Knowledge of the U.S. Social Sciences

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Getting Started

Dear reader,

Welcome! This study is available as a website, https://brooksambrose.github.io/portfolio, and as a PDF document downloadable from the website. Both are great ways to read the study. The PDF makes for a quicker read, while the website offers additional interactivity in figures and tables that will help you dive more deeply into the exhibits.

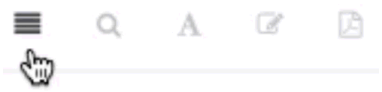

Figure 1: Explore your options!

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Best,

Brooks

Abstracts

What to Read? How the Archive pits Profession against Education

As scholarly fields of cultural production grow their discourses tend to undergo a phase transition where hot global tele-communication breaks down into cool parochial epicentrism. I describe three structures–archives, profession, and education–whose relationships explain the social and cultural forces leading to the opening up and closing off of scholarly discourses. Given an archival context, where expansive media collections give unlimited scope to potential conversation topics, education tends to heat to a boil and profession tends to cool to a condensation of discourses. When such discursive tendencies (genres) are embedded in universities (disciplines) the attendant competition over resources pits professionals against educators and makes it possible to arrest cultural dynamism into relatively static historical configurations. Such a social domestication of cultural wildness allows knowledge to be harnessed for economic purposes, namely workforce development (teaching) and product design (research), and sometimes for political ends. These heteronomous interests in predictable output from universities depresses their cultural generativity. Such macroscopic historical tendencies are difficult for the local agents of their development to recognize; their myopic experience in university arenas is that of status conflicts around investments in academic genres and fiscal conflicts around investments in disciplinary personnel. Using the focal question scholars new and old must answer–"What to read?"–I posit the genre-like qualities of scholarly discourses and suggest the cognitive, institutional, and social, that is disciplinary, consequences of adhering to or abrogating genre conventions.

Keywords: profession, education, discipline, genre, labeling, status exclusion

Social Science Disciplines Today

Social science is arranged into disciplines in a manner similar to the genre systems of commercial fields of cultural production (FCP) like music, yet evolving at a slower pace. Genres appear static and given in the form of the labeling schemes of archivists and librarians. Such schemes aim to describe academic genres objectively, yet in so doing referencers and indexers reify them historically. Such genre classifications are at times useful, frustrating, or didactic for the academic "disciples" or knowledge workers of higher education. This study maps the cognitive system of genre classifications in one particular labeling scheme, that of the JSTOR historical archive, as applied to one aspect of academic FCPs, journals. The

patterns of interdisciplinary cross labeling, of allowing journals to bear multiple labels, are represented as a network and then visualized to reveal how global axes among science, social science, and humanities condition the local relationships of disciplines like sociology and anthropology.

Keywords: discipline, genre classification, network visualization, community detection

Genre and the Literature

In English the term *genre* is a loanword from the French term for *kind*. As an analytical term in the social sciences genre is a loanword from the humanities. The use of the term varies greatly within and between disciplines. This study attempts a metadisciplinary literature review of genre as a term found in a corpus of JSTOR articles. I cast a very wide net by including any document in English that includes the term genre in the title or abstract. The resulting thousands of documents are "read" with the assistance of a statistical topic model to classify documents into topics, that is, strata of common vocabulary. I then perform content analysis on a stratified sample of classified texts to compare their different uses of the term genre. In an examination of the benefits and hazards of such a distant reading approach, I outline a battery of diagnostics to examine the validity of the topic model from both quantitative and qualitative perspectives. Through a combination of machine distant reading and human close reading, I arrive at a schema of five theories of the term genre. In an argument for pandisciplinarity, I conclude with an analysis of the logical possibility of new metaconcepts of genre that satisfy the strictures of multiple disciplines.

Keywords: genre, disciplines, computational text analysis, topic modeling, content analysis, digital humanities, distant reading

Vocabularies of Anthropology and Sociology, 1888-1922

Knowledge development of journals in sociology and anthropology is measured as the change in topic prevalence over time.

Keywords: sociology of knowledge, topic modeling, history of social science

The Social Science Citation Landscape, 1900-1940

Knowledge mapping of academic journals promotes the conservation of intellectual history and stimulates discovery of underexplored intellectual opportunities. Treated as a large network community detection problem, I demonstrate how

to apply the clique percolation method to map two kinds of recorded knowledge: citations and full text. The features of generated maps are explained, and interpretive methods including visualization are presented. We use American social science scholarship in the first third of the 20th century prior to U.S. entry into World War II as a case, and describe how the intellectual landscape of four separate social science disciplines developed.

Keywords: citations, k-clique communities, community detection, landscape

Chapter 1

What to Read? How the Archive pits Profession against Education

Abstract

As scholarly fields of cultural production grow their discourses tend to undergo a phase transition where hot global tele-communication breaks down into cool parochial epicentrism. I describe three structures–archives, profession, and education–whose relationships explain the social and cultural forces leading to the opening up and closing off of scholarly discourses. Given an archival context, where expansive media collections give unlimited scope to potential conversation topics, education tends to heat to a boil and profession tends to cool to a condensation of discourses. When such discursive tendencies (genres) are embedded in universities (disciplines) the attendant competition over resources pits professionals against educators and makes it possible to arrest cultural dynamism into relatively static historical configurations. Such a social domestication of cultural wildness allows knowledge to be harnessed for economic purposes, namely workforce development (teaching) and product design (research), and sometimes for political ends. These heteronomous interests in predictable output from universities depresses their cultural generativity. Such macroscopic historical tendencies are difficult for the local agents of their development to recognize; their myopic experience in university arenas is that of status conflicts around investments in academic genres and fiscal conflicts around investments in disciplinary personnel. Using the focal question scholars new and old must answer–"What to read?"–I posit the genre-like qualities of scholarly discourses

and suggest the cognitive, institutional, and social, that is disciplinary, consequences of adhering to or abrogating genre conventions.

Keywords

profession, education, discipline, genre, labeling, status exclusion

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The question of what to read is simple to be sure, but in fields of scholarly consumption and production it is nonetheless fundamental. Scholarship is a creative profession where a stock of cultural knowledge forms a greater part of the infrastructure of production than in other fields. This is not to say that other occupations, especially manual ones, lack creativity. It is to say that in such fields knowledge has a limited infrastructure. Whereas the know-how of the brick layer is black boxed in her tools and technology and in the human capital she develops by experience and tacit social learning, for the scholar as bricoleur there exists in addition the distinctively overdeveloped feature of cultural archiving as a universal memory. Except perhaps in outstanding feats of primary research, contributions to scholarship are legitimate to the extent that they have used the archive correctly. This problem of using the archive, by which I mean all libraries and other organizations that help scholars find published work, is easily expressed by the question, "what to read?" Paradoxically, the over-development of the archive induces a functional imperative: to the extent that more and more of scholarship is memorable, mechanisms must develop to forget large swaths of intellectual history. A person who studied a random draw from the archive, even a monumental one, would no doubt qualify as an educated person. Professionally, however, they would have answered the question in a tragically wrong way. From the perspective of other scholars, there are right and wrong choices about what to read. Because it is so easy to access scholarly memory, the operative question really becomes "what not to read?"

Most occupations are not saddled with a heavy burden of memory, remembering in the fashion of a Markov chain only the most recent chapter in their history. Rather than in archives, memory is codified in tools and technology. Though Internet search and self-publishing services, especially video and image based ones, are creating archive-like infrastructure for even manual occupations, the functions are different. Contemporary Internet repositories provide knowledge as factors of production to anyone who queries them, but many do not purport to be archives in the sense that a historical record of cultural products is preserved for posterity. They are much more concerned with access to contemporaneous than to

historical material, and indeed the particular configuration of the contemporary that sells the most advertisements ahead of search results. True historical archives of the Internet, such as the Internet Archive or Common Crawl, are not used by the public. Indeed why would they be; they expose the dizzying complexity of the history of the Internet, which, even in only its contemporaneous facet is already overwhelming. The Internet searcher tends to be satisficing, and the search companies have refined their ranking of results to meet their users' search budgets efficiently.

Searching and finding are different procedures; to search is to turn over every rock, whereas to find is to turn over only the correct rock. The searcher encounters many tricks before alighting on a treat, and must make an effort to reject the false positives. The finder exploits indexing technology that allows her to bypass the wrong material altogether. Without a normative compulsion to make history accessible, Internet search engines, which are actually find engines, avoid the scholarly paradox of memory, which is that in the university system great pains are made to remember everything just so that the correct material may be forgotten. Scholars do not yet have find engines that protect them from encountering irrelevant material, and it is a professional competency to be able to quickly separate wheat from chaff.

