interesting patterns. There are a few CS departments who hire their own graduates, namely MIT, University of Toronto, University of Waterloo, and to a lesser extent UCLA. MIT's preference to hire its own graduates is well known. Even more noticeably, there is a strong flow of PhDs among the top schools: Berkeley, CMU, Stanford and MIT.

Some rather large departments, for example at Georgia Tech and Purdue, do not have graduates on the faculty at many other top ranked departments. And some rather small departments, such as those of Caltech (14) and Harvard (21), have had strong success in placing their graduates in many of the top departments. There also seems to be a flow of California faculty to UCSD, with a full 13 Berkeley and 7 Stanford graduates there. Likewise, there is a strong trend for Canadian schools to hire from one another's graduates; Waterloo's preference for Toronto graduates is particularly evident in Figure 5.6.

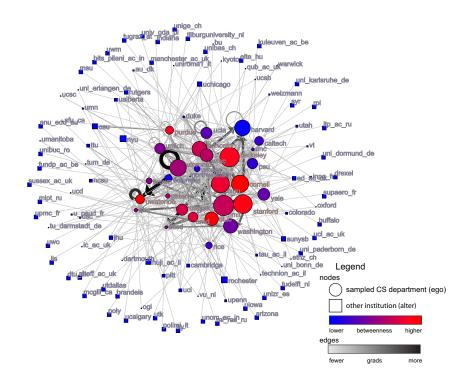


Figure 5.6: Network Visualization of Hiring in Top Computer Science Departments

# 5.3.3 Measuring Diversity in Hiring Networks

Schools follow varying strategies to build a strong faculty; some are highly specialized while others are highly interdisciplinary. Two information entropy calculations provide measures of diversity in hiring sources and in areas of subject specialization, by applying the calculation from Shannon (1948):

(5.1) 
$$\sum -f(\log f)$$

where f is the number of faculty in a given category, either based on their area of

expertise or the institution from which they received their degrees. When applied to the hiring data for each school, the hiring diversity measure reflects both the variety and strength of connections to other schools. Schools that hire preferentially from a small handful of highly-respected sources will have low hiring diversity scores and schools that hire from a wide variety of institutions without strong favorites will have high diversity scores. The hiring diversity measure was generated for both networks.

In addition to hiring diversity, an additional measure for disciplinary diversity was included for the iSchools. The same information entropy formula was applied to the number of faculty with degrees in each subject family. The resulting disciplinary diversity scores are highest for the most interdisciplinary schools and lowest for schools with a very strong disciplinary focus, as reflected in the subject areas studied by their faculty, discussed further in Section 5.4.

# 5.3.4 Comparing the iSchools to the Computer Science Departments

The visual combination of node size, shape and color in Figures 5.5 and 5.6 show notable differences between the two networks. One immediate observation is related to node size, which represents the number of graduates employed in the network. Among the CS departments, there are no large non-ego (square) nodes, and most of the nodes with high betweenness (red and purple) are not small. In the iSchool visualization, however, most of the nodes with high betweenness are medium or small in size, and many of the largest nodes are not egos. An exception among the CS departments is Harvard; although it is a large node, with many graduates employed in the network, it has the lowest nonzero betweenness in the CS network ego, as shown in Table 5.8.

By comparing the network visualizations, we can also see some structural differences. Generated with the same data processing methods and output formatting scripts, the Kamada-Kawai layout algorithm produces a network diagram with a densely connected, tightly woven center for the CS departments. In contrast, the iSchools network diagram shows a more loosely connected network, with fewer nodes clustered tightly together in the center and more small nodes around the periphery of the network.

These observations are in keeping with the network statistics, shown in Table 5.1. The iSchools network has a lower density, lower average degree, lower clustering coefficient, and lower average edge weight than the CS network; the number of degrees summarized in each network is the primary reason for this difference. While the number of egos in each network plays a significant role in determining these statistics, one notable difference between the two networks is seen in the ratio of alters to egos. The iSchools have more than twice as many alters for every ego as do the CS departments, indicating that the iSchools hire from a greater diversity of sources than the CS departments.

# 5.4 Faculty Areas of Study

The graduating department or program of study for the faculty of iSchools was a point of interest for two reasons. First, in the event of self-loops, where a university has hired its own graduate, it is useful to know whether these individuals were hired by the same department from which they had graduated, or from a different school within the university. A second reason to examine faculty areas of study is that identity characteristics for each iSchool, such as programs of study and courses, are both influenced by the areas of expertise represented on its faculty, and influential to hiring choices.

# 5.4.1 Coding Faculty Areas of Study

As mentioned in Section 4.3.1, collecting the department for each faculty member in the sample offered challenges. Once the data were collected, 172 distinct areas of study were coded into subject families according to the Classification of Instructional Programs (CIP) from Morgan and Hunt (2002). There was some ambiguity regarding how to best classify programs entitled *library and information science* or *information and library science*; these were all coded as *library science* because there was a substantial and clearly differentiated population of faculty with degrees in *information science*.

The initial coding of the faculty areas of study to CIP families yielded 24 categories; however, some categories such as *family sciences* included very few individuals and other categories, such as *engineering* and *engineering technologies* were sufficiently similar as to provide little additional insight. For analysis purposes, these 24 categories were compressed into the summary list of 13 categories presented in Table 5.2 and Figure 5.7.

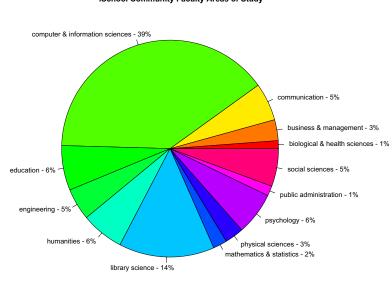
The majority of the 693 faculty degrees in the sample were in *computer and information sciences*, making up about 43% of sample. The next most common area of study, for 14% of the faculty, was *library science*; however, some portion of those degrees classified in the former category might arguably have fit into the latter, if consistent detail about the program of study had been available for faculty with degrees in such areas as *information studies*. In some programs, a degree specialization may differentiate between a traditional LIS focus or another information science focus, but data at a level of granularity to allow discrimination between degree programs were not universally available.

Aggregated CIP Families (N=674)	Original CIP Families (where aggregated)	Mean Year PhD Granted
Biological and Health Sciences, $n = 8$	Biological and Biomedical Sciences, $n = 4$ Health Professions, $n = 4$	1999.8
Business and Management, $n = 21$	-	1996.1
Communication, $n = 38$	Communication and Journalism, $n = 35$ Communication Technologies, $n = 3$	1991.8
Computer and Information Sciences, $n = 267$	-	1993.4
Education, $n = 45$	-	1989.4
Engineering, $n = 32$	Engineering, $n = 25$ Engineering Technologies, $n = 7$	1988.6
Humanities, $n = 43$	Architecture, $n = 1$ English Language and Literature, $n = 7$ Foreign Languages and Literature, $n = 4$ History, $n = 15$ Multi and Interdisciplinary Studies, $n = 6$ Philosophy, $n = 8$ Visual and Performing Arts, $n = 2$	1985.3
Library Science, $n = 96$	-	1990.3
Mathematics and Statistics, $n = 14$	-	1987.2
Physical Sciences, $n = 19$	-	1981.8
Psychology, $n = 43$	-	1985.2
Public Administration, $n = 10$	-	1993.3
Social Sciences, $n = 38$	Family Sciences, $n = 1$ Social Sciences, $n = 37$	1985.7

Table 5.2: Faculty Areas of Study in the iSchool Community

## 5.4.2 Analysis of Faculty Areas of Study

It comes as no surprise that the majority of faculty in the iSchools hold PhD degrees in *computer and information science* or *library science*, since the field of information has roots in both of these academic disciplines. However, a full 43% of the faculty studied in other fields, bringing great diversity of expertise to the iSchool community, shown in Figure 5.7.



iSchool Community Faculty Areas of Study

Figure 5.7: Pie Chart of iSchool Faculty Areas of Study

In terms of the diversity of faculty expertise, there is significant variation between schools, as shown in Appendix B. One interpretation would gauge the interdisciplinarity of study in the schools by the distribution of areas of study represented in the faculty; some schools have chosen to pursue a rich but narrow focus, such as the University of North Carolina, whose faculty's studies are strongly centered around library science and computer and information science. In contrast, schools such as the University of Michigan have made a specific goal of cultivating a broadly interdisciplinary faculty, and have faculty representing 11 of the 13 aggregated CIP families.

The faculty interdisciplinarity measure, calculated on the faculty areas of expertise with the information entropy formula in Section 5.3.3, seems to support this interpretation. Michigan and Syracuse stand out with the highest scores, indicating the greatest interdisciplinarity, while schools such as UNC and the University of Toronto cluster together with the lowest scores, indicating the greatest focus in subject specialization.

The differences shown by the faculty expertise are clear indicators from hiring practices of different approaches to building an institutional identity at each iSchool. Naturally, a small faculty will tend to represent fewer disciplines. In the iSchools, a full-time faculty of 25 or fewer persons will most likely have faculty expertise in five or fewer broad disciplines; one notable exception is the University of Maryland, where a small faculty of seventeen individuals spans seven disciplines. Above the threshold of 25 full-time faculty, the iSchools usually employ a faculty with expertise in eight or more academic areas of study.

# 5.4.3 Self-Hiring in the iSchools

Seventeen of the eighteen iSchools hire faculty from their own parent institution. There are at least two reasons for this phenomenon; first, the faculty may come from other departments within the institution, and second, the iSchools' hiring choices for faculty specializing in such areas as archives and librarianship are more constrained due to the relative rarity of PhD granting programs in these disciplines. In the first case, where faculty are hired from other departments within the institution, the iSchool network departs significantly from the social science departments in Burris' study, which hired from their own graduates.

In this regard, self-hiring in iSchools may actually represent greater diversity in their interdisciplinary nature; Pennsylvania State University's iSchool was founded recently enough to have none of its own graduates on faculty, as is also the case for the University of Washington. At PSU, however, nearly 15% of faculty received their degree from PSU, where hiring from other departments in the university may support interdisciplinary diversity within the faculty of the iSchool. In contrast, Washington's faculty is comprised entirely of faculty from other institutions with no self-hires whatsoever, making their iSchool the single exception in the community with regard to self-hiring.

The iSchools, on average, hired 13% of their faculty from their own institutions. For the 17 iSchools which had hired faculty with a degree from their own institution, approximately 64% of the self-hires were graduates of the program which later employed them. In nearly every case, these were faculty with degrees in library science, supporting the idea that faculty specialization in this areas is subject to greater hiring constraint. UCLA is an interesting exception in that most of its self-hires were graduates of its education program, rather than library science as in most iSchools.

Self-hiring is not necessarily a case of a school's graduates immediately joining the faculty of the school granting their degrees; it is more likely that a significant proportion of these individuals had their start in academia in another institution and have returned to their alma mater some years later as accomplished scholars. Analysis of the full CVs for the iSchool faculty would be required to further investigate the question of self-hiring practices in the iSchools, but these data were not collected for this study as faculty CVs were not universally available from all of the schools in the sample.

# 5.5 Prestige

In academic hiring networks, high indegree indicates hiring from a diverse set of sources, and high outdegree is achieved by placement of PhD graduates in a diverse group of schools. Outdegree measures were used to calculate centrality and closeness measures due to the inherent indegree bias resulting from data collection methods for ego networks. Because these measures are normalized, simply having the greatest number of faculty in the data set is not enough to rank highly; for example, Berkeley has the fewest faculty degrees in the data set, but ranks above significantly larger iSchools in some measures.

## 5.5.1 Outdegree Prestige Measures

Outdegree prestige is a straightforward ranking of the schools by the number of different institutions at which graduates are placed, standardized by the network size; schools having greater diversity in placements of PhD graduates rank highly by this measure. Outdegree prestige accounts only for the direct links in the network, where output domain accounts for indirect links as well, representing the influence that each node exerts on the network as defined by the percentage of all other nodes that are connected from it (Nooy et al. 2005). Well-connected schools whose neighbors are also well-connected rank highly by this measure.

Building on output domain, proximity prestige is a directional measure of closeness between nodes based upon the distance to the node rather than from it, indicating how reachable a node is from any other node. To properly reflect the prestige structure indicated by out proximity prestige, low values represent a greater reach, calculated as the proportion of all nodes in the output domain of the school, divided by the mean distance to all nodes in its output domain. Out proximity prestige is

Outdegree	Between-	Total	PageRank	Number of	USNWR LIS
	ness	Degree	Score	Grads	rating
pitt (12)	indiana	indiana $(59)$	indiana	ucla $(27)$	uiuc $(4.5)$
ucla (11)	pitt	gatech $(45)$	unc	berkeley $(26)$	unc $(4.5)$
umich (11)	ucla	rutgers $(41)$	washington	uiuc (23)	syr (4.3)
uiuc (11)	umich	uci (40)	uci	pitt (23)	washington $(4.2)$
utexas (11)	uci	ucla $(39)$	gatech	unc (19)	umich $(4)$
berkeley (10)	uiuc	pitt (36)	uiuc	umich (18)	rutgers $(3.9)$
syr (9)	syr	umich $(34)$	utexas	indiana $(17)$	pitt $(3.8)$
indiana (8)	gatech	syr $(31)$	ucla	syr $(17)$	utexas $(3.8)$
unc (8)	unc	psu $(31)$	$_{ m syr}$	utexas $(16)$	indiana $(3.8)$
utoronto (8)	rutgers	uiuc $(27)$	$_{ m pitt}$	utoronto $(16)$	fsu $(3.7)$
uci (7)	washington	washington (26)	umich	umd (11)	drexel $(3.6)$
umd (7)	drexel	utexas $(25)$	drexel	rutgers $(11)$	-
rutgers (6)	$_{\rm psu}$	unc $(23)$	fsu	uci (10)	-
washington (5)	utexas	drexel $(22)$	rutgers	umd (10)	-
gatech (4)	umd	umd $(21)$	psu	gatech $(9)$	-
drexel (3)	fsu	fsu $(19)$	umd	washington $(7)$	-
psu (3)	utoronto	berkeley $(15)$	utoronto	fsu $(6)$	-
fsu (3)	berkeley	utoronto (15)	berkeley	psu (4)	-

Table 5.3: Rankings of the iSchools by Network Prestige and Centrality Measures

a measure that rewards schools having a high proportion of direct to indirect links in their output domain; in the case of the iSchools, all of these measures produced identical rankings of the schools, so only outdegree prestige is shown in Table 5.3.