1.1 Status exclusion

Though cultural abundance may be cultivated on the universal egalitarian grounds that knowledge be made accessible to all, the complexity of the archive creates an opportunity for the establishment of social hierarchy. Because the archive's size so wildly outstrips individual and organizational capacities to know its contents, methods of selection become paramount. Indeed the power to control what counts as a legitimate selection becomes a basis for authority and the conferral of status. Status reflects a person's generalized ability or inability to accrue resources to herself over the claims of others. Social institutions define the conditions of status attainment, and different institutions validate statuses according to different norms, truths, and values. Knowledge as a valued resource mediates social relationships and stabilizes status hierarchies differently in professions than in education. The stability of status hierarchies depends on a qualified segregation of these institutions, as the norms of one can be corrosive to the norms of the other.

In the cynical view of professions, scholarship is the encryption of memory by secret sets. If each field of professional scholarship is a club, their passwords are particular lists of items from the archive. Comers arriving with off list items or without enough of the correct items may be held at the door, or if they are given entry, will be marked with a scarlet letter. To say that the password items are the only ones relevant to knowledge in the field is incredible; the depth of the archive

always impresses even the most experienced divers. The importance of the list is not only in its knowledge potential but also in its exclusionary function. Knowledge of the list is a qualification, ignorance a disqualification for club membership.

Why check qualifications at all? The archive, in rendering knowledge accessible and transparent, obviates a conventional function of professions which is to restrict their ranks by controlling access to secret knowledge. If the knowledge is not secret, a field must find other mechanisms of exclusion to establish itself as a profession. To make matters worse, the university contexts in which scholars work tend to confront them with a public and to impose on them a duty of education or service. Professionals who are embedded in markets trade the products of their capacities, goods and services, for money. Their clients have no serious interest in acquiring the professional's capacity to produce, and this inscrutable cognitive base (DiMaggio and Powell, 1983, 152) constitutes the client's experience of the professional's expertise.

Scholarship is based in the university and not in the market, and here the value orientation to knowledge is very different. Professionals default to entering into client, rather than peer, relationships. The scholar's "clients"–students, the public, and other scholars–may be as interested in the production as they are in the product. From an intellectual property perspective, "ideas are strongly nonrival (they are not used up) and only weakly excludable (they are difficult to protect from use by others)" (Thompson, 1995, 278). Because educational commitments promote the free flow of ideas, knowledge qua knowledge cannot be the basis of professional exclusion within an institution designed to diffuse it.

Knowledge qua password is arbitrary with respect to content in that club knowledge is not of better quality than other resources made accessible by the archive. Whereas in unarchived fields knowing is enough to gain club membership, archived fields require a substitute exclusion mechanism to safeguard hierarchy. This explains the prominence of priority in the attribution of discovery over the mere fact of possessing knowledge, yet priority defines hierarchy internal to professions and would be overkill in defining the external relations of the profession. Simply, members of a scholarly field need not have invented knowledge to use it to assert their membership status against nonmembers. But the question of knowledge quality, why club knowledge is not substitutable for other available knowledge, is a constant erosive force against the club's foundation. For the more status insecure in the profession, pride in ignorance of foreign content becomes a weak value to paper over the contradiction, whereas the status secure, who have enjoyed better employment contracts and more time to explore the archive, understand that forbidden fruit are in fact interesting and no real threat to them.

This constant need to build redoubts against deteriorating club walls exists only because scholarship has, in the United States at least, been embedded in educational networks whose value orientation to knowledge opposes that of professions.

One modification of professional esotericism is that the passwords are a group secret, which means that anyone who knows they exist can find them out, master them, and gain club membership (if not club rewards). This satisfies the openness required by universalist educational values. To satisfy the closure required by the professions, password mastery must have nontrivial costs. In making the password mandatory clubs construct excludability in an arbitrary set of ideas whose components are not naturally excludable. This encryption cost, like the blockchain, makes the detection of fakes easy while creating trust between incumbents and the newcomers who pledge to honor the prior commitments of the field.

This password structure faces destabilizing threats. The entropic force of the archive has already been mentioned, which by itself stresses scholarly boundaries because anyone can acquire expertise independently of professions and then use that to make claims on club goods. Clubs are able to deflect these claims only when the the symbolic value of the password is not deflated. The other destabilizer is educational values, which mandate that rewards accrue to mastery of process (learning) rather than mastery of products (knowing). Educational values are equitable and universalistic and therefore delegitimize all nonrandom exclusion mechanisms like the password system. But when compromised by professional values education merely requires scholars to reduce the costs of password mastery by forcing investments in pedagogy. If they were ever able to dominate professions education would force open club boundaries and destroy field cohesion. Defenders of professions would label this a situation of hackery, while detractors would contend that it would still be productive to resource people with idiosyncratic knowledge bases, i.e. those who eschewed the password system. When education and profession are in balance, the password system integrates the conflict between them, forcing some egalitarian openness to replenish the ranks of professions.

This functioning of the password system in not how it is experienced by people. Phenomenologically knowledge sets are not viewed as arbitrary but are rather shrouded in a reputational aura. This aura is manifest as a taste for scholarship. To be professional is to trade in status, to know what are the tasteful combinations of resources. To be a successful professional is to never have wasted time tasting forbidden fruit. It is the laity who bear the brunt of the exclusion mechanism, while clergy who have long ago armed the traps spectate. A lay seeker approaches the academic archive and at great cost of attention plumbs its depths for enlightenment. The archive's complexity dooms her to check out a curriculum so hopelessly tacky that it will only certify her lay status. In her humiliation she feels a deep injustice that her knowledge is not recognized. A different seeker with guile enough to learn the password first plumbs only the relevant parts of the archive, and upon mastery enters the social compact with incumbent professionals. The two seekers stand next to each other but on either side of a gate.

That they are equally educated is clear, but their paths at this point will diverge, one toward the interior of a profession and the other into the wilderness.

In this fable the archivists themselves are tragic figures, stretched as they are between people who profess (declare publicly) and people who educate (lead out). Librarians much prefer to help laity who in their tastelessness welcome guides who will lead them through the grandeur of the archive. The archivists gifted scholars with access to an immortal memory, and looking the horse in the mouth scholars made rules to protect themselves from the responsibilities of using most of it. Paradoxically, in taking the burden of memory off of the shoulders of scholars, thereby freeing them of the pain of legacy suffered by other artists (Lang and Lang, 1988), librarians created a maze of knowledge in which clergy could trap laity.

1.2 Generic isomorphism

How does an established scholar know what are the lucrative curricula that can be developed from the archive? Notwithstanding its knowledge-agnostic role in reifying social hierarchy, the password list is one answer to the question of what to read, and the rules for putting the list together are not entirely arbitrary. There are tacit conventions that both legitimate the password list within the profession and make it possible to recognize whether newly encountered work is relevant to the field. The password list answers the question of what to read only in a very narrow sense that guards the exterior of a scholarly field, the relationship between clergy and laity. Given password mastery, how then do professional scholars know what (not) to read as they extend the field while avoiding an internal erosion bubbling up from their own scholarly creativity? How do dislocated scholars coordinate their activity so as to produce self-similar work in the interests of the profession? There are several formal and informal structures that facilitate and compel scholars to make the same choices about what to read.

An obvious one is the supposed normative isomorphism of graduate program syllabi, which act like maps to navigate the maze of the archive. These syllabi may or may not also teach the password of a field, a fact that may be difficult for students to discern. Universities tend to grant great autonomy to professors in writing syllabi, who in the course of their professional travails may not be given opportunities to read what they want. In being forced to carve out time with subordinates, faculty are caught between personal indulgence and a more or less strongly felt fiduciary responsibility to set students on the correct path. Students, having at most a weak basis for discerning whether a syllabus serves their interests or not, would have little recourse but to trust faculty even if that were not already built into the role relationship. If we have less than perfect faith in

the strength of educational ethics among faculty, then we should expect that among graduate syllabi are many lists of what not to read. Students who trust too much in the formal curriculum may be lead astray, and even without trust, they may still be left ignorant of where to invest their labor.