Centrality measures provide additional perspective on the importance of an institution in the network. Betweenness centrality, a standardized index of betweenness, is the probability that a node lies on a shortest path (geodesic) between any two other nodes. Schools with a high betweenness typically have a high total degree count, rewarding those programs with larger faculty; these schools are more likely to have numerous leaf nodes, schools to which no other institutions are connected. Betweenness is an undirected measure, ignoring network features such as link reciprocity, in which a pair of schools engage in mutual exchange of graduates. Betweenness measures are inherently biased in ego networks due to their structure, so only egos have betweenness scores; while network alters have a null betweenness, the measure is meaningful for comparing the egos of the network.

## 5.5.2 PageRank

In a network based on association and social exchange, a single institution's prestige is based upon the prestige of the schools with whom it is linked. All of the previously mentioned measures of prestige and centrality fail to take edge weighting into account, losing important information about the strength of the ties between schools; this is not the case with weighted PageRank. PageRank was originally designed as a method of ranking Web pages in search engine results, and is defined as follows (Page et al. 1999):

Let u be a Web page. Then let  $F_u$  be the set of pages u points to and  $B_u$  be the set of pages that point to u. Let  $N_u = |F_u|$  be the number of links from u. Then R(u), the rank assigned to web page u is given by

(5.2) 
$$R(u) = \alpha \frac{1}{n} + (1 - \alpha) \sum_{v \in B_u} \frac{R(v)}{N_v}$$

where  $\alpha$  is a tunable parameter.

Recursively defined, PageRank assigns a ranking to the nodes of a graph based on the ranks of its incoming edges. Like the Bonacich eigenvector centrality measure, PageRank corresponds to the eigenvector of a modification to the adjacency matrix. Without the modification, the eigenvector corresponds to the amount of time a random walker would spend at each node if he were to follow edges over many steps. With the modification in PageRank the random walker has a fixed teleportation probability  $\alpha$  at each step of making a random jump rather than following an edge. Weighted PageRank takes into account edge weighting and is defined as follows.

Let  $w_{uv}$  be the weight of the edge between nodes u and v. The normalization N'(u) is now the sum of the weights of all outgoing edges of node u:

(5.3) 
$$N'(u) = \sum_{v \in F_u} w_{uv}$$

The weighted PageRank for node R'(u) is given by

(5.4) 
$$R'(u) = \alpha \frac{1}{n} + (1 - \alpha) \sum_{v \in B_u} \frac{w_{vu}}{N'(v)} R(v)$$

The first term represents the probability that the walker arrives at the node with a random jump, the second term represents the probability that the walker arrived at the node by following a weighted edge. The probability is summed over all nodes v with an edge leading to u, weighted by the value of the edge between v and u, divided by the sum of the weights for all outgoing edges from node v.

From a social network analysis perspective, PageRank is a centrality measure for which network structural prestige is assigned by the prestige of a node's neighbors. This rewards schools whose graduates are hired at institutions that place their own graduates at other highly ranked schools. Using weighted PageRank to leverage the full data set for an affiliation network, this measure shows good potential as an indicator of a school's USNWR ratings.

# 5.5.3 Peer Ratings

Ratings such as those presented by USNWR and the NRC are considered important as indicators of institutional identity within the larger academic community context, as discussed in Section 3.1.1. In order to discover whether measures of centrality and prestige in these hiring networks can predict the ratings earned in the peer opinion surveys, the USNWR ratings in LIS were matched to the iSchools for which they were available. Similarly, the USNWR ratings and NRC ratings for the CS departments were collected for the egos of the network.

The USNWR and NRC ratings are based on peer review; both originate from surveys sent to members of the academic community every few years, in which respondents provide ratings of perceived quality for the programs in their discipline. It is reasonable to suspect that the data may be confounded by the respondents' preferences for their own alma maters, with the potential effect of inflating the prestige ratings for schools with larger numbers of graduates, simply by virtue of a greater number of their graduates being positioned to respond to the surveys. Individual identification with an institution also motivates this response; as the sociology literature has shown, an academic with a degree from a prestigious program may enjoy accumulative advantage.

The data for USNWR and NRC ratings are collected with varying frequency; the available NRC data for the CS departments was collected in 1993. USNWR rankings were based on a 2005 survey in both CS and LIS, which had respective response rates of 52% and 51%. The USNWR questionnaires for CS were sent to the department heads and directors of graduate studies at sampled institutions. In the LIS survey, questionnaires were sent to deans, program directors, and senior faculty at 50 schools with ALA-accredited master's programs.

# 5.6 Correlating Network Measures to USNWR Rankings

The null hypotheses propose that the social prestige measure of the USNWR ratings, representing the opinions of academic peers, is not correlated with network measures in the hiring networks for CS and iSchools. In testing these hypotheses, correlations between the network centrality and prestige measures yielded different results for each network.

#### 5.6.1 Computer Science

Differences in ratings present interesting points of comparison of hiring network dynamics as opposed to an overall measure of quality of based on "quality indicators" obtained through surveys by USNWR or the NRC. Considering only the egos in the CS network, the ratings from the NRC show a strong correlation with USNWR ratings ( $r = 0.9, p \ll 0.0001$ ). Simply counting the number of graduates employed as faculty at the top 26 computer science departments for which ratings were available also correlates very strongly with the USNWR ratings ( $r = 0.81, p \ll 0.0001$ ) and with the NRC ratings ( $r = 0.84, p \ll 0.0001$ ); individually, other network measures showed only weak correlation to USNWR ratings, as evident with visual examination of Figure 5.8.

The academic mobility of PhDs in the full CS network, with both alters and egos, provided another point for analysis. Prior studies have shown that academic mobility is typically downward or horizontal, and rarely upward (Burris 2004). The placements of PhD graduates in the full CS are in keeping with these results: 25% went to a school of equal rank and 21% acquired positions at a higher ranking school than their alma mater. The remaining 54% were hired at a department of lower rank, making it slightly more likely that a graduate will descend the prestige hierarchy rather than stay at the same level or ascend.

In this regard, the prestige structure in CS departments is less stratified than that of sociology departments, in which only 6% of PhDs found employment with a department of higher prestige. This difference in academic mobility may be an effect of other variables, such as publication venues and cycles. The publication process

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Figure 5.8: Scatter plot matrix of network prestige measures and peer ratings in CS

in sociology can be longer than in computer science, where graduates are able to generate publications more quickly via conferences and may build reputations which are less dependent upon the prestige of their school and advisor.

# 5.6.2 iSchools

In contrast to the CS departments, the iSchools showed only weak correlations between USNWR ratings and other individual network measures, as shown in Figure 5.9; this is most likely a result of the small sample size of egos and heterogeneity of the larger communities of context for the different measures. This may also be a reflection of the fact that the network measures are computed based on hiring within a somewhat different, although overlapping, academic community than the sample used for the USNWR survey.

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Figure 5.9: Scatter plot matrix of network prestige measures and peer ratings in iSchools

Seemingly significant correlations lose statistical power when the trivial correlations introduced by alters, which cannot be fairly compared to the egos, are removed. For example, the correlation between the PageRank score and betweenness is highly significant in the full network ( $r = 0.99, p \ll 0.0001$ ) but indeterminate in the network of egos alone (r = 0.39, p = 0.23). The alters in the full network introduce strongly correlated noise; in the case of these two statistics, this is because alters cannot have a positive betweenness value in this network, nor can they achieve any higher PageRank score than the same value that all of the alters share. This leads to strong but trivial correlations between the alters of the network, particularly for betweenness and PageRank, which would also correlate strongly with a null indegree for the majority of the nodes in the network. In general, however, the apparently significant relationships among network statistics in the full network of both egos and alters are not present upon examining network egos alone.

# 5.7 Linear Regression Results

In the CS network, the linear regression in Table 5.4 on indegree, weighted PageRankScore, and betweenness explained 79% of the variance in USNWR ratings with strong significance,  $F(3, 22) = 31.7, p \ll 0.0001$ , allowing the rejection of Null Hypothesis 2. All three of the one-degree-of-freedom contrasts of interest (weighted PageRank score, indegree, and betweenness) reached at least the 0.01 significance level, shown in Table 5.5.

In the iSchools network, the size of the sample for which existing USNWR ratings could be used for analysis was reduced to only 11 schools; with a more comprehensive set of USNWR ratings, it is possible that an increased sample size might yield stronger trends. As the visualizations of scatter plot matrices of the networks

Estimate Std. Error t value Pr(>|t|) 4.133242 0.135469 30.511 < 2e-16 \*\*\* (Intercept) cs\$pagerankscore 11.223359 2.613 0.0159 \* 4.294460 cs\$betweenness 0.006258 0.000670 9.340 4.12e-09 \*\*\* 0.011898 -5.733 9.12e-06 \*\*\* cs\$indegree -0.068210 \_\_\_ Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1 Residual standard error: 0.219 on 22 degrees of freedom Multiple R-Squared: 0.8121, Adjusted R-squared: 0.7865 F-statistic: 31.7 on 3 and 22 DF, p-value: 3.622e-08 Table 5.4: Regression Table for the CS Hiring Network

Df Sum Sq Mean Sq F value Pr(>F) cs\$pagerankscore 1 0.33299 0.33299 6.946 0.01511 \* cs\$betweenness 1 2.65057 2.65057 55.289 1.945e-07 \*\*\* cs\$indegree 1 1.57560 1.57560 32.866 9.119e-06 \*\*\* 22 1.05468 0.04794 Residuals Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1

Table 5.5: Analysis of Variance Table for the CS Hiring Network

measures demonstrate, however, there is little apparent direct relationship between variables. Although the analysis of correlations between variables in Section 5.6.2 indicated a low likelihood of a conclusive result from regression analysis, the same selection of variables were regressed on the USNWR ratings for LIS schools. The additional variable of interdisciplinarity scores was also tested.

Regression on the number of graduates of each school employed as faculty in the network (labeled *gradcount* in Table 5.6), weighted PageRank score, hiring diversity (labeled *hiringentropy*) and betweenness explained 77% of the variance in USNWR ratings with F(4,6) = 9.3, p = 0.01, allowing the rejection of Null Hypothesis 1. Two of the one-degree-of-freedom contrasts of interest (weighted PageRank score and number of graduates in the network) reached at least the 0.05 significance level, shown in Table 5.7.

Estimate Std. Error t value Pr(>|t|) (Intercept) 1.735052 0.743234 2.334 0.05828 . lis\$betweenness -0.004923 0.001131 -4.352 0.00481 \*\* lis\$pagerankscore 12.604780 2.966607 4.249 0.00539 \*\* 0.053361 0.010957 lis\$gradcount 4.870 0.00279 \*\* lis\$hiringentropy 0.574079 0.247805 2.317 0.05972 . Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1 Residual standard error: 0.1532 on 6 degrees of freedom Multiple R-Squared: 0.8605, Adjusted R-squared: 0.7675 F-statistic: 9.251 on 4 and 6 DF, p-value: 0.009727 Table 5.6: Regression Table for the iSchool Hiring Network Df Sum Sq Mean Sq F value Pr(>F) 1 0.01592 0.01592 0.6786 0.441591 lis\$betweenness lis\$pagerankscore 1 0.27743 0.27743 11.8231 0.013827 \* lis\$gradcount 1 0.44901 0.44901 19.1351 0.004697 \*\*

Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1

lis\$hiringentropy 1 0.12594 0.12594 5.3669 0.059722 .

6 0.14079 0.02347

Table 5.7: Analysis of Variance Table for the iSchool Hiring Network

#### 5.7.1 Fitted Ratings of CS Departments

Residuals

The coefficients and intercept values from linear regression for the betweenness, weighted PageRank score, and indegree for each department allow a fitted rating that includes three top Canadian CS departments, as shown in Table 5.8. The University of Waterloo appears in the fifth position, and the University of British Columbia and University of Toronto are in the seventeenth and eighteenth positions.

Most departments' rating shows little change, though Pennsylvania State University, Harvard University and Purdue University all enjoy larger gains in their scores. Stanford University is promoted from a top ranking USNWR rating of 4.9 to a fitted rating of 5.1, which is above the USNWR rating scale maximum of 5.0. Conversely, three schools have sizable downward adjustments in their ratings; MIT, University of Texas Austin, and University of Washington saw the greatest decreases from the USNWR ratings to the fitted ratings.

#### 5.7.2 Fitted Ratings of the iSchools

Among the iSchools, applying the regression coefficients to each school's betweenness, weighted PageRank score, hiring diversity score, and number of graduates in the network generates a fitted rating based on the LIS ratings from USNWR. There were some very small changes to the original ratings; the University of Texas Austin saw the most adjustment, with a 0.3 point increase over its original rating. The overall relative positioning of the iSchools also saw some small changes, with Texas rising up the ranks while Michigan experienced a downward shift in its positioning.

The additional seven iSchools which were previously unrated are added in to the rankings shown in Table 5.9, in a fairly even distribution. The top three rankings go to the schools that previously held the top three ranking positions and most of the previously unranked schools appear in the middle of the ranking distribution.

School	usnwr	Fitted			
School	Inde- gree	Be- tween- ness	Weighted PageRank	Rating (CS)	Rating
Stanford University	18	265	0.051	4.9	5.1
Carnegie Mellon University	17	238	0.033	4.9	4.8
University of California Berkeley	21	262	0.039	4.9	4.8
University of Waterloo	30	303	0.069	n/a	4.8
Massachussetts Institute of Technology	13	167	0.025	4.9	4.6
University of Illinois Urbana-Champaign	28	286	0.05	4.6	4.6
Cornell University	30	346	0.025	4.5	4.5
Princeton University	16	182	0.02	4.3	4.4
University of Wisconsin Madison	18	153	0.036	4.1	4.3
University of Maryland	30	225	0.054	4	4.1
University of Texas Austin	27	197	0.046	4.4	4
California Institute of Technology	8	64	0.004	4.1	4
Purdue University	33	245	0.052	3.7	4
University of Michigan	21	124	0.046	3.9	4
Harvard University	9	39	0.017	3.7	4
University of Washington	15	98	0.018	4.4	3.9
University of British Columbia	22	129	0.041	n/a	3.9
University of Toronto	23	147	0.036	n/a	3.9
Brown University	17	124	0.012	3.9	3.9
University of North Carolina	17	65	0.044	3.8	3.9
Yale University	12	67	0.01	3.6	3.8
University of California Los Angeles	15	66	0.029	3.9	3.8
Georgia Institute of Technology	28	150	0.058	4	3.8
Rice University	13	64	0.007	3.8	3.7
University of California San Diego	21	106	0.028	3.7	3.7
Columbia University	17	55	0.03	3.7	3.7
Pennsylvania State University	16	63	0.016	3.2	3.6
Duke University	16	40	0.028	3.7	3.6
University of Massachussetts	21	60	0.038	3.6	3.5

Table 5.8: Fitted Ratings of the CS Departments

School	Be- tween- ness	Number of Grads	Weighted PageRank	Hiring Diver- sity	USNWR Rating (LIS)	Fitted Rating
University of North Carolina	172	19	0.0914	2.55	4.5	4.5
University of Illinois Urbana-Champaign	189	23	0.0629	2.75	4.5	4.4
Syracuse University	181	17	0.0554	2.98	4.3	4.2
Georgia Institute of Technology	174	9	0.0630	3.46	n/a	4.1
University of California Irvine	194	10	0.0677	3.41	n/a	4.1
University of Washington	156	7	0.0833	2.97	4.2	4.1
University of Texas Austin	139	16	0.0572	2.53	3.8	4.1
University of California Los Angeles	312	27	0.0556	2.96	n/a	4.0
University of California Berkeley	7	26	0.0005	1.63	n/a	4.0
Rutgers University	167	11	0.0406	3.49	3.9	4.0
University of Michigan	209	18	0.0470	3.03	4.0	4.0
Indiana University	442	17	0.1040	3.65	3.8	3.9
Pennsylvania State University	146	10	0.0357	3.16	n/a	3.8
Pittsburgh State University	345	23	0.0551	3.08	3.8	3.7
University of Toronto	30	16	0.0143	1.86	n/a	3.7
Florida State University	86	4	0.0444	2.75	3.7	3.7
University of Maryland	131	11	0.0329	2.67	n/a	3.6
Drexel University	146	6	0.0450	2.89	3.6	3.6

Table 5.9: Fitted Ratings of the iSchools

# CHAPTER VI

# Conclusions

# 6.1 Discussion of Results

The results of regression on the CS and iSchool hiring networks presented in Section 5.7 are indicative of underlying similarities in the structure of the two networks, whereas analysis of other aspects of the networks highlights some interesting differences between them, particularly with respect to the diversity of hiring sources accessed by the egos of each network. In the context of the academic communities of computer science and information, the amount of variance explained by regression and level of confidence are evidence that the CS departments form a social structure that is more stable, cohesive and predictable than the iSchool community at this point in time. A much younger discipline, such as the emerging field of information, would not have the same context for describing itself through a peer evaluation as a more established discipline like CS. In the case of the iSchools, these aggregated peer ratings only evaluate a portion of the community on a subset of its programs. This incomplete context makes it difficult to determine the value of these peer prestige ratings to the iSchools in understanding the roles of hiring and prestige in a developing community identity.

# 6.1.1 Regression and Fitted Ratings

In both networks, betweenness and weighted PageRank were two factors significant in explaining variance in USNWR. The calculation of betweenness and PageRank's centrality vector evaluate similar qualities of the schools in the network, but from different perspectives. Where PageRank rewards the nodes on the most frequently trafficked routes in the network, betweenness rewards the nodes that have the greatest number of unique connections as well as connectivity to hubs, and therefore to the rest of the network. Weighted PageRank takes into direct account the directedness of the links in the hiring networks as well as the weights on the edges, while betweenness is not concerned with the direction or weight of the edges in the network.

Additional variables were required in each regression, however, and it is interesting to consider why the variables are different for the two networks. In the iSchools, the variables are the number of graduates of each school employed in the network and the school's hiring diversity score; for CS, it is the indegree for each department. The negative coefficient for indegree from the CS regression means that a higher indegree has a negative effect on a school's rating. In effect, the CS departments receive lower ratings if they choose to hire from a greater number of sources. While hiring diversity was rejected as a regression coefficient for the CS network, it was rejected because it was only slightly outperformed by indegree, which reinforces the interpretation of the negative coefficient for indegree.

The negative regression coefficient for indegree can be interpreted as evidence of prestige stratification in the network; a good example of the effect can be seen in the difference in fitted ratings for Stanford and Maryland, shown in Table 5.8. Both Stanford, in the first position of the rankings, and Maryland, in the seventh position, have fairly similar values for betweenness and PageRank scores. Maryland, however, has hired faculty from 30 departments to Stanford's selection of only 17, and this has a strong negative effect on Maryland's rating. The University of Waterloo has overcome its high indegree by virtue of having the network's highest PageRank score, but still lands in the fourth position in the fitted ranking, behind schools which have lower scores for both of the variables with positive coefficients, weighted PageRank and betweenness.

The number of graduates employed in the network is a third variable in the iSchool regression, and is a relatively straightforward measure of a school's prominence in or influence on the community. Although easily computed and understood, this measure is representative of more than one identity-related characteristic of an iSchool; the number of graduates employed in the network is a function of several indirect factors. A school with a long history of producing high-quality academics may have a higher number of graduates than a larger but more recently founded department. The measure incorporates graduates of the iSchools along with all other graduates of the same institution, so the number of graduates employed in the network is must be provide a greater or lesser reflection of a halo effect of the parent institution's prestige.

The final variable in the iSchool regression is hiring diversity. In counterpoint to the apparent negative effect of hiring diversity in the CS network, hiring faculty from a broader range of schools is a practice that is rewarded with higher rankings in the iSchool network. Including hiring diversity in the regression explains an additional 15% of the variance, and upon inspecting the fitted ratings and variables in Table 5.9 it is interesting to note that the two highest ranked schools without USNWR LIS rankings, Georgia Tech and UC Irvine, appear to have achieved their position in the fitted rankings due to their above average hiring diversity and weighted PageRank scores.

Unlike the CS network, the regression coefficient for betweenness is negative for the iSchools. This means that having too many unique connections to leaf nodes (schools from which no other iSchools have hired) and not enough connections to the most central schools returns a lower rating. Like the negative regression coefficient for indegree in the CS network, this could lower the ratings of schools with a more diverse set of connections. Betweenness is a more complex characteristic of the network than indegree, however, and evaluates not only unique links but also the strength of a node's connections to the most central actors in the network. Because multiple aspects of link topology are represented in a node's betweenness score, we cannot conclude that a negative coefficient for betweenness punishes hiring diversity in the fitted ratings for iSchools.

# 6.1.2 Faculty Areas of Study

Diversity of faculty expertise as measured by an entropy calculation on the areas of study for each iSchool's faculty reveal that the earliest and most enthusiastic flag bearers of the iSchool movement, Michigan and Syracuse, display the greatest interdisciplinarity. Likewise, programs known for the strength of their subject focus get appropriately lower scores. The interdisciplinarity scores for the schools easily cluster into several groupings, and while it is easy to interpret the meanings of the relative positioning of the most and least interdisciplinary schools, the majority in the center have not as clearly defined themselves based upon the interdisciplinarity of their faculty's expertise. While hiring diversity is strongly correlated with program size interdisciplinarity is not simply a matter of size; for example, UC Irvine and Georgia Tech are two of the larger schools in the network, but both have interdisciplinarity scores that are approximately 66% of the network average. By contrast, Berkeley's very small full-time faculty of 6 achieves a similar interdisciplinarity score to that of Washington, with 21 faculty members.

The diversity of the faculty expertise in iSchools is partially dependent upon the size of the faculty in question, as discussed in Section 5.4. As a community, the interdisciplinarity of the field is self-evident, as represented by the range of academic disciplines in Table 5.2. The iSchools have varying levels of focus on specific aspects of the information field, detailed in Appendix B; this is a strategy by which schools differentiate themselves with respect to the community. Coding the faculty degree programs and departments into CIP families obscures the true diversity of the academic studies in iSchools, especially within the category of computer and information sciences. The breadth of the academic traditions represented in the schools currently granting degrees in information science or information studies means that the expertise of faculty with degrees in these areas may be very diverse as well.

# 6.1.3 Graduate Areas of Study

A halo effect refers to the phenomenon in which institutional prestige improves the perceived prestige of an academic unit within that institution, mentioned in Section 6.1.1. To better understand the potential of a halo effect in the iSchools, Appendix C shows the areas of study for graduates of iSchools' parent institutions. Some of these are clearly the graduates of an iSchool, but the delineation between *library science* and *computer and information sciences* is often semantic, so faculty with degrees from either area of study may be graduates of the same iSchool, depending upon the name of the program at the time that a degree is granted. For example, Berkeley has graduated faculty in both degree areas, but ceased maintenance of ALA accreditation in the 1980's, so the faculty with degrees in these two areas from Berkeley are representatives of a case where the school has experienced significant

changes in name and emphasis of the curriculum over time.

In some institutions, however, there is a clear and meaningful difference between degrees in these two areas, such as at the University of North Carolina and University of Toronto, both of which have esteemed computer science departments that are entirely separate from their library science programs. Caution is therefore required in the interpretation of the balance of graduates from these two areas of study due to contextual variations between iSchools.

Despite these variations, examining the areas of study for the graduates of iSchool institutions does provide some frame of reference to understanding how well the number of graduates of an iSchool's institution represents the community prestige of the iSchool itself as opposed to the institution in which it operates. It is very clear in several cases, such as that of Syracuse University, that within the iSchools network, the network prestige measures are reflective of the iSchool itself. 15 of the 17 Syracuse graduates employed on iSchool faculty are graduates of the School of Information Studies as opposed to receiving their degrees from another school within Syracuse University. Other schools exhibiting this characteristic include Georgia Tech and UC Irvine. In these cases, one possible explanation is that the identity of the school itself has remained stable over the time period represented by the graduates in the network.

This is a plausible scenario for Syracuse, which was among the first to drop the reference to librarianship from the naming of its degree program, and the school's only library science PhD currently employed in the network is the earliest, granted in 1978. For Syracuse and UC Irvine in particular, it is clear that the iSchool's prestige is reflected by its network measures, as the overwhelming majority of the institutions' graduates in the network received degrees from the iSchool. Institutional prestige doubtless plays a role in the employment prospects of these graduates as well, but for most iSchools, it is harder to conclude whether network measures represent the prestige of the iSchool versus the prestige of the university at large without knowing significant detail about the organizational history of both the school and the university.

# 6.2 Relevance of Results

Finding that peer prestige measures such as USNWR ratings can be predicted with hiring network statistics is reason to question what these ratings really mean to a school's identity. Peer ratings can play an important part in perceptions of a school's prestige and role in the academic community; as these ratings are targeted to prospective graduate students, managing the prestige aspects of image and identity may be a matter of particular interest to iSchool administrators. The iSchool community itself has expressed concern over explaining the academic identity of the information field, a challenge that extends to the degree to which peer prestige rankings do or do not reflect the true community identity. Because the peer prestige ratings are subject to accreditation-based populations for sampling, an interdisciplinary community will continue to face challenges in achieving a good representation of the identities of its constituents.

For the iSchool community, the results of this study provide a different perspective on prestige rankings as it relates to community identity. As the iSchool community matures, it is likely that a linear regression model based on hiring network statistics will provide more statistically powerful results than this early examination. Future research to track the changes in the hiring network structure in iSchools could determine whether this interdisciplinary field will follow the trend of most academic disciplines, in which a stratified prestige structure becomes one of the strongest determinants in the placement of graduates. While the existence of a prestige structure based on library science program ratings from the USNWR provides a partial representation of comparative prestige, the interdisciplinarity of the iSchool community could prevent the level of prestige-based academic inbreeding seen in some social sciences.

# 6.2.1 Creating a Sociotechnical Artifact

This study is itself a sociotechnical artifact of the iSchools movement. One potential effect of community interaction with the information presented in this study could be the acceleration of the hiring-prestige feedback loop. If we assumed a basic system of rational self-interested agents whose hiring decisions were made entirely based upon the prestige of the sources of faculty, we would expect to see a swift aggregation of institutions into prestige strata, which would become institutionalized within the iSchool community. Making apparent the strata existing within the community could certainly lead to more attempts to hire from schools with higher prestige rankings, but this type catalyst effect is a possibility that we cannot prove or disprove, as there is no control group of iSchools. Fortunately, hiring decisions are not based solely on the prestige of the candidate's alma mater but also on such universalistic criteria as demonstrated abilities. In this regard, the results of analysis could help set or maintain goals for intellectual diversity in hiring, which is generally considered an asset in interdisciplinary fields.

A desirable positive outcome is for the data collected in this study to assist iSchool faculty in identifying good potential research collaborators, either based on the existence of ties between institutions or identification of complementary areas of faculty expertise. For example, a graduate has the experience of an alma mater in common with the faculty of that institution, and this provides a context within which communication and collaboration may be facilitated. By highlighting the places where relationships exist based on faculty pedigree, this research creates a way to see where relationships might develop based on the existence of links between institutions.

As a sociotechnical artifact, this study holds a mirror up to the iSchool community, but it must be clear that there is no "fairest of them all" despite existing or fitted prestige rankings. The multiplicity of criteria that are relevant to the true measures of success in an institution may be commonly held among many of the schools in the network, but the valuation of those factors is unique to each institutional context. Schools attempt to achieve their own conception of prestige through a variety of strategies, and while hiring is one appropriate approximation, it is only a means to an end.

#### 6.3 Future Work

Several interesting possibilities for future research arise from this study. A natural extension would involve re-collecting the data every few years to generate a series of data sets that reflect the evolution of the hiring networks. There are several ways to recreate the analyses using, for example, a different set of more inclusive prestige rankings, or identifying and testing an additional measure. Generating a hiring network for all ALA-accredited institutions for comparison to the iSchools might highlight interesting differences between the traditional LIS programs and the interdisciplinary iSchools.