In each graduate program there then must be a hidden curriculum, a map of the archive of higher quality than the formal syllabi. The argument of this study addresses the question of where such a curriculum comes from. The provisional answer is that in the informal spaces of graduate programs knowledge of scholarly genre is learned from extracurricular engagement with professional conferences. It is in conference programs that the tacit rules of academic genre are learnable. These genres form the first parsing of the archive for neophytes. Indeed at the most generic level graduate students, if they are confident enough to locate themselves quickly, develop a taste for what not to read. Genre as the foundation for a taste for scholarship serves to restrict a student's wandering to a delineable sector of the maze. If they can develop this proto-taste early enough in their careers, they will be armed with the stereotypes necessary to stop reading the wrong and start reading the right material. While this is not enough certainly to make clergy of laity, it is the first step.

Genre is the tacit essence of the password list, the interpretive code that is the taste for scholarship. Genre rules may be difficult to describe explicitly, and it is easier to argue about whether particular cultural items (ever available in the archive) are genre conforming or not. Genres bear labels that are too easy to reference, and when it comes time to describe their content it is those particular items whose classification status is unassailable that will serve to represent genre content, paradigms in the pre-Kuhnian sense of a primitive standard against which others may be compared.

The indulgences of syllabi are pejorative only in the sense that they represents genre nonconformity. Indeed scholarly indulgence may be educationally beneficial to students even while it is, as an opportunity cost, professionally wasteful. The opposite of generic here is not specific but rather idiosyncratic; a species has a known genre classification, whereas idiosyncrasy is unclassifiable, or at least unclassified. Indulgent idiosyncrasy, for instance the reading of a great book of a bygone era, may be very interesting especially when genre conforming content is boring precisely because it is generic. Yet for all its charm idiosyncrasy, if it cannot be accurately classified by professionals, does not advance professional interests. Students who wish to be educated may enjoy it, but those who wish to be professionalized ought to avoid it. So there is indeed a correct way to approach the archive, correct in the sense that certain draws establish eligibility to access scholarly professions. The reward relevant to neophytes is access to the first job, which if it can be secured grants access to facilities and some scope for indulgences.

This is not to say that students must directly encounter conference programs to learn genres. Genres may be communicated as stereotypes within local departmental codes and discourses. Such local cultures may either proudly or unwittingly contradict national genre standards, yet they will face perennial alignment challenges when departments interview candidates for jobs. Candidates have tailored themselves for a national market and will likely resemble the national genre code (that of our professional conference). Even if a candidate prepares a version of herself to convey the right "fit" in a particular locale, her actual scholarship will likely have been prepared for the generic rather than the specific audience. Thus while it may seem that the job holder would take priority over the job seeker, both contest and contestant have conditioned their expectations to maximize their appeal to as broad a field as possible.

The maximization strategy is simple: conform to the national genre system. The power of genre is this regulation of expectations across the supply and demand sides of the market. If either the local departmental culture or the candidate abrogates the national genre system with an indulgent idiosyncrasy, an exchange that would have been mere performance will devolve into a status challenge. The ornery party will have deflated the discursive potential that genres enable and will have raised the hackles of its interlocutors by requiring additional effort to recognize the unlabeled work before them. This cognitive tax created by the defiance of genre will need to be paid with a loan taken using one's reputation as collateral.

The abrogation gambit is as risky for the contest as for the contestant, but to call it a gambit assumes a high level of sophistication. At one level genres are the most accessible form of knowledge in a cultural field. Everyone may know that classical is a genre of music without knowing much of anything about classical music. Knowing the label is the primitive form of genre knowledge; knowing how to categorize a particular unlabeled cultural object the next most primitive, and so on through gradations of knowledge that at the most advanced level reflect a performer's ability to strategically mobilize genre conventions to control an audience's experience.

Nonetheless, the reputation sanction for genre abrogation will be assessed regardless of whether the performer colors wittingly or unwittingly outside of the lines.

Several fields of scholarship apply the term genre to describe or explain variations in content in other fields of cultural production, most commonly in literature and music. Though genres are commonly accepted to be classification systems in particular cultural domains, their ontology and hence validity tends to be assumed rather than demonstrated. Given fields of cultural production and consumption (or poiesis and esthesis depending on one's discipline) that are prolific and innovative, one would expect genres to be soluble. In fact they are highly durable. The disciplinary structure of higher education offers

an example of one of the more durable cultural classification systems.

1.3 Influence

Parsons (1963) used the term influence to describe generalized knowledge-based authority. Influence is a symbolic medium of communication like money, which represents a value without being the value. Symbols are more easily transacted than the real resources they represent, and they allow trades to be constructed as social commitments before real resources are mobilized. The password list is a symbol of a supplicant's capacity to uphold genre conventions and safeguard the status of a field, a promise which they aim to transact for access to real resources, namely employment, in a scholarly profession. Like money, influence is subject to inflation (requiring a candidate to know even more than the password list) and deflation (being unimpressed no matter how much a candidate knows). Importantly influence is not reputation; it is a feature of the status of the field rather than the status of an individual. All knowledge holders transacting with a club will be similarly affected by inflation or deflation of the field's influence.

1.3.0.1 Forgetting

Library technology, paradoxically, makes it easy to forget scholarship. (Cevolini, 2016) A scholar who is confident that knowledge is safely protected in archives and who believes that it can always be accurately retrieved is relieved of the urgency of digesting it now. Punting on understanding *from* texts opens space for exogenous understandings *of* texts. Contemporaneous cultures and societies constraining the reader prejudge the meanings of texts. While scholars genuflect to a quest for truth, the practical incentive to minimize time spent reading leads to several methods of collusion in the reduction of texts.

First, any text that can be commonly declared irrelevant need not be bothered with it all. Forgetting is the most efficient way to deal with a text.

Second, a text need not be read to be understood, as their meanings are common sense. Texts then have reputations and reputed meanings. These reputations like those of people stand in for the real thing in scholarly discourse. These mediated versions of the truth act as promissory notes in scholarly transactions; where the reputed meaning is accurately conveyed the issuing party is given credit for knowing the underlying truth, without burdening the transaction with a test of the truth. Like all symbolic currencies, the pace of commerce quickens where the symbol of the good is exchanged prior to the good itself

needing to be mobilized.

The utility of reputed rather than real meanings functions to save scholars from the existential crisis besieging them: the pace of the publication of scholarship has long outpaced anyone's capacity to read it. The existence of subdisciplines is an obvious symptom of this trend bemoaned by every generation of scholars.

1.3.0.2 Collins

Genre is a form of meta-expertise called *ubiquitous discrimination* (Collins and Evans, 2007, 45), which reflects a layperson's ability to make judgments (genre classifications) about what might otherwise be considered esoteric content. Ubiquitous knowledge is assumed to be available to all members of a society, even if not everyone necessarily acquires it. This absolute criterion is not strictly necessary.

Bodies of knowledge and practice, cultures, exist because of yet apart from particular people. While some cultures are ubiquitous and inculcated in all members of the societies in which they are substantiated, others are esoteric and marked by significant barriers to learning them. Such esoteric cultures are as inaccessible as they are unnecessary. A child who does not learn what to eat and how to eat it in her local culture will have great difficulty doing anything else in her society. Food culture is of the ubiquitous type and is not difficult to learn. On the other hand, a child who does not master scripture will be ashamed at temple, but shame is bearable in a way that hunger is not. Scripture is of the esoteric type; knowledge of it enables special abilities and grants access to restricted aspects of a society, but ignorance of it does not threaten one's lay livelihood. Even in religiously totalitarian societies, what religious knowledge is necessary will be ubiquitous. What religious knowledge is esoteric can be safely left to the clergy. It is not too narrowly circular to say that the knowledge that informs daily life is the easiest to acquire, and that the mere act of living also reproduces that knowledge within contexts that are themselves ubiquitous. Whether relationships of ubiquity are familial, economic, or state relations varies by society, but no society lacks ubiquitous culture and the means of reproducing it.

Esoteric cultures, then, are removed from ubiquitous ones though they depend on them. They require specialized social relationships for their reproduction in populations. These special relationships may be called fields of cultural production (FCP). FCPs are both reproductive of extant knowledge and productive of novel knowledge relevant usually only to the field itself. To the extent that esoteric cultures are complicated or otherwise have high entropy, the failure to reproduce their cultural content is always an existential threat. While it is a guarantee that cultural content is constantly actually lost

to reproduction failures, cultures that nonetheless persist historically must always have a socially structured FCP that, in inculcating new members and reinforcing the knowledge of extant members, resists the entropic decay that would otherwise lead to extinction.

The scope of a culture has a knowledge and a social dimension. Units of knowledge are both discrete and combinatoric. Discretely, the size of a culture can be measured by a count of co-occurring ideas and skills. The utility of knowledge, for instance as instantiated in an FCP, often depends on the combination and interaction of such discrete elements. The mass of knowledge in a culture is related to the count of units and to the ease with which those units can be learned, thought, or deployed in meaningful activity. Some cultures are easier than others, and it is the effort-adjusted size that is the real mass of the ideational content of a culture.

Not all sociologically relevant information is cultural. In the triadic relationship among culture, social structure, and personality, psychological concepts like schema that are sometimes treated as constitutive of social structure (Sewell, 1992) do not belong in the category of culture. Schemas allow personalities to organize their responses to a world that includes many things beside culture. In order for cultures and social structures to function stably in time, they depend on the successful operation of schemas, but they do not necessarily provision them. An only partial exception is the limiting and very specialized cases of pedagogical institutions. A culture can only exist if people can reproduce it, but the people must solve the psychological problems of cognition on their own. Whereas culture is fungible in its different mediated forms, there is no reason to believe that a "single schema" occurs across a population of people. There are no one-size-fits-all solutions to human motivation, and schemas will to a large extent be idiosyncratic, adapted as they must be to the particular circumstances in which people as träger find themselves.

What cultures can do to hedge their bets against the instability of personalities is to introduce kinds of knowledge adapted to cognitive problems. Schutz identifies systems of relevance from the side of personalities, and here we understand the same from the side of cultures.

People know culture and it does not appear apart from them. Put differently, culture is information and people are the media that concretely manifest it. The size of a culture is the count of the unique ideas and idea combinations appearing in a deduplicated media catalog, excluding possible but unrealized combinations. The potential of a culture is the size of the realized and unrealized combinations, where the number of elements in a set is limited by a given historical cognitive and technological memory capacity. The potential of a real culture is always greater than its size, as combination novelty always

easily exceeds the available media.

The social mass of the culture is the enumeration of the media in which cultural content actually appears historically. The cultural mass is copied piecemeal among a population of knowers. The mass may be enlarged by information technology by making it easier to access and transmit culture, but the artifacts and technology themselves do not count in the mass of the culture. Real, historical human nervous systems, including language expression,

Dead cultures cannot live again because the dead part, the social part, is highly ephemeral. Even if a culture leaves material and symbolic artifacts, the "dead" parts are precisely those human relationships that would socialize new members in particular ways that cannot be deduced by people who never belonged to begin with, namely the archaeologists of the future. Such archaeologists belong to the FCP of their own time, and approach the historical artifacts of a dead culture as any other FCP approaches regular patterns in the world, as subject to their own particular cultural logics.

Reproduction does not necessarily imply long term consistency of cultural content, indeed a high level of knowledge loss may be a sign of historical stability in an esoteric culture if it results from a highly productive FCP. An oversupply of cultural content increases the chances that some, any culture can be conveyed into the future in a chain of descent.

Esoteric knowledge is essentially cryptic, ubiquitous knowledge essentially evident. Crypticism means that laity cannot acquire knowledge on their own, that is, without socially structured access to an FCP. Esotericism is the social consequence of crypticism. Cultures vary by knowledge features, as knowledge is a social axis of power along which status hierarchy necessarily develops. Knowledge asymmetry structures social relationships, usually leading to status inequality.

High entropy cultures must socialize new and maintain existing members like any culture, but their complications also tend to be generative of novelty.

The ubiquitous cultures will be learned because there is nothing in a society to do without knowing them, while esoteric ones are guaranteed to be forgotten by most, swapped easily for the always ready ubiquitous alternatives. Ubiquitous cultures have high ambient findability (Morville, 2009), they can be transparently acquired for instance through mimicry (DiMaggio and Powell, 1983).

FCPs are social structures that can be thought of as the articulation points between people and a special type of culture that is associated with higher education.

To be sure, if esoteric cultures are marked by asymmetries of knowledge between laity and clergy, to continue with the religious example, one must admit that such asymmetries exist in ubiquitous culture as well, as in the supposed ignorance of

a child against the learning of an adult. The ignorance of children combined with their megalomania is a useful example of how social structures operate. Social structures are always culturally conservative; a child's ignorance is a generative force, as they may attempt to solve problems in novel ways, and their efforts will frequently be corrected by the experts. Whether the correction takes marks the chagrin of the parent. Children quickly become specialists in their own FCPs, but this is never because they aren't also aware of the ubiquity. They may know it, it may bore them, and they efface it for fun. But they know what is ubiquitous; their proximity to ignorance of it may animate their creative abrogation of culture. The essentially conservative function of pedagogy will stamp out that creative flame in time. Indeed children are a great source of entropy for ubiquitous culture, hence the large investment in education generally.

This evolutionary argument can be more simply stated as, complicated cultures cannot exist for very long without stewardship.

1.4 Discipline

To return to disciplines, answering such questions would put the researcher in an adisciplinary predicament, for it would mean eschewing the scope restrictions cherished by disciples. The challenges of a meta-disciplinary analysis are manifold and uncertain. One is as likely to grow her audience as to lose it altogether. She risks the dilettantism of a jack-of-all-trades. What's worse, she exposes herself to a dizzying scale of content to consider. If disciplines are indeed functional, then the meta-analysis that effaces disciplines risks being dysfunctional. The upside, however, is appealing. If the universe of meanings given to the term genre does contain complementary uses, a meta-analysis will allow one to consider the consequences of the now arbitrary segregation of a superior metaconcept across disciplinary boundaries. Both sides of the divide could be strengthened by a cultural exchange of their respective terms. The redundancy of parallel discovery can be avoided.

Pathologies of disciplinarity can be diagnosed and treated. Disciplines are social substructures embedded in a larger society and culture. Disciplinarity is a kind of controlled ignorance exchanged for access to secret knowledge. The wayward uses of a term like genre are always lurking at the edges of the firelight defined by a particular disciplinary camp. Discipline as rigor instructs disciples to resist flirtations with the available complexity of the term. The essential tension is very rarely between what is known and unknown; rather it is more commonly between what is known "here" versus what we are conditioned to be willfully ignorant of "there".

This definition of discipline is isomorphic with that of genre, in that disciplines are another form of categorical decision making, just at a higher level. Disciplines are supergenres that reflect the nesting of categories. In music Lena and Petersen (2008, 698) have followed Ennis (1992) in referring to supergenres like rock-n-roll or rhythm and blues "streams", which are genres linked in time by any of a number of contiguities, e.g. sound, scene, artist, or market. What may distinguish disciplines in a more serious way is the institutional underpinning of the category. If genres are formed by the categorical thinking of disciples, disciplines are formed by the categorical thinking of patrons, the powerful actors like university administrators, state legislators, and grant makers who manage the economic foundation of scholarly careers, as well as the elite disciples who interface with these stakeholders. Where genre labels are inscribed onto cultural products, texts, discipline labels are inscribed onto cultural infrastructure like funding lines, buildings, and personnel themselves.

To impose a sociological gloss on the term, these varied uses of genre would make reviewing the literature on the topic difficult, were it not for the discipline structure of the academy. The uses of the term genre are themselves systematically organized by discipline, and a disciple who is adequately trained will know the correct ways to use the term in her local context. To use genre as a disciplinary convention means to first identify your location in the disciplinary field, and then to accept the limitations on scope by excluding those treatments of the term that are extradisciplinary, that is, irrelevant. Disciplinary structure reduces the true cultural complexity of the meaning of genre to a restricted form, which in turn allows humble knowledge workers to engage upon a set of shared assumptions. Such simplicity begets new complexity as disciples spin out the consequences of their local use of genre.

In the sociology of culture, genre is a form of classification enacted by people in various social contexts. In the context of industrial capitalism, genre is an economic principle helping to organize supply and demand within markets for cultural products. There actors see genres among the borders between economic, social, and cultural uses, as a market category helping them acquire or produce content, as a card in proximate games of prestige, or as something to taste, to consume and enjoy directly. Less often genre is knowledge, a component of culture separate from taste, that is a factor in the formation of ideas and skills, whether these lead in turn to economic production or not.