There may also be other ways to predict the entropy measures of hiring diversity and interdisciplinarity, perhaps via analysis of topic taxonomies generated from curricular text content course descriptions. In addition, the data from and results

of this study could be compared to a complementary network representing iSchool PhD graduate placement. Finally, analysis merging iSchool hiring and PhD graduate placement data sets would offer a more holistic view of the interactions of intellectual exchange within the community.

APPENDICES

# APPENDIX A

# iSchool Profiles

Data collection for this study yielded a variety of potentially useful data points for individuals seeking to understand the differences between various iSchools, particularly prospective students. Brief network demographic profiles for each iSchool are included to aggregate this information and supplement tables and figures.

## A.1 University of California at Berkeley

iSchool Name: School of Information Accreditation: ABET Number of full-time faculty: 14 Faculty title distribution: 1 dean, 7 professors, 2 assistant professors, 2 associate professors Number of PhDs in data set: 12 Average year faculty PhD granted: 1985.8 Indegree: 6 Outdegree: 10 Number of grads on iSchool faculty: 26 USNWR rating: n/a Self-hires: 4

#### A.2 Drexel University

iSchool Name: College of Information Science and Technology
Accreditation: ABET, ALA
Number of full-time faculty: 25
Faculty title distribution: 1 dean, 7 professors, 6 assistant professors, 10 associate professors
Number of PhDs in data set: 24
Average year faculty PhD granted: 1987
Indegree: 20
Outdegree: 3
Number of grads on iSchool faculty: 6
USNWR rating: 3.6
Self-hires: 4

#### A.3 Florida State University

iSchool Name: College of Information
Accreditation: ABET, ALA
Number of full-time faculty: 25
Faculty title distribution: 1 dean, 2 associate deans, 4 professors, 13 assistant professors, 5 associate professors
Number of PhDs in data set: 25
Average year faculty PhD granted: 1995.8
Indegree: 17
Outdegree: 3
Number of grads on iSchool faculty: 4
USNWR rating: 3.7
Self-hires: 2

#### A.4 Georgia Institute of Technology

iSchool Name: College of Computing
Accreditation: ABET
Number of full-time faculty: 79
Faculty title distribution: 1 dean, 28 professors, 20 assistant professors, 29 associate professors
Number of PhDs in data set: 78
Average year faculty PhD granted: 1992.1
Indegree: 42
Outdegree: 4
Number of grads on iSchool faculty: 9
USNWR rating: n/a in LIS
Self-hires: 6

## A.5 Indiana University

iSchool Names: School of Informatics, School of Library and Information Science
Accreditation: ALA
Number of full-time faculty: 66 at the School of Informatics, 22 at the School of Library and Information
Science, 2 shared; 86 total
Faculty title distribution: 2 deans, 30 professors, 32 assistant professors, 23 associate professors
Number of PhDs in data set: 87
Average year faculty PhD granted: 1991
Indegree: 52
Outdegree: 8
Number of grads on iSchool faculty: 17
USNWR rating: 3.8
Self-hires: 10

#### A.6 University of Pittsburgh

iSchool Name: School of Information Sciences
Accreditation: ALA
Number of full-time faculty:32
Faculty title distribution: 1 dean, 7 professors, 9 assistant professors, 14 associate professors
Number of PhDs in data set: 31
Average year faculty PhD granted: 1987.6
Indegree: 25
Outdegree: 12
Number of grads on iSchool faculty: 23

USNWR rating: 3.8 Self-hires: 5

# A.7 Pennsylvania State University

iSchool Name: College of Information Sciences and Technology
Accreditation: none
Number of full-time faculty: 50
Faculty title distribution: 1 dean, 2 associate deans, 16 professors, 20 assistant professors, 9 associate professors
Number of PhDs in data set: 48
Average year faculty PhD granted: 1993.5
Indegree: 29
Outdegree: 3
Number of grads on iSchool faculty: 10
USNWR rating: n/a
Self-hires: 7

### A.8 Rutgers University

iSchool Name: School of Communication, Information and Library Studies
Accreditation: ALA
Number of full-time faculty: 50
Faculty title distribution: 1 dean, 1 associate dean, 9 professors, 19 assistant professors, 17 associate professors
Number of PhDs in data set: 47
Average year faculty PhD granted: 1991.4
Indegree: 36
Outdegree: 6
Number of grads on iSchool faculty: 11
USNWR rating: 3.9
Self-hires: 3

#### A.9 Syracuse University

iSchool Name: School of Information Studies
Accreditation: ABET, ALA
Number of full-time faculty: 34
Faculty title distribution: 1 dean, 9 professors, 10 assistant professors, 13 associate professors
Number of PhDs in data set: 33
Average year faculty PhD granted: 1991.8
Indegree: 23
Outdegree: 9
Number of grads on iSchool faculty: 17
USNWR rating: 4.3
Self-hires: 5

# A.10 University of California Irvine

iSchool Name: The Donald Bren School of Information and Computer Sciences Accreditation: none Number of full-time faculty: 56 Faculty title distribution: 1 dean, 27 professors, 18 assistant professors, 10 associate professors Number of PhDs in data set: 56 Average year faculty PhD granted: 1992.3 Indegree: 34 Outdegree: 7 Number of grads on iSchool faculty: 10 USNWR rating: n/a Self-hires: 2

#### A.11 University of California Los Angeles

iSchool Name: Graduate School of Education and Information Studies
Accreditation: ABET, ALA
Number of full-time faculty: 66
Faculty title distribution: 1 dean, 39 professors, 12 assistant professors, 14 associate professors
Number of PhDs in data set: 66
Average year faculty PhD granted: 1985.7
Indegree: 29
outdegree: 11
Number of grads on iSchool faculty: 27
USNWR rating: n/a
Self-hires: 13

## A.12 University of Illinois Urbana-Champaign

iSchool Name: The Graduate School of Library and Information Science
Accreditation: ABET, ALA
Number of full-time faculty: 22
Faculty title distribution: 1 dean, 8 professors, 3 assistant professors, 10 associate professors
Number of PhDs in data set: 22
Average year faculty PhD granted: 1988
Indegree: 17
Outdegree: 11
Number of grads on iSchool faculty: 23
USNWR rating: 4.5
Self-hires: 3

#### A.13 University of Maryland College Park

iSchool Name: College of Information Studies Accreditation: ALA Number of full-time faculty: 17 Faculty title distribution: 1 dean, 5 professors, 8 assistant professors, 3 associate professors Number of PhDs in data set: 17 Average year faculty PhD granted: 1994.2 Indegree: 15 Outdegree: 7 Number of grads on iSchool faculty: 11 USNWR rating: n/a Self-hires: 2

#### A.14 University of Michigan

iSchool Name: School of Information Accreditation: ABET, ALA Number of full-time faculty: 42 Faculty title distribution: 17 professors<sup>1</sup>, 9 assistant professors, 13 associate professors Number of PhDs in data set: 39 Average year faculty PhD granted: 1987.8 Indegree: 24 Outdegree: 11 Number of grads on iSchool faculty: 18 USNWR rating: 4.0 Self-hires: 4

## A.15 University of North Carolina Chapel Hill

iSchool Name: School of Information and Library Science
Accreditation: ALA
Number of full-time faculty: 25
Faculty title distribution: 1 dean, 10 professors, 6 assistant professors, 7 associate professors
Number of PhDs in data set: 24
Average year faculty PhD granted: 1990.7
Indegree: 19
Outdegree: 16
Number of grads on iSchool faculty: 19
USNWR rating: 4.5
Self-hires: 1

# A.16 University of Texas Austin

iSchool Name: School of Information
Accreditation: ALA
Number of full-time faculty: 21
Faculty title distribution: 1 dean, 1 associate dean, 8 professors, 7 assistant professors, 4 associate professors
Number of PhDs in data set: 21
Average year faculty PhD granted: 1988.4
Indegree: 16
Outdegree: 8
Number of grads on iSchool faculty: 16
USNWR rating: 3.8
Self-hires: 2

#### A.17 University of Toronto

iSchool Name: Faculty of Information Studies Accreditation: ALA Number of full-time faculty: 14 Faculty title distribution: 1 dean, 3 professors, 2 assistant professors, 9 associate professors Number of PhDs in data set: 15 Average year faculty PhD granted: 1993.5 Indegree: 8 Outdegree: 8 Number of grads on iSchool faculty: 16 USNWR rating: n/a Self-hires: 5

<sup>&</sup>lt;sup>1</sup>At the time of data collection, the School of Information operated under the leadership of Dr. C. Olivia Frost in the dual roles of interim dean and professor; she is included in the sample in her long-term role as a professor.

# A.18 University of Washington

iSchool Name: Information School
Accreditation: ALA
Number of full-time faculty: 30
Faculty title distribution: 1 dean, 1 associate dean, 6 professors, 11 assistant professors, 10 associate professors
Number of PhDs in data set: 29
Average year faculty PhD granted: 1993.3
Indegree: 21
Outdegree: 5
Number of grads on iSchool faculty: 7
USNWR rating: 4.2
Self-hires: 0

# APPENDIX B

# Faculty Areas of Study in iSchools

iSchool, $(N = 674)$	Faculty Areas of Study	Mean Year PhD Granted	Inter- disci- plinarity Z-Score
University of California - Berkeley, $n = 12$	Computer and Information Sciences, 3 Humanities, 1 Library Science, 2 Public Administration, 1 Social Sciences, 5	1985.8	-0.25
Drexel University, $n = 24$	Computer and Information Sciences, 11 Engineering, 2 Humanities, 2 Library Science, 5 Psychology, 4	1987	-0.32
Florida State University, $n = 25$	<ul> <li>Biological and Health Sciences, 1</li> <li>Business and Management, 1</li> <li>Communication, 4</li> <li>Computer and Information Sciences, 6</li> <li>Humanities, 3</li> <li>Library Science, 10</li> </ul>	1995.8	-0.01
Georgia Institute of Technology, $n = 78$	Communication, 1 Computer and Information Sciences, 59 Education, 1		-1.46
Indiana University, $n = 87$ , both schools together	<ul> <li>Biological and Health Sciences, 2</li> <li>Communication, 2</li> <li>Computer and Information Sciences, 40</li> <li>Education, 3</li> <li>Engineering, 4</li> <li>Humanities, 8</li> <li>Library Science, 6</li> <li>Mathematics and Statistics, 5</li> <li>Physical Sciences, 7</li> <li>Psychology, 5</li> <li>Public Administration, 1</li> <li>Social Sciences, 4</li> </ul>	1991	1.03

 $Continued \ on \ next \ page$ 

iSchool, $(N = 674)$	Faculty Areas of Study	Mean Year PhD Granted	Inter- disci- plinarity Z-Score
University of Pittsburgh, $n = 31$	Computer and Information Sciences, 11 Education, 1 Engineering, 5 Humanities, 1 Library Science, 5 Physical Sciences, 2 Psychology, 3 Public Administration, 2 Social Sciences, 1	1987.6	0.91
Pennsylvania State University, $n = 48$	<ul> <li>Biological and Health Sciences, 1</li> <li>Business and Management, 8</li> <li>Communication, 2</li> <li>Computer and Information Sciences, 20</li> <li>Education, 2</li> <li>Engineering, 5</li> <li>Humanities, 1</li> <li>Mathematics and Statistics, 1</li> <li>Physical Sciences, 3</li> <li>Psychology, 3</li> <li>Social Sciences, 2</li> </ul>	1993.5	0.95
Rutgers University, $n = 47$	Communication, 19 Computer and Information Sciences, 10 Education, 2 Engineering, 1 Humanities, 3 Library Science, 4 Physical Sciences, 2 Psychology, 2 Social Sciences, 4	1991.4	0.67
Syracuse University, $n = 33$	Business and Management, 7 Communication, 3 Computer and Information Sciences, 7 Education, 1 Humanities, 1 Library Science, 3 Psychology, 3 Public Administration, 3 Social Sciences, 5	1991.8	1.32
University of California - Irvine, $n = 56$	<ul> <li>Biological and Health Sciences, 1</li> <li>Communication, 1</li> <li>Computer and Information Sciences, 40</li> <li>Engineering, 5</li> <li>Mathematics and Statistics, 6</li> <li>Physical Sciences, 1</li> <li>Psychology, 1</li> <li>Social Sciences, 1</li> </ul>	1992.3	-1.21

iSchool, $(N = 674)$	Faculty Areas of Study	Mean Year PhD Granted	Inter- disci- plinarity Z-Score
University of California - Los Angeles, $n = 66$	Business and Management, 1 Communication, 4 Computer and Information Sciences, 2 Education, 29 Humanities, 6 Library Science, 5 Mathematics and Statistics, 1 Psychology, 11 Public Administration, 1 Social Sciences, 5	1985.7	0.67
University of Illinois Urbana-Champaign, $n = 22$	Communication, 1 Computer and Information Sciences, 7 Humanities, 4 Library Science, 8 Social Sciences, 2	1988	-0.31
University of Maryland, $n = 17$	Business and Management, 1 Computer and Information Sciences, 6 Education, 3 Humanities, 1 Library Science, 3 Psychology, 2 Social Sciences, 1	1994.2	0.55
University of Michigan, $n = 39$	<ul> <li>Biological and Health Sciences, 1</li> <li>Business and Management, 3</li> <li>Communication, 1</li> <li>Computer and Information Sciences, 12</li> <li>Education, 1</li> <li>Engineering, 1</li> <li>Humanities, 4</li> <li>Library Science, 4</li> <li>Physical Sciences, 1</li> <li>Psychology, 5</li> <li>Social Sciences, 6</li> </ul>	1987.8	1.38
University of North Carolina - Chapel Hill, n = 24	Biological and Health Sciences, 1 Computer and Information Sciences, 7 Education, 1 Library Science, 15	1990.7	-1.57
University of Texas - Austin, $n = 21$	Computer and Information Sciences, 5 Humanities, 3 Library Science, 10 Psychology, 1 Social Sciences, 2	1988.4	-0.46
University of Toronto, $n = 15$	Computer and Information Sciences, 8 Humanities, 1 Library Science, 6	1993.5	-1.66