Genre's meaning is context specific and variable across sociological subfields, though it is amplified in empiricist fashion by economy and society approaches that reduce genre to the act of classification itself. I say empiricist because of the empirical ease with which the classification or labeling actions are observed. Especially with Internet distribution systems, it becomes trivial for corporations to observe when a consumer labels her preferences while browsing a content catalog; it is

much harder to observe the ideas that consuming a particular piece of content sparks in the mind.

In cultural studies genre is used much differently and much more in accordance with its etymology. To the humanist, genre is an ontological phenomenon, which is to say, genres are differentiated from each other by combinations of discrete features of signs and signifieds. Humanists are trained to establish these ontologies through methodological readings of texts and through cultivation of theories of genre types. These methods are at the same time empirical and interpretive, because in consuming objective texts the researcher actually observes the ideas that form in her own consciousness, and they may hope that others have a resonant experience. Genres have more substance to them for humanists than they do for sociologists. For sociologists of culture, genres are how people use genre labels, while for humanists, genres are knowledge.

As I have said, the meaning of genre for a sociologist of culture is economistic, at the same time a market category and a taste configuration for consumers. The term differs for a sociologist of knowledge, and perhaps for a cultural sociologist. It is ontology as it is for the humanist, however it is not the ontology as represented to the researcher in the consumption of texts. It is the hopelessly unobservable distribution of ontologies appearing in a population of consumers attending to similar texts. The sociologist of knowledge accuses the sociologist of culture of reducing internalist concepts, thought and experience, to externalist ones, taste and preference. The sociologist of culture rejoins, show me proof, and on and on the interlocutors spin around the axis defining the boundary between their subfields.

But this description of subdisciplinary differences really is just an example of a structural theory of genre that is within scope for the sociologist of knowledge and beyond it for the sociologist of culture, due to their epistemological differences. If genres are ontological, then they deeply structure a person's experience of reality. Ontologies form basic perceptual categories, and people with different ontologies of an object experience different things even if oriented to the same objective phenomenon. A ontological theory of genre would, for example, attempt to explain differences in taste as differences in phenomenological perception, whereas a taste theory of genre treats consumption behavior as revealing preferences whose downstream consequences are then explored.

Yet for all the differing treatments of genre mentioned above, do these views really contradict, or are they in fact complementary? Does genre as distribution serve the economic sociologist's goals, or does a lack of ontological substance lead her astray? Does genre as knowledge remain hopelessly unverifiable, or are theoretical constructs necessary to achieve a correct interpretation of facts? Is everyone at the club listening to the same song hearing the same thing?

1.5 History

A final strategy for choosing what to read is a genealogical approach (Foucault, 2002)

Chapter 2

Social Science Disciplines Today

Abstract

Social science is arranged into disciplines in a manner similar to the genre systems of commercial fields of cultural production (FCP) like music, yet evolving at a slower pace. Genres appear static and given in the form of the labeling schemes of archivists and librarians. Such schemes aim to describe academic genres objectively, yet in so doing referencers and indexers reify them historically. Such genre classifications are at times useful, frustrating, or didactic for the academic "disciples" or knowledge workers of higher education. This study maps the cognitive system of genre classifications in one particular labeling scheme, that of the JSTOR historical archive, as applied to one aspect of academic FCPs, journals. The patterns of interdisciplinary cross labeling, of allowing journals to bear multiple labels, are represented as a network and then visualized to reveal how global axes among science, social science, and humanities condition the local relationships of disciplines like sociology and anthropology.

Keywords

discipline, genre classification, network visualization, community detection

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The classification of cultural products according to genre systems has been treated both as a top-down institutional process conditioning the development of entire markets (Lena and Peterson, 2008; Brook, 1994) and as "nothing but" an

emergent, bottom-up process of individual acts of labeling and interpretive judgement (Lamont, 2010; Hitters and van de Kamp, 2010). A middle range approach requires understanding how actors distributed across the roles that constitute structure, the top down perspective, make local judgements that either do or do not have global consequences. The idea of genre as a cognitive institution that is diffused across a wide variety of actors gives the appearance of a cultural integrator, something given in the environment of all actors and not controlled by any of them. Players on fields of cultural production regardless of their role or status are, like price takers in a market, cultural name takers. Once genre labels are established they are immutable and given as terms in the language. The content to which they refer, however, is historically variable and debatable.

The explanation of how genre labels and the content to which they refer develops over time requires a mapping of the structure of genre labels at particular moments. In this study I estimate a mapping of the cognitive associations among genre categories of scholarship according to one interested role position in the scholarly field of cultural production, the archivist. Archives play a constitutional role for scholarly fields, forming a necessary infrastructure for scholars' work, but scholars are not the only interests served by archives. Students and educators as well as the public, also draw on knowledge resources contained in the archive. To make this knowledge accessible archivists use genre classifications to organize content. The classifications meet the practical needs of serving both the producers and consumers of the content. The granularity of the classification system that would be useful to producers is, however, much finer than what is useful for consumers (note that the same item may either be factor of production or a product). The bias of the archive skews toward the courser grained consumer classification system in part because the needs of producers are highly idiosyncratic, shifting, and difficult to predict.

Producers tend to dismiss the consumers' ways of thinking about their field, but there is one situation in which producers are reduced to consumers; in scholarly professions the coarse version of classification is a communicative infrastructure for foreign correspondence. These coarse categories are what we call disciplines. Disciplines are nothing but a genre like classification system; they are merely integrative of global transactions among scholars at a distance and between scholarship as a whole and its macroscopic interlocutors, namely education, grant making, and university administration. Thus when scholars view content situated outside of their local epicenters of research, they necessarily shift from fine to coarse grained judgements. This switch on the tracks may be jolting, as it connotes what they feel to be a demotion of their usual status.

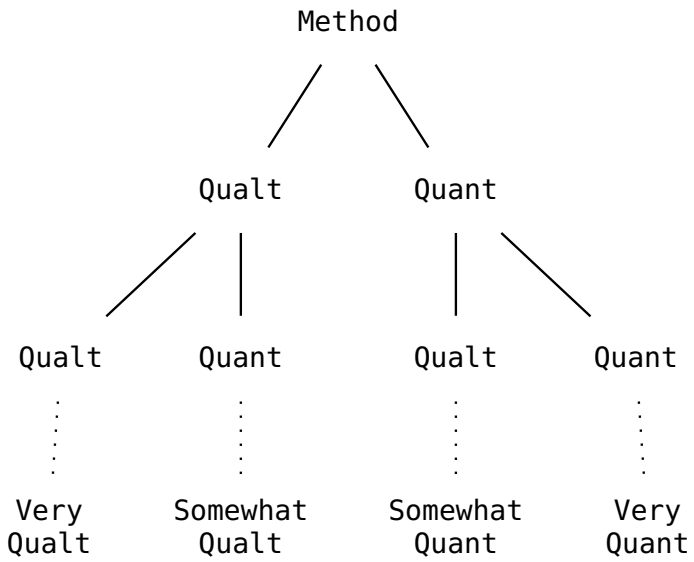

Figure 2.1: Fractal Evaluation and Commensurated Scale. Adapted from Abbott (2011:11).

Facing inwardly, they deploy value standards rather than classifications. In their own field, scholars grant themselves moral and aesthetic authority to judge the quality of content. In communicating outside of their field, where they have no jurisdiction, assessment of cultural items becomes value neutral, a mere matter of taste. Such internal values may even be simple dualisms compared to the more complicated disciplinary categories, but rather than creating simple genre-like schemes they create scales of gradient evaluation. Abbott (2001) shows that these scales, for instance from idiographic to nomathetic, are established by the accumulation of simple judgments by separate individuals in the direct and often pairwise comparisons of discrete works or authors. This pattern of evaluation is chaotic and produces a fractal organization of content with only approximate correspondence among judges. Though Abbott (2001, 14) suggests that these fractals are irreducible to simple one or two-dimensional scales, it is likely that the chaotic outcomes are collapsed into a reified commensuration standard when facilities and rewards are distributed (Espeland and Stevens, 1998).

Disciplines are much more like genres than the constellation of fields and subfields that scholars may be accustomed to thinking with in the course of their work. Genres function to the extent that they are globally recognizable, that is, ubiquitous. Ubiquity means that all members of a field regardless of status are able to learn enough about the genre to make accurate classifications of cultural objects. This does not mean that everyone will always necessarily be aware of all genre labels, or that their classifications will always be accurate, but it does mean that they will be able to learn the rules when it becomes necessary. Subfield categories are not ubiquitous in this way; subfield labels only become genre-like by restricting the reference group to a more esoteric level. Whereas all members of a university, for instance, may easily become aware of the discipline of sociology, written as it may be on a building, only disciples of sociology are likely to become aware of the subfield of conversation analysis. And while disciples may learn the label, it takes some real experience with the content of the discipline, if not necessarily the subfield, to understand that conversation analysis is more qualitative than population research and more quantitative than ethnography.

In this way the classification schemes are nested in a functional hierarchy that shifts according to which role relationships are activated in the field. The more fine grained distinctions among genres are derivable from the collapsed fractal patterns. The highest level of granularity one is able to discuss may be a status signal of where they belong within a disciplinary stratification system. Furthermore the interactional capacities of disciples are nested. Denizens of more interior spaces in a subdiscipline, the spaces of fractal evaluation, are always able to operate successfully in more granular interactions, but the reverse is not true.

Everyone starts at the more ubiquitous level. It is only through education or professional socialization that newcomers can learn

Table 2.1: Classificatory Schema by Role Relationship

Accessibility	Schema	Ego	Alter
esoteric	fractal evaluation	scholar	scholar
.	genre class	scholar	student
..			publisher
...			archivist
....			department
ubiquitous	discipline class	scholar	administrator
			public

2.1 JSTOR Journals

I rely on the JSTOR digital archive which gives access to optical scans of historical journals. JSTOR provides a title list of their journal coverage (JSTOR, 2018). The coverage of journals in the archive is very complete for those journals chosen for the database. As of this writing JSTOR contained 4,224 different journal titles and 2,738 journals from 1,147 different publishers. The different journal counts are due to some journals changing titles at least once.[1] The JSTOR coding contains 79 subject labels. These labels refer to eight superdisciplines under which may be found 71 disciplines.

Most journals are given more than one discipline label, and the superdisciplines are not marked as such in the database creating some redundancy. For instance, a journal labeled as "Sociology" will also be labeled as "Social Sciences". Most academics will be familiar with whether a label is for a superdiscipline or a subdiscipline, yet for outsiders or for skeptical insiders, the only clue is in the frequency with which a label is applied. Counting labels, however, does not unambiguously place a journal in one discipline or another because journals may bear multiple labels, even multiple superdiscipline labels.

2.2 Network Mode Projection

To assess the size of the disciplines and to disentangle their hierarchies it will be helpful to have a mutually exclusive labeling scheme that draws on the JSTOR curators' judgement while simplifying it. I rely on network methods to accomplish this labeling in a data driven and reproducible way. In a network representation of journal discipline labels, two journals may be said to be be related if they carry the same label. In network terms this can be represented as a bipartite or bimodal network. In a bimodal network there are two types (modes) of nodes, a journal and a label, and ties can only be registered between, not within, these modes. So journals are not tied directly to other journals and labels are not tied directly to other labels.

Given any bimodal network, one may translate or project it into either of two unimodal forms. In a single mode or unimodal projection of a bimodal network there is only one type of node, in my case either a journal or a label, but not both. The omitted type is instead represented as a set of ties among the included type. Though the bimodal network is a more elegant representation, it is technically necessary to project it into one of its two bimodal forms to leverage network methods that are designed with unimodal data in mind.

Using the list of subjects associated with each journal in the JSTOR title list, I construct the bimodal *journal-label*

[1] To avoid over counting, title histories are collapsed into their most recent record, meaning all subsequent counts are out of 2,738. Even though one might expect disciplinary identity to change over time, JSTOR discipline labels do not vary within title histories. One journal–Scientific American Mind–lacked any discipline labels and is excluded from tabulations.

network with journals in the first mode bearing ties to discipline labels in the second mode. I then project the bimodal network into two unimodal networks, one where journals are connected by ties equal to the number of discipline labels they have in common, and another where labels are tied by the number of articles carrying both labels. Call each of these unimodal networks, the (*journal-label-journal*) journal network and (*label-journal-label*) label network, a facet of the original bimodal network.

Figure 2.2 illustrates the effects of network mode projection on a random sample of 300 edges from the full JSTOR title list network. The first panel illustrates the bimodal network where journals are yellow dots and labels are blue dots. As an artifact of sampling, most journals here are shown tied to only one label. In fact this is never the case in the full network; as each journal has at least one discipline and one superdiscipline label the minimum number of labels is two, which is the median case accounting for 53.9 percent of journals. The most labels any journal bears is 10, but these are outliers with most journals bearing only a few labels.

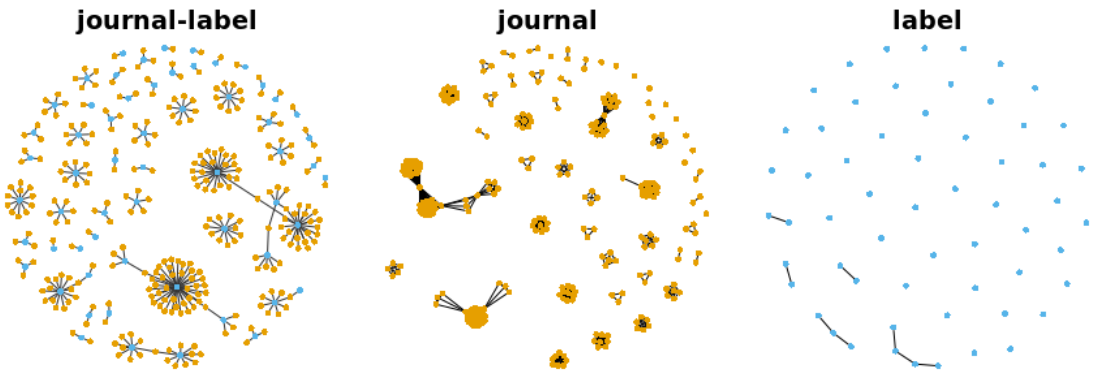

Figure 2.2: Mode Conversion on a 300 Edge Random Sample of the JSTOR Title List Label Network

It is worth noting a few features of the unimodal projections or facets illustrated in the second and third panels. First, unimodal projections will always be made of overlapping cliques. Take the journal facet; each journal bearing a particular label will be tied to each other journal with the same label. Together they will form a clique, a subnetwork of maximum density where all possible ties exist. Such cliques grow nearly exponentially, as each additional journal with the same label joins the clique and adds a number of ties equal to the former size of the clique. In practice this means that very common labels like “Social Sciences” can easily dominate the unimodal projection of the network. Here the weighting of edges becomes important; if two labels overlap because some nodes bear both labels, then within the intersection of the two cliques the ties may be treated as “weighing more” by adding the contribution of each label separately. The exception is if the

cliques overlap by only one node, in which case they have a node but no ties in common. Nevertheless using methods that take edge weights into account is a good way to ameliorate the exponential influence of popular labels.

Second, though the unimodal facets of a bimodal network represent the same data, each may have different characteristics especially in the common case of a large population imbalance between modes. In the full network there are 35 times as many journals as labels and each journal sends multiple ties. This degree imbalance between the two modes may mean that one facet is more dense than its inverse. Density is the proportion of actual ties out of all possible ties. In Figure 2.2 an imbalance may be observed where the journal facet has many dense free floating or overlapping cliques and where the label network appears to be mostly made of isolated labels save for the few larger components. In the sampled network the journal facet is 10 times more dense than the label facet. In the case of our full network, the potential imbalance in degree distribution between facets happens to be offset by the population imbalance itself. The densities in the full journal and label facets are comparable, 26.2 and 27.3 percent respectively, meaning that analysis will not merely hinge on which facet is analyzed.

Third, unimodal projection has the effect of pruning what are sometimes referred to as pendants, which are simply nodes with only a single tie. Each of the isolates in the label facet represents a larger or smaller number of journals, which may be observed in the different sizes of the free floating cliques of the journal facet, yet no matter their size they supply no information about interdisciplinarity. Because the journal facet captures both size (of cliques) and relatedness (clique overlap) it is a better representation of the information of the original bimodal network. Its drawback is that it is larger and more unwieldy to analyze. The label facet offers a simpler picture of interdisciplinarity.