 $Continued \ on \ next \ page$ 

iSchool, $(N = 674)$	Faculty Areas of Study	Mean Year PhD Granted	Inter- disci- plinarity Z-Score
University of Washington, $n = 29$	<ul> <li>Biological and Health Sciences, 1</li> <li>Computer and Information Sciences, 13</li> <li>Education, 1</li> <li>Engineering, 1</li> <li>Humanities, 1</li> <li>Library Science, 10</li> <li>Psychology, 1</li> <li>Public Administration, 1</li> </ul>	1993.3	-0.25

APPENDIX C

Faculty Areas of Study for Graduates of iSchools

iSchool, $(N = 269)$	Graduate Areas of Study	Mean Year PhD Granted
University of California - Berkeley, $n = 26$	Computer and Information Sciences, 8 Education, 6 Engineering, 1 Library Science, 6 Mathematics and Statistics, 1 Physical Sciences, 1 Psychology, 1 Social Sciences, 2	1990
Drexel University, $n = 6$	Computer and Information Sciences, 4 Library Science, 2	1984
Florida State University, $n = 4$	Communication, 1 Computer and Information Sciences, 1 Library Science, 2	2000
Georgia Institute of Technology, $n = 9$	Communication, 1 Computer and Information Sciences, 5 Engineering, 1 Mathematics and Statistics, 1 Psychology, 1	1991
Indiana University, $n = 17$	Business and Management, 1 Computer and Information Sciences, 5 Education, 1 Humanities, 3 Library Science, 5 Social Sciences, 2	1998
University of Pittsburgh, $n = 23$	Communication, 1 Computer and Information Sciences, 11 Education, 1 Humanities, 1 Library Science, 8 Psychology, 1	1988
Pennsylvania State University, $n = 10$	Business and Management, 3 Communication, 1 Computer and Information Sciences, 2 Education, 1 Humanities, 1 Physical Sciences, 2	1988

iSchool, $(N = 269)$	Graduate Areas of Study	Mean Year PhD Granted
Rutgers University, $n = 11$	Business and Management, 1 Communication, 1 Computer and Information Sciences, 6 Library Science, 2 Social Sciences, 1	1993
Syracuse University, $n = 17$	Computer and Information Sciences, 14 Education, 1 Library Science, 1 Psychology, 1	1991
University of California - Irvine, $n = 10$	Business and Management, 1 Computer and Information Sciences, 7 Social Sciences, 2	1989
University of California - Los Angeles, $n = 27$	Business and Management, 1 Communication, 1 Computer and Information Sciences, 5 Education, 9 Humanities, 1 Library Science, 6 Psychology, 3 Social Sciences, 1	1993
University of Illinois Urbana-Champaign, n = 23	Communication, 2 Computer and Information Sciences, 9 Humanities, 1 Library Science, 9 Psychology, 2	1990
University of Maryland, $n = 11$	Computer and Information Sciences, 4 Engineering, 1 Library Science, 6	1989
University of Michigan, $n = 18$	Computer and Information Sciences, 7 Education, 2 Engineering, 2 Library Science, 4 Psychology, 3	1988
University of North Carolina - Chapel Hill, n = 19	Communication, 2 Computer and Information Sciences, 5 Education, 1 Humanities, 1 Library Science, 8 Physical Sciences, 1 Social Sciences, 1	1997
University of Texas - Austin, $n = 16$	Business and Management, 2 Communication, 1 Computer and Information Sciences, 5 Engineering, 2 Library Science, 3 Psychology, 2 Social Sciences, 1	1989

iSchool, $(N = 269)$	Graduate Areas of Study	Mean Year PhD Granted
University of Toronto, $n = 15$	Biological and Health Sciences, 1 Computer and Information Sciences, 11 Education, 1 Engineering, 1 Library Science, 2	1996
University of Washington, $n = 7$	Biological and Health Sciences, 1 Communication, 1 Computer and Information Sciences, 4 Education, 1	1996

APPENDIX D

# iSchool Data

Name	Faculty	Title	PhD	Year	Dept. of PhD
aakhus, mark	rutgers	assoc	arizona	1997	communication
abels, eileen	drexel	assoc	ucla	1985	library_information_science
abney, steven	umich	assoc	$\operatorname{mit}$	1987	linguistics
abowd, gregory	gatech	assoc	oxford	1991	computing
ackerman, mark	umich	assoc	$\operatorname{mit}$	1994	$information\_technologies$
adamic, lada	umich	asst	stanford	2001	$applied_physics$
agosto, denise	drexel	asst	rutgers	2001	$communication\_library\_science$
agre, philip	ucla	assoc	$\operatorname{mit}$	1989	computer_science
ahamad, mustaque	gatech	$\operatorname{prof}$	$\operatorname{sunysb}$	1985	computer_science
allen, robert	drexel	assoc	ucsd	1978	$experimental_psychology$
allen, walter	ucla	$\operatorname{prof}$	uchicago	1975	sociology
alspaugh, thomas	uci	asst	ncsu	2002	computer_science
ammar, mostafa	gatech	$\operatorname{prof}$	uwo	1985	electrical_engineering
annabi, hala	washington	asst	syr	2005	$information\_science\_technology$
apostolico, alberto	gatech	$\operatorname{prof}$	unina_it	1973	electronic_engineering
applegate, rachel	indiana_slis	asst	wisconsin	1995	library_information_studies
arkin, ronald	gatech	$\operatorname{prof}$	amherst	1987	computer_science
arvo, james	uci	assoc	yale	1995	computer_science
aspray, william	indiana_info	$\operatorname{prof}$	wisconsin	1980	history_of_science
atkins, daniel	umich	$\operatorname{prof}$	uiuc	1970	computer_science
atwood, michael	drexel	$\operatorname{prof}$	colorado	1976	$cognitive_psychology$
bader, david	gatech	assoc	umd	1996	electrical_engineering_computer_sci
bagby, john	psu	$\operatorname{prof}$	utulsa	1976	law_JD
baik, mu hyun	indiana_info	asst	unc	2000	$theoretical\_inorganic\_chemistry$
bailey, alison	ucla	assoc	harvard	1995	human_development_psychology
baker, eva	ucla	$\operatorname{prof}$	ucla	1967	education
balch, tucker	gatech	assoc	gatech	1998	computer_science
baldi, pierre	uci	prof	caltech	1986	mathematics
ball, mary, alice	indiana_slis	asst	arizona	2000	higher_education
bao, lichun	uci	asst	ucsc	2002	computer_science
bardzell, jeffry	indiana_info	asst	indiana	2004	comparative_literature
barlow, diane	umd	prof	umd	1989	library_science
barreau, deborah	unc	asst	umd	1997	library_information_services
barzilai nahon, karine	washington	asst	tau_ac_il	2004	management_information_systems
basu, saugata	gatech	assoc	nyu	1996	computer_science
beer, randall	indiana_info	prof	cwru	1989	computer_science
beghtol, clare	utoronto	assoc	utoronto	1991	library_information_science
belkin, nicholas	rutgers	prof	lon_ac_uk	1977	information_studies
benjamin, robert	syr	prof	upenn	1948	BA
bernard, scott	syr	asst	vt	2001	public_administration_policy
berring, robert	berkeley	prof	berkeley	1974	law_JD

Name	Faculty	Title	PhD	Year	Dept. of PhD
bertot, john	fsu	prof	syr	1996	information_studies
bhavnani, suresh	umich	asst	cmu	1998	computer_science
biagini, mary	pitt	assoc	pitt	1980	information_science
bias, randolph	utexas	assoc	utexas	1978	human_experimental_psychology
bic, lubomir	uci	prof	uci	1979	computer_science
bishop, ann	uiuc	assoc	syr	1995	information_studies
blake, catherine	unc	asst	uci	2003	$information\_computer\_science$
blanchette, jean francois	ucla	asst	rpi	2002	science_technology_studies
blevis, eli	indiana_info	asst	queensu_ca	1990	computer_science
blouin, francis	umich	$\operatorname{prof}$	uminn	1978	history
bobick, aaron	gatech	$\operatorname{prof}$	$\operatorname{mit}$	1987	cognitive_science
bolden, galina	rutgers	asst	ucla	2005	applied_linguistics
boldyreva, alexandra	gatech	asst	ucsd	2004	computer_science
bonnici, laurie	drexel	asst	fsu	2001	library_science
bonzi, susan	syr	assoc	uiuc	1983	library_information_science
borgman, christine	ucla	$\operatorname{prof}$	stanford	1984	communication
borner, katy	indiana_slis	assoc	uni_kl_de	1997	computer_science
bozorgzadeh, elaheh	uci	asst	ucla	2003	computer_science
bramley, randall	indiana_info	prof	uiuc	1989	computer_science
bratich, jack	rutgers	asst	uiuc	2001	communications_research
braunstein, yale	berkeley	prof	stanford	1975	economics
brooks, robert	fsu	assoc_dean	fsu	2001	communication
brooks, terrence	washington	assoc	utexas	1981	library_science
brown, geoffrey	indiana_info	assoc	utexas	1987	electrical_engineering
brown, ken	gatech	asst	berkeley	2003	theoretical_chemistry
bruce, chip	uiuc	prof	utexas	1971	computer_science
bruce, harry	washington	dean	unsw_au	1996	information_science
bruckman, amy	gatech	assoc	mit	1997	epistemology_learning
brusilovsky, peter	pitt	assoc	msu_ru	1987	computer_science
burke, darrell	fsu	asst	vcu	2002	health_services_organization_resea
burley, diana	syr	asst	cmu	1998	organization_science
burnett, gary	fsu	assoc	princeton	1988	english
burnett, kathleen	fsu		berkeley	1989	library_information_studies
cai, guoray		assoc	pitt	1989	information_science
	psu utoronto	assoc	ucla	1999 2001	information_studies
caidi, nadia cameron, brian		assoc		2001 2004	
,	psu indiana_info	prof	psu	1996	management_information_system
camp, l. jean		assoc	cmu	$1990 \\ 1982$	engineering_public_policy
cantwell smith, brian	utoronto	dean	mit		computer_science
carbo, toni	pitt	prof	drexel	1977	information_studies
carlyle, allyson	washington	assoc	ucla	1994	library_information_science
carr, david	unc	assoc	rutgers	1979	library_science
carroll, john	psu	prof	columbia	1976	psychology
cassell, kay	rutgers	asst	iugrad	2004	library_science
catterall, james	ucla	$\operatorname{prof}$	stanford	1982	educational_policy_analysis
chang, mitchell	ucla	assoc	ucla	1996	education
chauhan, arun	indiana_info	asst	rice	2003	computer_science
chen hsin, liang	utexas	asst	pitt	1999	$library\_information\_science$
chen, chaomei	drexel	assoc	liverpool	1995	computer_science
chen, yan	umich	assoc	caltech	1995	economics
cherry, joan	utoronto	$\operatorname{prof}$	pitt	1983	information_science
cheshire, coye	berkeley	asst	stanford	2005	sociology

Name	Faculty	Title	PhD	Year	Dept. of PhD
christensen, henrik	gatech	$\operatorname{prof}$	au_dk	1990	electrical_engineering
christopher, lee	unc	asst	umich	2005	information
chu, chao hsien	psu	assoc	psu	1984	$business\_administration$
chu, clara	ucla	assoc	uwo	1992	library_information_science
chuang, john	berkeley	assoc	cmu	1998	$engineering\_public\_policy$
chukumba, celestine	psu	asst	nd	2005	$economics\_econometrics$
clark, shawn	psu	$\operatorname{prof}$	psu	1999	$business\_administration$
clarkson, gavin	umich	asst	harvard	2004	business
clement, and rew	utoronto	$\operatorname{prof}$	utoronto	1986	computer_science
cogburn, derrick	syr	asst	howard	1996	political_science
cohen, michael	umich	$\operatorname{prof}$	uci	1972	social_science
cohen, sol	ucla	$\operatorname{prof}$	columbia	1964	history
connellly, kay	indiana_info	asst	uiuc	2003	computer_science
conway, paul	umich	assoc	umich	1991	information_library_studies
cooper, robert	ucla	asst	ucla	1996	education
courant, paul	umich	prof	princeton	1974	economics
cox, richard	pitt	prof	pitt	1992	information_science
craig, barbara	utoronto	assoc	ucl_ac_uk	1988	archive_studies
cronin, blaise	indiana_slis	dean	qub_ac_uk	1983	information_science
crowston, kevin	syr	prof	mit	1991	management_science
currim, sabah	fsu	asst	arizona	2006	management_information_system
cutzu, florin	indiana_info	asst	weizmann_ac_il	1997	computer_science
dalbello, marija	rutgers	assoc	utoronto	1999	information_studies
dalkilic, mehmet	indiana_info	asst	indiana	2000	computer_science
daniel, evelyn	unc	prof	umd	1974	library_science
davis, susan	uiuc	prof	psu	$1974 \\ 1973$	folklore
davis, susan	umd	asst	wisconsin	2003	library_science
day, ronald	indiana_slis			1990	-
0 /		assoc	binghamton ucla		comparative_literature
dechter, rina	uci	prof		1985	computer_science
dellaert, frank	gatech	asst	cmu	2001	computer_science
demillo, richard	gatech	dean	gatech	1972	computer_science
deredita, michael	syr	prof	syr	1998	experimental_cognitive_psycholog
desouza, kevin	washington	asst	uiuc	2006	management_information_system
detlefsen, eleen	pitt	assoc	columbia	1975	library_science
diker, vedat	umd	asst	albany	2003	information_science
dilevko, juris	utoronto	assoc	uwo	1999	library_information_science
dilevko, juris	utoronto	assoc	missouri	1990	english_literature
dillencourt, michael	uci	assoc	$\operatorname{umd}$	1988	computer_science
dillon, andrew	utexas	dean	lboro_ac_uk	1991	information_science
ding, yan	gatech	asst	harvard	2001	computer_science
do, ellen yi luen	gatech	assoc	gatech	1998	$design\_computing$
doerfel, marya	rutgers	assoc	buffalo	1996	$organizational\_communication$
dorr, aimee	ucla	dean	stanford	1970	psychology
doty, philip	utexas	assoc	syr	1995	information_studies
douglas, ian	fsu	asst	gcal_ac_uk	1996	computer_science
dourish, paul	uci	$\operatorname{prof}$	ucl_ac_uk	1996	computer_science
dovrolis, constantine	gatech	asst	wisconsin	2000	$computer_engineering$
downie, stephen	uiuc	assoc	uwo	1999	library_information_science
dresang, eliza	fsu	prof	wisconsin	1981	library_information_studies
drott, m. carl	drexel	assoc	umich	1973	industrial_operations_engineering
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Name	Faculty	$\mathbf{Title}$	PhD	Year	Dept. of PhD
druzdell, marek	$\operatorname{pitt}$	assoc	cmu	1992	$engineering_public_policy$
duff, wendy	utoronto	assoc	pitt	1996	information_science
dunn, michael	indiana_info	dean	pitt	1966	philosophy
durfee, edmund	umich	$\operatorname{prof}$	umass	1987	$computer\_science\_engineering$
durrance, joan	umich	$\operatorname{prof}$	umich	1980	$library\_information\_science$
dutt, nikil	uci	$\operatorname{prof}$	uiuc	1989	computer_science
dybvig, r, kent	indiana_info	$\operatorname{prof}$	unc	1987	computer_science
eastman, charles	gatech	$\operatorname{prof}$	berkeley		M_Arch
edwards, keith	gatech	assoc	gatech	1995	computer_science
edwards, paul	umich	assoc	ucsc	1988	history
efron, miles	utexas	asst	unc	2003	$information\_library\_science$
efthimiadis, efthimis	washington	assoc	city_ac_uk	1992	informatics
eisenberg, michael	washington	$\operatorname{prof}$	syr	1986	$information\_science\_technology$
ekbia, hamid	indiana_slis	assoc	indiana	2003	$computer\_cognitive\_science$
elichirigoity, fernando	uiuc	asst	uiuc	1994	history_of_science
el-zarki, magda	uci	$\operatorname{prof}$	columbia	1988	electrical_engineering
enyedy, noel	ucla	asst	berkeley	2000	education
eppstein, david	uci	$\operatorname{prof}$	columbia	1989	computer_science
erickson, frederick	ucla	$\operatorname{prof}$	northwestern	1969	education
essa, irfan	gatech	assoc	mit	1995	computer_science
estabrook, leigh	uiuc	$\operatorname{prof}$	boston	1980	sociology
everhart, nancy	fsu	assoc	fsu	1990	library_science
faniel, ixchel	umich	asst	usc	2004	information_systems
feamster, nick	gatech	asst	mit	2005	computer_science
fenske, david	drexel	dean	wisconsin	1973	music
ferguson, ronald	gatech	asst	northwestern	2001	computer_science
fidel, raya	washington	$\operatorname{prof}$	umd	1982	library_information_science
finholt, thomas	umich	assoc	cmu	1993	social_decision_science
fisher, karen	washington	assoc	uwo	1998	library_information_science
fishman, barry	umich	assoc	northwestern	1996	learning_sciences
flammini, alessandro	indiana_info	asst	uniroma1_it	1993	physics
fleischmann, kenneth	umd	asst	rpi	2004	information_science
flynn, roger	pitt	assoc	pitt	1978	information_science
foley, henry	psu	dean	psu	1982	physical_chemistry
foley, james	gatech	$\operatorname{prof}$	umich	1969	electrical_engineering
fonseca, frederico	psu	asst	umaine	2001	spatial_information_science_engineer
fox, geoffrey	indiana_info	$\operatorname{prof}$	cambridge	1967	theoretical_physics
francisco revilla, luis	utexas	asst	tamu	2004	computer_science
franke, megan	ucla	assoc	wisconsin	1990	$educational_psychology$
franz, michael	uci	$\operatorname{prof}$	$ethz_ch$	1994	computer_science
frieden, robert	psu	$\operatorname{prof}$	virginia	1980	law_JD
friedman, batya	washington	prof	berkeley	1988	$science_mathematics_education$
friedman, daniel	indiana_info	prof	utexas	1973	computer_science
frost, c. olivia	umich	prof	uchicago	1977	library_science
frost, robert	umich	assoc	wisconsin	1983	history
fujimoto, richard	gatech	prof	berkeley	1983	computer_science
fuller, sherrilynne	washington	prof	usc	1984	library_information_science
furnas, george	umich	prof	stanford	1980	cognitive_psychology
furner, jonathan	ucla	assoc	sheffield	1994	information_studies
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furst, merrick	gatech	prof	cornell	1980	computer_science

Name	Faculty	Title	PhD	Year	Dept. of PhD
gallimore, ronald	ucla	$\operatorname{prof}$	northwestern	1964	psychology
galloway, patricia	utexas	assoc	unc	2004	anthropology
galloway, patricia	utexas	assoc	unc	1973	$comparative\_literature$
gandel, paul	syr	$\operatorname{prof}$	syr	1986	information_studies
gannon, dennis	indiana_info	$\operatorname{prof}$	ucd	1974	mathematics
gannon, dennis	indiana_info	$\operatorname{prof}$	uiuc	1980	computer_science
gant, john	syr	asst	cmu	1998	$public_policy_management$
garcia murillo, martha	syr	assoc	usc	1998	political_economy_public_policy
garrison, guy	drexel	$\operatorname{prof}$	uiuc	1960	library_science
garwood, steve	rutgers	asst	rutgers	1999	MLIS
gasser, les	uiuc	prof	uci	1984	information_science
gasser, michael	indiana_info	assoc	uiuc	1988	applied_linguistics
gasson, susan	drexel	assoc	warwick	1998	information_systems
gathegi, john	fsu	assoc	berkeley	1990	library_information_studies
geisler, gary	utexas	asst	unc	2003	information_library_science
gibbs, jennifer	rutgers	asst	usc	2002	communication
giffin, jonathon	gatech	asst	wisconsin	2006	computer_science
giles, c. lee	psu	prof	arizona	1981	optical_sciences
gillen, daniel	uci	asst	washington	2003	biostatistics
gilliland, anne	ucla	prof	umich	1995	information_library_studies
givargis, tony	uci	asst	ucriverside	2001	computer_science
goel, ashok	gatech	assoc	osu	1989	computer_information_science
gollop, claudia	unc	assoc	pitt	1903	library_information_science
goodman, seymour	gatech	prof	caltech	$1955 \\ 1970$	physics
goodrich, michael	uci	prof	purdue	1970	computer_science
gordon, carol		assoc	boston	1987 1995	education
gracy, david	rutgers utexas	prof	ttu	1995 1971	history
		1	ucla	2001	library_information_science
gracy, karen	pitt	asst	ucla		education
graham, sandra	ucla	prof		1982	
gray, alexander	gatech	asst	cmu	2003	computer_science
greenberg, david	rutgers	asst	columbia	2001	american_history
greenberg, jane	unc	assoc	pitt	1998	library_information_science
greene, kathryn	rutgers	assoc	uga	1992	speech_communication
griffiths, jose marie	unc	dean	ucl_ac_uk	1978	information_science
grinter, beki	gatech	assoc	uci	1996	information_science
gross, melissa	fsu	assoc	ucla	1998	library_information_science
groth, dennis	indiana_info	asst	indiana	2002	computer_science
gupta, minaxi	indiana_info	assoc	gatech	2004	computer_science
gutierrez, kris	ucla	$\operatorname{prof}$	colorado	1987	english
guzdial, mark	gatech	$\operatorname{prof}$	umich	1993	$education\_computer\_science$
gwizdka, jacek	rutgers	asst	utoronto	2004	mechanical_industrial_engineer
haas, stephanie	unc	$\operatorname{prof}$	$\operatorname{pitt}$	1989	library_information_science
haghverdi, esfandiar	indiana_info	asst	uottowa	2000	mathematics
hahn, matthew	indiana_info	asst	duke	2003	biology
hakken, david	indiana_info	$\operatorname{prof}$	american	1978	anthropology
hall, david	psu	$assoc_dean$	psu	1976	$astronomy\_astrophysics$
han, hyoil	drexel	asst	uta	2002	computer_science_engineering
hansen montgomery, carol	drexel	prof	drexel	1979	library_science
hanson, andrew	indiana_info	prof	mit	1971	physics
hara, noriko	indiana_slis	asst	indiana	2000	education
hardin, joseph	umich	asst	uiuc	n/a	ABD_speech_communication
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Name	Faculty	$\mathbf{Title}$	PhD	Year	Dept. of PhD
harding, sandra	ucla	$\operatorname{prof}$	nyu	1973	philosophy
harmon, e. glynn	utexas	$\operatorname{prof}$	cwru	1969	$information\_science$
harris, ian	uci	assoc	ucsd	1997	computer_science
harris, lydia	rutgers	asst	arizona	1976	education
harrold, mary jean	gatech	$\operatorname{prof}$	pitt	1988	computer_science
hawkins, john	ucla	$\operatorname{prof}$	vanderbilt	1973	$comparative_education$
hayes, wayne	uci	asst	utoronto	2001	computer_science
haynes, christopher	indiana_info	assoc	uiowa	1982	computer_science
haynes, steven	psu	asst	lse_ac_uk	2001	information_systems
haythornthwaite, caroline	uiuc	assoc	utoronto	1996	information_studies
he, daqing	pitt	asst	edinburgh_ac_uk	2001	informatics
healy, charles	ucla	$\operatorname{prof}$	columbia	1967	counseling_psychology
hearne, betsy	uiuc	prof	uchicago	1985	library_science
hearst, marti	berkeley	assoc	berkeley	1994	computer_science
hedstrom, margaret	umich	assoc	wisconsin	1988	history
heffner, richard	rutgers	prof	columbia	1947	MA
heidorn, bryan	uiuc	assoc	pitt	1997	information_science
hemminger, bradley	unc	asst	uu_nl	2001	computer_science
hendry, david	washington	asst	rgu_ac_uk	1996	computer_science
herring, susan	indiana_slis	prof	berkeley	1991	linguistics
hewitt, joe	unc	prof	colorado	1976	library_science
hill, raquel	indiana_info	asst	harvard	2002	computer_science
hirschberg, daniel	uci	prof	princeton	1975	computer_science
hirtle, stephen	pitt	prof	umich	1982	psychology
hislop, gregory	drexel	assoc	drexel	1993	computer_science
hoadley, christopher	psu	assoc	berkeley	1999	science_mathematics_education
hofstadter, douglas	indiana_info	prof	uoregon	1975	physics
holland, maurita	umich	assoc	umich	n/a	AMLS
honeyman, peter	umich	prof	princeton	1980	computer_science
howard, tyrone	ucla	assoc	washington	1998	education
howarth, lynne	utoronto	assoc	utoronto	1990	information_library_science
howes, carollee	ucla	prof	boston	1979	developmental_psychology
hu, xiaohua	drexel	asst	regina	1995	computer_science
hughes hassell, sandra	unc	assoc	unc	1998	information_library_science
hurtado, sylvia	ucla	prof	ucla	1990	education
immroth, barbara	utexas	prof	pitt	1990	library_information_science
irani, sandra	uci	prof	berkeley	1980	computer_science
irwin, marilyn	indiana_slis	assoc	indiana	1991	library_information_science
isbell, charles	gatech		mit	$1991 \\ 1998$	computer_science
jablonski, judith		asst	wisconsin		•
jacko, julie	pitt gatech	asst	purdue	$2006 \\ 1993$	library_science computer_science
	umich	prof	-		computer_science
jackson, steven		asst	ucsd	2005	
jacob, elin	indiana_slis	assoc	unc c	1994	information_library_science
jaeger, paul	umd	asst	fsu	2006	information
jain, ramesh	uci	prof	iit_in	1971	industrial_engineering
jakobsson, markus	indiana_info	assoc	ucsd	1997	computer_science
janes, joseph	washington	assoc	syr	1989	information_science_technolog
jansen, jim	psu	asst	tamu	1999	computer_science
jarecki, stanislaw	uci	asst	mit	2001	computer_science
jenkins, christine	uiuc	assoc	wisconsin	1995	library_science
johnson, ronald	washington	assoc	usc	1975	MSLS

Name	Faculty	Title	PhD	Year	Dept. of PhD
johnson, steven	indiana_info	$\operatorname{prof}$	indiana	1983	computer_science
johnson, wesley	uci	$\operatorname{prof}$	umn	1979	statistics
jones, william	washington	assoc	cmu	1982	$experimental_psyschology$
jorgensen, corinne	fsu	$assoc_dean$	syr	1995	$information\_studies$
joshi, james	pitt	asst	purdue	2003	$electrical\_computer\_engineering$
kaarst brown, michelle	syr	assoc	yorku	1995	$administrative\_studies$
kabara, joseph	pitt	asst	vanderbilt	1997	$electrical\_computer\_engineering$
kafai, yasmin	ucla	assoc	harvard	1993	$human\_development\_psychology$
kalai, adam	gatech	asst	cmu	2001	computer_science
kalai, yael	gatech	asst	$\operatorname{mit}$	2006	cryptography
kantor, paul	rutgers	$\operatorname{prof}$	princeton	1963	$theoretical_physics$
karimi, hassan	pitt	assoc	calgary_ca	1991	geomatics_engineering
kasari, connie	ucla	$\operatorname{prof}$	unc	1985	education
katz, james	rutgers	$\operatorname{prof}$	rutgers	1974	sociology
kazmer, michelle	fsu	asst	uiuc	2002	library_information_science
keith, susan	rutgers	asst	unc	2003	journalism_mass_communication
kellner, douglas	ucla	prof	columbia	1973	philosophy
kelly, diane	unc	asst	rutgers	2004	information_science
kendall, lori	uiuc	assoc	ucd	1998	sociology
kern, montague	rutgers	assoc	jhu	1979	advanced_international_studies
khot, subhash	gatech	asst	princeton	2003	computer_science
khumar, akhil	psu	prof	berkeley	1988	information_systems
kim, jeffrey	washington	asst	uci	2000	information_computer_science
kim, kyung	fsu	asst	rutgers	2002	information_systems_services
kim, sun	indiana_info	asst	uiowa	1997	computer_science
king, john	umich	prof	uci	1977	administration
kingma, bruce	syr	prof	rochester	1989	economics
klavans, judith	umd	prof	ucl_ac_uk	1980	linguistics
kobsa, alfred	uci	prof	univie_ac_at	1985	computer_science
kolodner, janet	gatech	prof	yale	1980	computer_science
koshman, sherry	pitt	assoc	pitt	1996	information_science
kourilsky, marilyn	ucla	prof	ucla	1968	communication
krishnamurthy, prashant	pitt	assoc	wpi	1999	electrical_computer_engineering
kubey, robert	rutgers	prof	uchicago	1984	behavioral_sciences
kumar, deepa	rutgers	asst	pitt	2001	communication
kumara, soundar	psu	prof	purdue	1985	industrial_engineering
kvasny, lynette	psu	asst	gsu	2002	computer_information_systems
kwasnik, barbara	syr	prof	rutgers	1989	communications_info_library_stud
la barre, kathryn	uiuc	asst	indiana	2006	library_information_science
lambert, joseph	psu	$assoc_dean$	purdue	1970	mathematics
lankes, r david	syr	assoc	syr	1999	information_studies
larsen, ronald	pitt	dean	umd	1981	computer_science
larson, ray	berkeley	prof	berkeley	1986	library_information_studies
latham, don	fsu	asst	uga	1995	english
lathrop, richard	uci	prof	mit	1990	artificial_intelligence
lavender, kenneth	syr	asst	ucsb	1972	english
lawton, patricia	pitt	asst	wisconsin	1990	library_science
leake, david	indiana_info	prof	yale	1990	computer_science
leazer, gregory	ucla	assoc	columbia	1993	library_service
lee, dongwon	psu	asst	ucla	2002	computer_science