2.3 Network Community Detection

Each facet described above will help answer a different question about disciplinarity in the JSTOR archive as indicated by JSTOR's labeling policy. I aim to resolve the uncertainty about which labels count as superdisciplines and to reveal patterns of sorting not apparent in the labels themselves. The rationale for doing this is to observe not the choices of JSTOR coders, but the tacit judgement they likely used in applying labels. I expect that the 79 fine grained labels belie a simpler classification scheme of academic genres.

I will use two techniques, community detection and graph visualization, to answer these questions. Communities are really subnetworks of high density, or clusters. I operationalize disciplinarity as the presence of clusters within the journal

facet network. Community detection on the journal facet will answer how many superdisciplines there are and the size of each in terms of the number of journals belonging to it. Visualization of the label facet will show how hard or soft are the boundaries between disciplines and where the strongest interdisciplinary relationships lay.

First, I use community detection to partition the JSTOR journals into mutually exclusive disciplines. Community detection is a set of network methods designed to expose clusters by grouping nodes together such that they send more ties to members of their own group than they send to members of different groups. There is a cottage industry around developing algorithms and statistical models to learn an unobserved community structure of a network (see Fortunato and Hric, 2016, for an excellent review). The choice of the right community detection method is controversial especially for very large networks in which cross-validation is difficult. Fortunately the network at hand is small enough to validate directly which lowers the risks of choosing the wrong method .

To wit I adopt the well-known Louvain method of community detection based on hierarchical modularity maximization. (Blondel et al., 2008) Modularity is a quality metric quantifying the trade off between within-group and between-group ties. The modularity of any given partition of a network into clusters is equal to the proportion of ties that fall within clusters minus the expected proportion of within-group ties if ties were distributed randomly. A division that is as good as chance would have a modularity value of zero, a division better than chance a value between zero and one, and a division worse than chance a value between negative one and zero. (Newman and Girvan, 2004, 8) Higher modularity scores indicate a better sorting of the network into densely tied clusters.

The Louvain method is a bottom-up agglomerative algorithm. The procedure starts by assigning each node to its own community. Then, for each node, it assigns the node to the neighbor's group that would most improve global modularity. It repeats this until no move improves modularity. This forms the first layer in the hierarchy. It then collapses groups into nodes and repeats the algorithm on the condensed network, stopping at the first level where there is no modularity improving move to make. The first layer represents the most local, the last layer the most global resolution of community structure.

Modularity-based methods are tried and true, and their drawbacks are well-known. The Louvain method is not deterministic, as the outcome may (but usually does not) depend on the ordering of the nodes in the reassignment queue. However Louvain has several features that recommend it. It is computationally fast on small to medium graphs and it is freely available in network analysis software. It also gives a hierarchical solution that provides the analyst with options to inspect community structure at a range of local and global resolutions, akin to a cartography of counties versus one of

continents. Given the small size of our network, a local resolution will not be overwhelming, so Louvain is preferable to other methods that only offer the coarser global view.

Table 2.2 summarizes the results of applying the Louvain method to the journal facet and taking the most localized layer of the community structure. Learned labels are applied to the clusters by assigning each the name of its most frequent label. Community detection sharpens the boundaries between fields by placing each journal unambiguously in one superdiscipline or another. This mutual exclusivity is apparent by the sum of the given labels exceeding 100 percent.

Table 2.2: JSTOR Journal Counts

Superdiscipline	Learned	Pct	Given	GPct
Social Sciences	790	28.9	916	33.5
Humanities	664	24.3	719	26.3
Area Studies	357	13	499	18.2
Science & Mathematics	307	11.2	360	13.1
Business & Economics	266	9.7	285	10.4
Arts	240	8.8	293	10.7
Law	84	3.1	132	4.8
Medicine & Allied Health	30	1.1	52	1.9
Total	2738	100.1	3256	118.9

The first finding is that of the 79 labels these eight form the top of a hierarchy of superdisciplines. Area Studies stands apart and is not subsumed under either Social Sciences or Humanities. Social Sciences journals predominate due to JSTOR's initial focus in that area, even without counting economics among them, and Science & Mathematics counts for a larger than one might think. Economics stands apart from the Social Sciences, and indeed Business & Economics marks the transition from the larger academic journal space to the smaller professional space of Arts, Law, and Medicine & Allied Health.

The given labels do overlap and one can recover a picture of interdisciplinary by clustering and visualizing the label facet. This facet presents a simplified view. Recall that each facet represents the same data, the difference being whether a journal or a label is represented as a node or an edge, and that there is a population imbalance in favor of journals over labels. The larger the population the easier it is to partition into a greater number of subpopulations. Conversely, because there are far fewer labels than journals, one would expect the clustering to be less granular for the label network than for the journal network. In fact there is only one less cluster–Law–which is subsumed under Social Sciences.

2.4 Network Visualization

Figure 2.3 visualizations the relationships among disciplines, where again the strength of ties is equal to the number of journals bearing both labels. Here the label with highest number of ties within its cluster becomes the category name of the cluster. That label is then omitted as a node and is instead visualized as a color coding of its cluster, reflecting the special status of the superdiscipline labels.

Unlike traditional graph visualizations that are designed to be pleasing to the eye, this one is drawn according to a statistical model called a latent position or latent space model. It starts with a simple idea that the weight of the edges (the number of journals carrying both labels) is a count that follows a Poisson distribution. This distribution may be modeled by log-linear regression where the logarithm of the mean of the distribution is a linear function of an intercept term and covariates. What is interesting about the model is that the covariate of interest is treated as the distance between the nodes in an unobserved or latent space. The distance is treated as negative such that as nodes get closer together (as the negative distance increases) the count of the edge weight between them increases (technically the logarithm of the mean of the count increases).

It is an elegant idea, but estimating the model is complicated. The distances are metaphorical, and to realize them requires positing a euclidean space in which each node has coordinates. From the coordinates the distances can be easily calculated, but knowing which are the right coordinates requires a complicated estimation routine based on optimizing goodness of fit between guesses of the coordinates and the actual count data. The estimator begins with coordinates taken from the conventional Fruchterman Reingold layout algorithm and uses Markov Chain Monte Carlo simulation to converge toward the positions that optimally fit the latent space assumption (See Krivitsky and Handcock, 2008, for details of the model, estimation, and software). Even if the estimator does not arrive at a perfect solution it improves upon a conventional layout in the direction of meaningful, and not just pretty, aesthetics thereby helping the viewer to avoid artifacts and perceive real information about the network.

Another great feature of the latent space model is that it allows additional terms to be fit alongside the latent distances. It is possible to control for or net out the effect of nuisance terms like any other regression. As discussed above there is a concern about the undue effect of popular labels. I have already tried to remove the superdiscipline labels from the label network, preferring to represent them as color coded categories rather than nodes. Popular labels may still remain, however, and due to the exponential growth of ties during downmode conversion even a handful of them will have a disproportionate

influence on the global layout of the graph.

This degree distortion can be controlled for by what is called a sociality term, which can be thought of as a measure of a node's popularity. A sociality term is a score for every node that if positive means a node is more attractive and if negative means a node is actually repulsive of ties. When viewing the positions of a latent space model also fit with a sociality term, the space will measure relatedness without the effects of popularity.

Figure 2.3 plots the results of a latent space model on the label facet omitting superdiscipline nodes. Figure 2.4 plots the same in an animation comparing the latent space and traditional Fruchterman Reingold layouts. I will interpret the substance of the latent space layout below, but first I will comment briefly on some of the differences between it and the traditional layout.