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Name	Faculty	Title	PhD	Year	Dept. of PhD
leivant, daniel	indiana_info	prof	uva_nl	1975	mathematics
lesk, michael	rutgers	prof	harvard	1970	chemical_physics
levy, david	washington	$\operatorname{prof}$	stanford	1979	computer_science
lewis, laurie	rutgers	assoc	ucsb	1994	communication
lewis, michael	pitt	prof	gatech	1986	psychology
li, chen	uci	asst	stanford	2001	computer_science
liang, gang	uci	asst	berkeley	2004	statistics
liddy, elizabeth	syr	prof	syr	1988	information_studies
lievrouw, leah	ucla	prof	usc	1986	$communication_theory$
lim, youn kyng	indiana_info	asst	iit	2003	design
lin, jimmy	umd	asst	mit	2004	linguistics
lin, xia	drexel	assoc	umd	1993	information_science
lipton, richard	gatech	prof	cmu	1973	computer_science
litman, jessica	umich	prof	columbia	n/a	law_JD
liu, ling	gatech	assoc	sfu_ca	1995	computer_science
liu, peng	psu	assoc	gmu	1999	information_technology
loh, gabriel	gatech	asst	yale	2002	computer_science
lopes, cristina	uci	assoc	northeastern	1998	computer_science
lorence, daniel	psu	asst	eiu	1997	business_administration
losee, robert	unc	prof	uchicago	1986	library_information_science
lowry, charles	umd	prof	ufl	1979	history
lu, ya ling	rutgers	asst	ucla	2005	information_studies
lueker, george	uci	prof	princeton	1975	computer_science
lukenbill, w. bernard	utexas	prof	indiana	$1970 \\ 1973$	library_science
lumsdaine, andrew	indiana_info	prof	mit	1992	electrical_engineering_computer_scie
lustria, mia liza	fsu	asst	uky	2005	communication
lyman, peter	berkeley	prof	stanford	1961	political_science
lynch, beverly	ucla	prof	wisconsin	$1901 \\ 1972$	library_science
maack, mary	ucla	prof	columbia	1972	library_science
macias, reynaldo	ucla	prof	georgetown	1978	linguistics
macinnes, ian		assoc	usc	1979	political_economy_public_policy
macintyre, blair	syr gatech	assoc	columbia	1998	computer_science
machie mason, jeffrey	umich		mit	1999 1986	economics
		prof		2000	
mai, jens, erik	utoronto	assoc	utexas		library_information_science
maitland, carleen	psu	asst	$tudelft_nl$	2001	technology_policy_management
majumder, aditi	uci drexel	asst	unc	2003	computer_science
mancall, jacqueline		prof	drexel	1978	library_information_science
mandelbaum, jenny	rutgers	assoc	utexas	1987	communication_studies
manolios, panagiotis	gatech	asst	utexas	2001	computer_science
marchi, regina	rutgers	asst	ucsd	2005	communication
marchionini, gary	unc	prof	wayne	1981	mathematics_education
marcoux, elizabeth	washington	asst	arizona	1999	library_information_science
mark, gloria	uci	assoc	columbia	1991	psychology
mark, leo	gatech	assoc	au_dk	1985	computer_science
markey, karen	umich	prof	syr	1981	information_studies
marshall, joanne gard	unc	prof	utoronto	1987	community_health
martin, thomas	syr	assoc	stanford	1974	communication
marty, paul	fsu	asst	uiuc	2002	library_information_science
mason, bob	washington	$assoc_dean$	gatech	1973	industrial_systems_engineering
mccain, katherine	drexel	prof	drexel	1985	information_studies
mcclure, charles	fsu	prof	rutgers	1977	library_information_services

Name	Faculty	Title	PhD	Year	Dept. of PhD
mcdonald, david	washington	asst	uci	2000	information_computer_science
mcdonough, jerome	uiuc	asst	berkeley	2000	library_information_studies
mcdonough, patricia	ucla	prof	stanford	1992	$administration\_policy\_analysis$
mcinernery, claire	rutgers	assoc	albany	1998	information_science
mckechnie, lynne	washington	prof	uwo	1996	$library\_information\_science$
mcknight, lee	syr	assoc	mit	1989	economics
mclaren, peter	ucla	prof	utoronto	1983	education
mcneese, michael	psu	assoc	vanderbilt	1992	cognitive_science
mcquaid, michael	umich	asst	arizona	2003	management
mcrobbie, michael	indiana_info	prof	anu_au	1979	mathematics
medina, eden	indiana_info	asst	mit	2005	history
meenakshisundaram, gopi	uci	asst	unc	2001	computer_science
meho, lokman	indiana_slis	asst	unc	2001	information_science
mehrotra, sharad	uci	prof	utexas	1993	computer_science
menczer, filippo	indiana_info	assoc	ucsd	1998	computer_science_cognitive_science
mersky, roy	utexas	prof	wisconsin	1952	law_JD
metoyer, cheryl	washington	assoc	indiana	1976	library_information_science
metzler, douglas	pitt	assoc	ucd	1981	cognitive_psychology
michalak, sarah	unc	prof	ucla	n/a	MLS
mihail, milena	gatech	assoc	harvard	1989	computer_science
miksa, francis	utexas	prof	uchicago	1974	library_science
miller, rush	pitt	prof	msstate	1973	history
mills, jonathan	indiana_info	assoc	asu	1988	computer_science
mistry, rashmita	ucla	asst	utexas	1999	child_development_family_relations
mitra, prasenjit	psu	asst	stanford	2004	electrical_engineering
mjolsness, eric	uci	assoc	caltech	1985	physics_computer_science
mohr, stewart	rutgers	asst	rutgers	n/a	ABD
mokros, hartmut	rutgers	$assoc_dean$	uchicago	1984	behavioral_sciences
mon, lorri	fsu	asst	washington	2006	information_science
moore, adam	washington	assoc	osu	1997	philosophy
moran, barbara	unc	prof	buffalo	1982	library_science
morrell, ernest	ucla	asst	berkeley	2001	education
mostafa, javed	indiana_info	assoc	utexas	1994	information_science
mostafa, javed	indiana_slis	assoc	utexas	1994	information_science
mueller, milton	syr	prof	upenn	1989	communication
mukudi omwami, edith	ucla	asst	buffalo	1998	education
mullen, tracy	psu	asst	umich	1999	computer_science_engineering
munro, paul	pitt	assoc	brown	1983	physics
muresan, gheorghe	rutgers	asst	rgu_ac_uk	2002	computer_mathematical_sciences
muthen, bengt	ucla	prof	uu_se	1977	statistics
myers, steven	indiana_info	asst	utoronto	2005	computer_science
mynatt, elizabeth	gatech	assoc	gatech	1995	computer_science
nakanishi, don	ucla	prof	harvard	1978	political_science
nardi, bonnie	uci	prof	uci	1977	anthropology
navathe, shamkant	gatech	prof	umich	1976	computer_science
nersessian, nancy	gatech	prof	cwru	1977	philosophy
neuman, m delia	umd	assoc	osu	1986	education
newell, terrence	fsu	asst	wisconsin	2006	library_information_studies
nicholson, scott	syr	asst	unt	2000	information_science
nicolau, alexandru	uci	prof	yale	1984	computer_science
niemier, michael		-	yale nd		
Continued on next nage	gatech	asst	nu	2003	computer_science_engineering

Name	Faculty	$\mathbf{Title}$	PhD	Year	Dept. of PhD
nilan, michael	syr	assoc	washington	1985	communication
nisonger, thomas	indiana_slis	$\operatorname{prof}$	$\operatorname{columbia}$	1976	political_science
oakes, jeannie	ucla	$\operatorname{prof}$	ucla	1980	education
oakleaf, megan	syr	asst	unc	2006	$information\_library\_science$
oard, douglas	umd	assoc	umd	1996	$computer\_science$
obidah, jennifer	ucla	assoc	berkeley	1995	education
oconnor, daniel	rutgers	assoc	syr	1978	library_science
ogan, christine	indiana_info	$\operatorname{prof}$	unc	1976	$mass\_communication\_research$
olson, gary	umich	$\operatorname{prof}$	stanford	1970	psychology
olson, judith	umich	$\operatorname{prof}$	umich	1969	$experimental_psychology$
omiecinski, edward	gatech	assoc	$\operatorname{northwestern}$	1984	computer_science
orellana, marjorie	ucla	assoc	usc	1994	education
orso, alessandro	gatech	asst	polimi_it	1999	computer_science
osterlund, carsten	syr	asst	mit	2003	management_science
palmer, carole	uiuc	assoc	uiuc	1996	library_information_science
pande, santosh	gatech	assoc	ncsu	1993	computer_engineering
paolillo, john	indiana_info	assoc	stanford	1992	linguistics
paolillo, john	indiana_slis	assoc	stanford	1992	linguistics
park, haesun	gatech	$\operatorname{prof}$	cornell	1987	computer_science
park, joon	syr	asst	gmu	1999	information_technology_engineering
park, jung ran	drexel	asst	hawaii	2003	linguistics
patterson, donald	uci	asst	washington	2005	computer_science_engineering
pavlik, john	rutgers	prof	umn	1983	$mass\_communication$
pavlovsky, lilia	rutgers	asst	rutgers	2003	communication_info_library_studie
petrick, irene	psu	prof	psu	1997	engineering_business_administrati
plale, beth	indiana_info	assoc	binghamton	1998	computer_science
pomerantz, jeffrey	unc	asst	syr	2003	information_studies
potts, colin	gatech	assoc	sheffield	1980	psychology
pratt, wanda	washington	assoc	stanford	1999	medical_informatics
preece, jennifer	umd	dean	open_ac_uk	1985	educational_technology
preer, jean	indiana_slis	assoc	gwu	1980	american_civilization
prvulovic, milos	gatech	asst	uiuc	2003	computer_science
przulj, natasa	uci	asst	utoronto	2005	computer_science
pu, calton	gatech	prof	washington	1986	computer_science
purao, sandeep	psu	assoc	wisconsin	1995	management_science
purdom, paul	- indiana_info	prof	caltech	1966	physics
qin, jian	syr	assoc	uiuc	1996	information_library_science
qu, yan	umd	asst	umich	2006	information
radev, dragomir	umich	assoc	columbia	1999	computer_science
radford, marie	rutgers	assoc	rutgers	1993	communication_info_library_studie
radivojac, predrag	indiana_info	asst	temple	2003	computer_information_sciences
ram, ashwin	gatech	assoc	yale	1989	computer_science
ramachandran, umakishore	gatech	prof	wisconsin	1986	computer_science
randall, dana	gatech	assoc	berkeley	1994	computer_science
randeree, ebrahim	fsu	asst	buffalo	2006	management
raphael, christopher	indiana_info	assoc	brown	1991	mathematics
ravindran, arunachalam	psu	prof	berkeley	1969	industrial_engineering
rawlins, gregory	indiana_info	assoc	uwaterloo	1987	computer_science
ray, glenn	pitt	asst	mit	1980	earth_science
rayward, boyd	uiuc	prof	uchicago	1973	library_science
reddy, madhu	psu	asst	uci	2003	information_computer_science
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Name	Faculty	$\mathbf{Title}$	PhD	Year	Dept. of PhD
redmiles, david	uci	assoc	colorado	1992	computer_science
reed, barbara	rutgers	assoc	osu	1987	mass_communication
regan, amelia	uci	assoc	utexas	1997	$transportation\_systems\_engineering$
rehg, james	gatech	assoc	cmu	1995	electrical_computer_engineering
renear, allen	uiuc	assoc	brown	1988	philosophy
resnick, paul	umich	prof	mit	1992	electrical_engineering_computer_scienc
rhoads, robert	ucla	prof	psu	1993	higher_education
riccardi, greg	fsu	prof	buffalo	1980	computer_science
ricci, steve	ucla	asst	ucla	1996	film_television
rice lively, mary lynn	utexas	$assoc_dean$	utexas	1996	library_information_science
richardson, debra	uci	dean	amherst	1981	computer_information_science
richardson, john	ucla	prof	indiana	1978	sociology
rieh, soo young	umich	asst	rutgers	2000	communication_info_library_studies
ritter, frank	psu	assoc	cmu	1992	psychology
robbin, alice	indiana_slis	assoc	wisconsin	1984	political_science
robertson, edward	indiana_info	prof	wisconsin	1970	computer_science
robertson, scott paul	drexel	assoc	yale	1983	psychology_cognitive_science
robinson, jeffrey d	rutgers	assoc	ucla	1999	sociology
rocha, luis	indiana_info	assoc	binghamton	1997	computer_science
rogers, john	ucla	asst	stanford	1994	education
rogers, yvonne	indiana_info		wales	1994 1988	
rogers, yvonne rose, mike	ucla	prof	ucla	1980 1981	science_technology education
,		prof			
rosenbaum, howard	indiana_slis	assoc	syr	1996	information_transfer
rosenberg, victor	umich	assoc	uchicago	1970	library_science
rossignac, jarek	gatech	prof	rochester	1985	electrical_engineering
rosson, mary beth	psu	prof	utexas	1982	human_experimental_psychology
rothbauer, paulette	utoronto	asst	uwo	2004	information_media_studies
roy, loriene	utexas	prof	uiuc	1987	library_information_science
ruben, brent	rutgers	prof	uiowa	1970	communication
russell, dawn	psu	asst	northwestern	2000	civil_engineering
rust, val	ucla	prof	umich	1967	education
ryokai, kimiko	berkeley	asst	$\operatorname{mit}$	2005	architecture_fine_arts
sabry, amr	indiana_info	assoc	rice	1994	computer_science
sami, rahul	umich	asst	yale	2003	computer_science
samuelson, pamela	berkeley	$\operatorname{prof}$	yale	1976	law_JD
sandoval, william	ucla	assoc	northwestern	1998	learning_sciences
santoro, gerald	psu	asst	psu	1989	$communication\_information\_science$
santos, jose	ucla	asst	arizona	2004	higher_education
saracevic, tefko	rutgers	$\operatorname{prof}$	cwru	1970	information_science
sawyer, steven	psu	assoc	boston	1995	$management\_information\_systems$
sax, linda	ucla	assoc	ucla	1994	higher_education
saxenian, annalee	berkeley	dean	mit	1989	political_science
saxton, matthew	washington	asst	ucla	2000	library_information_science
saye, jerry	unc	prof	pitt	1979	library_science
schement, jorge reina	psu	prof	stanford	1976	mass_communications
scherson, isaac	uci	prof	weizmann_ac_il	1983	applied_mathematics
schiller, dan	uiuc	prof	psu	1978	journalism
schilling, katherine	indiana_slis	asst	boston	2002	education
schnell, santiago	indiana_info	asst	oxford	2002	applied_mathematics
scholl, jochen	washington	asst	albany	2002	public_affairs_policy
schwan, karsten	gatech	prof	cmu	1982	high_performance_computing
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Name	Faculty	Title	$\mathbf{PhD}$	Year	Dept. of PhD
scott, craig	rutgers	assoc	asu	1994	organizational_communication
seif el-nasr, magy	psu	asst	northwestern	2003	computer_science
seltzer, michael	ucla	$\operatorname{prof}$	uchicago	1991	education
shachaf, pnina	indiana_slis	asst	unc	2003	information_library_science
shankar, kalpana	indiana_info	asst	ucla	2002	library_information_science
shaw, debora	indiana_slis	prof	indiana	1983	information_science
sherrill, c. david	gatech	assoc	uga	1996	computational_quantum_chemistry
shivers, olin	gatech	assoc	cmu	1991	computer_science
shulman, stuart	pitt	asst	uoregon	1999	political_science
siegel, martin	indiana_info	prof	uiuc	1973	educational_psychology
silverstein, scot	drexel	asst	boston	n/a	MD
sim, susan	uci	asst	utoronto	2003	computer_science
small, ruth	syr	prof	syr	1985	education
smith, brian	psu	assoc	northwestern	1998	learning_sciences
smith, linda	uiuc	prof	syr	$1950 \\ 1979$	information_science
smyth, padhraic	uci	prof	caltech	1988	electrical_engineering
sochats, kenneth	pitt	asst	pitt	$1900 \\ 1975$	MBA
soergel, dagobert	umd	prof	freiberg_de	1970	political_science
		•	umd	1970	*
solomon, paul	unc	assoc			library_information_science
solomon, william	rutgers	assoc	berkeley	1985	sociology
solorzano, daniel	ucla	prof	claremont	1986	sociology
soloway, elliot	umich	prof	umass	1978	computer_science
song, il yeol	drexel	prof	lsu	1988	computer_science
spoerri, anselm	rutgers	asst	mit	1995	information_visualization
spring, michael	pitt	assoc	pitt	1979	education
srinivasan, ramesh	ucla	asst	harvard	2005	design
stahl, gerry	drexel	assoc	northwestern	1975	philosophy
stahl, gerry	drexel	assoc	colorado	1993	computer_science
stanton, jeffrey	$\operatorname{syr}$	assoc	uconn	1997	psychology
starner, thad	gatech	assoc	$\operatorname{mit}$	1999	media_lab
stasko, john	gatech	$\operatorname{prof}$	brown	1989	computer_science
steiner, linda	rutgers	$\operatorname{prof}$	uiuc	1979	journalism
stern, hal	uci	$\operatorname{prof}$	stanford	1987	statistics
stewart, lea	rutgers	$\operatorname{prof}$	purdue	1979	communication
stolterman, erik	indiana_info	$\operatorname{prof}$	umu_se	1991	informatics
sturm, brian	unc	assoc	indiana	1998	library_information_science
stvilia, besiki	fsu	asst	uiuc	2006	library_information_science
suda, tatsuya	uci	$\operatorname{prof}$	kyoto_u_ac_jp	1982	computer_science
sundaresan, shankar	psu	asst	rochester	1997	business_administration
sutton, stuart	washington	assoc	berkeley	1991	library_information_science
suzuki, gordon	ucla	prof	ucla	1998	curriculum_teaching_studies
szymczak, andrzej	gatech	asst	gatech	1999	mathematics
tan, zixiang	syr	assoc	rutgers	1996	telecommunications_policy_manageme
tang, haixu	indiana_info	asst	sibcb_ac_cn	1998	molecular_computational_biology
tapia, andrea	psu	asst	unm	2000	sociology
taylor, hazel	washington	asst	qut_au	2000	information_technology
taylor, richard	psu	prof	columbia	1978	mass_communications
taylor, richard	uci	prof	colorado	1978	computer_science
		-			-
teasley, stephanie	umich	assoc	pitt	1992	psychology
techatassanasoontorn, angsana	psu	asst	umn	2006	business_administration
tetali, prasad	gatech	prof	nyu	1991	computer_science

Name	Faculty	$\mathbf{Title}$	PhD	Year	Dept. of PhD
theiss, jennifer	rutgers	asst	wisconsin	2005	communication_arts
thomas, james	psu	$\operatorname{prof}$	utexas	1988	$strategic\_management$
thompson, richard	$\operatorname{pitt}$	$\operatorname{prof}$	uconn	1971	computer_science
tibbo, helen	unc	$\operatorname{prof}$	umd	1989	library_information_science
tidwell, romeria	ucla	$\operatorname{prof}$	ucla	1974	$counseling_psychology$
tipper, david	$_{ m pitt}$	assoc	arizona	1988	electrical_engineering
todd, peter	indiana_info	$\operatorname{prof}$	stanford	2002	psychology
todd, ross	rutgers	assoc	uts_au	1996	$media_arts_communication_informat$
tomer, christinger	$\operatorname{pitt}$	assoc	cwru	1978	library_science
tomlinson, bill	uci	asst	mit	2002	media_arts_sciences
torres, carlos	ucla	prof	stanford	1983	international_development_education
trauth, eileen	psu	prof	pitt	1979	information_science
tripp, lisa	fsu	asst	ucsd	2003	communication
tsudik, gene	uci	prof	usc	1991	computer_science
turk, greg	gatech	assoc	unc	1992	computer_science
turnbull, don	utexas	asst	utoronto	2002	computer_science
twidale, michael	uiuc	assoc	lancs_ac_uk	1989	computer_science
tygar, doug	berkeley	prof	harvard	1987	computer_science
unsworth, john	uiuc	dean	virginia	1988	literature
valadez, concepcion	ucla	assoc	stanford	1976	education
van der hoek, andre	uci	assoc	colorado	2000	computer_science
van dyk, david	uci	$\operatorname{prof}$	uchicago	1995	statistics
van house, nancy	berkeley	prof	berkeley	1979	library_information_studies
van houweling, douglas	umich	prof	indiana	1976	government
van, gucht, dirk	indiana_info	prof	vanderbilt	1985	computer_science
varian, hal	berkeley	prof	berkeley	1973	economics
varlejs, jana	rutgers	assoc	wisconsin	1996	library_science
vazirani, vijay	gatech	$\operatorname{prof}$	berkeley	1984	computer_science
veidenbaum, alexander	uci	prof	uiuc	1985	computer_science
vellucci, sherry	rutgers	asst	columbia	1995	library_science
vempala, santosh	gatech	prof	berkeley	2006	computer_science
venkatasubramanian, nalini	uci	assoc	uiuc	1998	computer_science
venkatesh, murali	syr	assoc	indiana	1991	management_information_systems
venkateswaran, h.	gatech	assoc	washington	1986	computer_science
vespignani, alessandro	indiana_info	prof	uniroma1_it	1993	physics
vigoda, eric	gatech	assoc	berkeley	1999	computer_science
von dran, gisella	syr	asst	asu	1992	public_administration
von dran, raymond	syr	dean	wisconsin	1976	information_science
wacholder, nina	rutgers	asst	cuny	1995	linguistics
wagoner, rick	ucla	asst	arizona	2004	higher_education
walker, bruce	gatech	asst	rice	2001	human_computer_interaction
walsh, john	indiana_slis	asst	indiana	2000	english
walter, virginia	ucla	prof	usc	1984	public_administration
wang, james	psu	prof	stanford	2000	medical_information_sciences
wang, ping	umd	asst	ucla	2005	management
wang, xiaofeng	indiana_info	asst	cmu	2003	computer_engineering
wathen, nadine	utoronto	asst	uwo	2004 2004	library_information_science
webb, noreen	ucla	prof	stanford	1978	educational_psychology
	drexel	asst	ufsc_br	1998	production_engineering
weper, rosina		0000	GT00_01	1000	Production_on8meeting
weber, rosina weech, terry	uiuc	assoc	uiuc	1972	library_science

Name	Faculty	Title	PhD	Year	Dept. of PhD
wei choo, chun	utoronto	$\operatorname{prof}$	utoronto	1993	information_studies
weiss, martin	pitt	assoc	cmu	1988	engineering_public_policy
welling, max	uci	asst	uu_nl	1998	computer_science
westbrook, lynn	utexas	asst	umich	1995	information_library_studies
whinston, and rew	utexas	$\operatorname{prof}$	cmu	1962	economics
wiedenbeck, susan	drexel	$\operatorname{prof}$	$_{ m pitt}$	1984	information_science
wiegand, wayne	fsu	$\operatorname{prof}$	siu	1974	history
wild, david	indiana_info	asst	sheffield	1994	information_studies
wildemuth, barbara	unc	$\operatorname{prof}$	drexel	1989	information_studies
wilensky, robert	berkeley	$\operatorname{prof}$	yale	1978	computer_science
wilkinson, alex	syr	$\operatorname{prof}$	umich	1977	psychology
wilms, wellford	ucla	$\operatorname{prof}$	berkeley	1973	education
winget, megan	utexas	asst	unc	2006	information_library_science
winship, michael	utexas	$\operatorname{prof}$	cornell	1992	history
winston, mark	unc	assoc	pitt	1997	library_information_science
wise, david	indiana_info	prof	wisconsin	1971	computer_science
wobbrock, jacob	washington	asst	cmu	2006	computer_science
wood, jeffrey	ucla	asst	ucla	2003	psychology
wu, yuqing	indiana_info	asst	umich	2004	computer_science
wyss, catharine	indiana_info	asst	indiana	2002	computer_science
xie, bo	umd	asst	rpi	2006	information_science
xu, heng	psu	asst	nus_sg	2005	information_systems
xu, jun	gatech	assoc	osu	2000	computer_science
yaeger, larry	indiana_info	$\operatorname{prof}$	poly	1974	aerospace_engineering
yakel, elizabeth	umich	assoc	umich	1997	information
yang, kiduk	indiana_slis	asst	unc	2002	information_library_science
yang, xiaowei	uci	asst	mit	2005	computer_science
yanovitzhky, itzhak	rutgers	asst	upenn	2000	communication
yen, john	psu	$\operatorname{prof}$	berkeley	1986	computer_science
yu, eric	utoronto	assoc	utoronto	1995	computer_science
yu, yaming	uci	asst	harvard	2005	statistics
zadorozhny, vladimir	pitt	asst	ras_ru	1993	computer_science
zegura, ellen	gatech	prof	wustl	1993	computer_science
zha, hongyuan	gatech	prof	stanford	1993	scientific_computing
zhang, ping	syr	assoc	utexas	1995	business_administration
zhang, xiangmin	rutgers	asst	utoronto	1998	information_studies
zhang, xiaolong	psu	asst	umich	2003	information
zheng, kai	umich	asst	cmu	2006	information_systems_health_informatics
zhu, sencun	psu	asst	gmu	2004	information_technology
znati, taieb	pitt	prof	msu	1988	computer_science

# APPENDIX E

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### ABSTRACT

Exploring Peer Prestige in Academic Hiring Networks

by

Andrea Wiggins

## Chair: McQuaid

Why do we care about prestige rankings? What does this preoccupation say about our implicit understanding of prestige as a function of image and identity? For an academic community in which identity matters, prestige rankings reveal an important dimension of identity in community context. In the case of existing rankings for the emergent iSchools, interdisciplinary growth has rendered the community context incomplete.

Exploring indicators of prestige in hiring networks as related to the measures of prestige presented in peer rankings such as US News & World Report rankings provides a new perspective on hiring and identity in the iSchools. This research collected data on the educational pedigrees of 693 full-time faculty at iSchools and constructed a hiring network of institutional affiliations, with connections between the schools based on the institutions from which current iSchool faculty received

their PhD degrees. The study quantitatively and qualitatively compares the iSchool hiring network structure to a similar hiring network in the more established academic discipline of Computer Science, and uses regression on network prestige and centrality measures to explain the variance in USNWR ratings. The study projects inclusive prestige ratings for the full CS and iSchool communities, which reveal underlying similarities in the structure of the two networks. Analysis of additional hiring network features, such as faculty areas of study and self-hiring in the iSchools, demonstrates the interdisciplinary diversity of the emergent field of information and its constituent institutions.