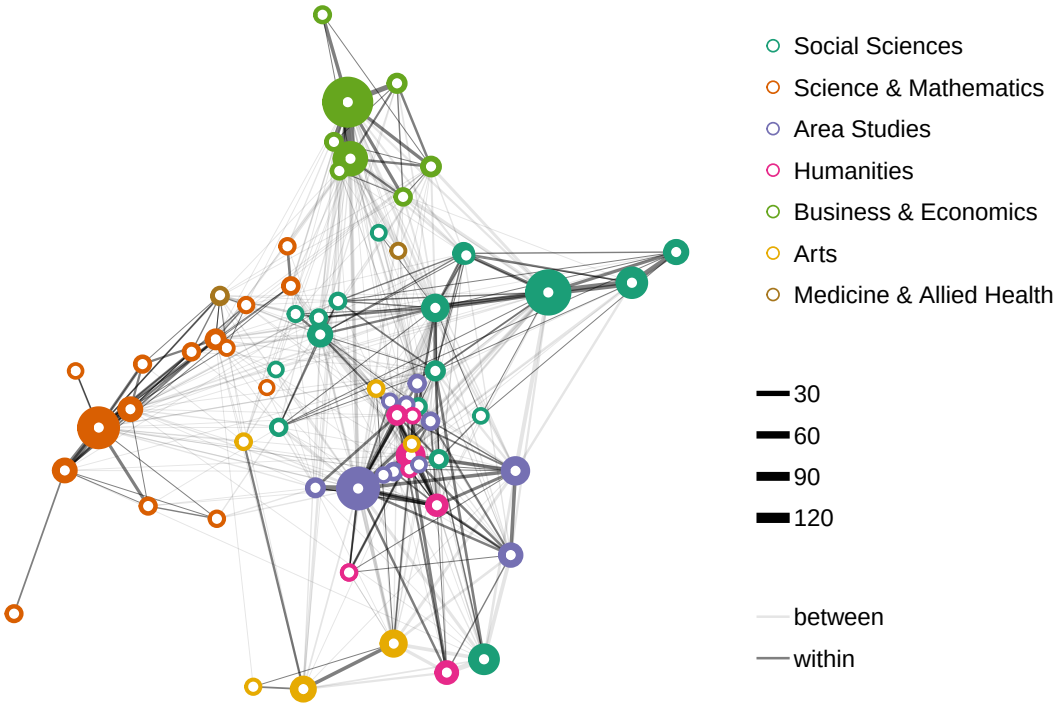

Figure 2.3: Discipline Network in Latent Space. Node size represents sociality. The larger a node, the more attractive it is, and the larger a white dot within a node, the more repulsive it is.

Figure 2.4: Fruchterman Reingold and latent space layouts compared

In the animation nodes are hollow shapes to make their overlaps more obvious. The size and shape of the nodes relates to their fitted sociality: circles indicate attractive and diamonds repulsive nodes, and the the larger the shape the more attractive and the smaller the more repulsive. The layouts differ in two important respects. First the global patterns are dissimilar. The latent graph has four discernible arms. The traditional graph is a cloud that at first glance seems evenly dispersed, however there is a prominent core periphery pattern, with circles concentrated in the center and diamonds displaced in a ring around them. Second, patterns of node proximity are distinct. In the latent graph, nodes may share or almost share a center, indicating structural equivalence. In the traditional layout concentric node positions are algorithmically prohibited by a repulsion radius, with apparent overlaps due only to the scaling of node size. The traditional core periphery pattern is the consequence of the imbalance between low and high degree nodes; by netting it out with the sociality term the latent model makes it possible for minor disciplines to cluster around the major ones to which they are anchored.

2.5 Results

Recall that the superdiscipline classifications are functions of their underlying subgraph densities, hence we should expect them to be clustered together in a layout that represents relatedness. For convenience we will refer to the cardinal directions to locate ourselves on the plot. The most prominent feature of the global patterns is the appearance of two axes. From west to east is an axis dividing the natural and the social sciences. From north to south is a more diffuse axis dividing Business & Economics from the Arts and Humanities. Though it is tempting to interpret the south to north axis as artistic opposition to profit, it is more plausible that they are each facing a different side of the Social Sciences, which neatly bifurcates them.

While superdiscipline members are usually near each other, they do not all bunch together in the same way. In the north Business & Economics is the most spherical cluster with its members much more strongly connected inside than outside the group. By comparison Science & Mathematics is extended between two internal poles, with life sciences pulled far to the west and statistics and mathematics interfacing with other central disciplines. The Social Sciences are similarly extended but with three poles: politics in the east, archaeology in the south, and geography in the west. Area Studies, which subsumes history, tends to closely overlap the Humanities with the exceptions of asian and middle east studies to the east, which are situated between political science and archaeology, American studies in the west, and the history of science and technology, which is closer to its subject matter in the west. Most of the Humanities is highly concentrated with the exceptions of bibliometry and library science on one hand and classical studies, which is close to archaeology, on the other. The arts is the most diffuse superdiscipline; several of its fields are on the margins with the exceptions of urban studies at the confluence of the Sciences and Social Sciences and music as well as performing arts sharing the interdisciplinary center with the Humanities and Area Studies. Finally, the three disciplines in Medicine & Allied Health are split between a Science (public health, health sciences) and Social Science (health policy) orientation.

There are several interesting cases of total or near structural equivalence. Total overlap for major fields suggests extra superdiscipline candidates, with biological sciences covering zoology and history covering American studies. Considering only minor discipline overlaps, the public health and health sciences labels overlap to the point of redundancy, as do library science and bibliography. Near overlaps between minor and major fields may indicate a theoretical (major) applied (minor) relationship. This is expectation is confirmed by the major law and minor criminology & criminal justice overlap, and contradicted by the major education and minor psychology overlap, where the minor psychology field would be considered the more theoretical. Interestingly, structural equivalence of fields in two different superdisciplines occurs only once, with

Table 2.3: Disciplines by sociality multiplier

Superdiscipline	Major Discipline	Soc.	Minor Discipline	Soc.
Area Studies	History	9.4	Irish Studies	0.93
	Asian Studies	4.35	Latin American Studies	0.86
	Middle East Studies	2.96	African Studies	0.84
	American Studies	1.5	African American Studies	0.45
	History of Science & Technology	1.38	Slavic Studies	0.22
	Jewish Studies	1.07	American Indian Studies	0.2
			British Studies	0.19
Arts	Art & Art History	3.91	Urban Studies	0.6
	Architecture & Architectural History	3.49	Music	0.58
			Garden & Landscape	0.42
			Performing Arts	0.31
Business & Economics	Business	11.94	Finance	0.99
	Economics	6.46	Labor & Employment Relations	0.86
	Public Policy & Administration	1.68	Development Studies	0.76
	Management & Organizational Behavior	1.45	Marketing & Advertising	0.72
Humanities	Language & Literature	4.46	Bibliography	0.5
	Classical Studies	2.72	Library Science	0.37
	Religion	2.26	Folklore	0.36
	Philosophy	1.5	Film Studies	0.2
Medicine & Allied Health			Health Sciences	0.86
			Public Health	0.7
			Health Policy	0.34
Science & Mathematics	Biological Sciences	9.09	Mathematics	0.88
	Botany & Plant Sciences	3.09	General Science	0.86
	Ecology & Evolutionary Biology	3.07	Aquatic Sciences	0.77
	Environmental Science	1.7	Paleontology	
	Zoology	1.43	Horticulture	0.72
			Geology	0.5
			Statistics	0.49
			Technology	0.44
			Engineering	0.28
			Developmental & Cell Biology	0.19
			Astronomy	0.04
Social Sciences	Political Science	10.26	Geography	0.82
	International Relations	5.43	Psychology	0.64
	Archaeology	5.16	Environmental Studies	0.63
	Sociology	4.04	Feminist & Women's Studies	0.58
	Peace & Conflict Studies	3.21	Criminology & Criminal Justice	0.46
	Education	3.15	Social Work	0.36
	Law	2.08	Population Studies	0.27
	Anthropology	1.45	Communication Studies	0.21
	Linguistics	1.12	Transportation Studies	0.2

religion (Humanities) and Jewish studies (Area Studies) tightly coupled.

A last topological feature of interest may strain the accuracy of the model, but I lodge it as a problem for further consideration. Within Area Studies there appears to be two differentiated fronts, a more southerly line of "white studies"–history, American studies, British studies, Irish studies, and Slavic studies–and a more northerly line of "brown studies"–American Indian studies, African American studies, Latin American studies, and African studies, which also includes a spot for feminist and women's studies from the Social Sciences. The distances in question are very close, and model variability may reveal them to be statistically insignificant. Even if they are significant their over interpretation risks a narcissism of small differences.

2.6 Discussion

There are many stories to tell about a map that we trust to be an accurate metaphor for closeness or relatedness in a cultural field. Recall that statistically, the closer two nodes are the greater the number of journals listing each as a subject category. The decision of how the subject labels were applied was a policy decision at JSTOR using an unknown procedure. Our interpretation of the map is affected by how credible we think the archivists' decisions were. Without knowing about their process, it becomes a matter of trust.

To begin with the weakest result, the purported fronts between white and brown studies,

Chapter 3

Genre and the Literature

Abstract

In English the term *genre* is a loanword from the French term for *kind*. As an analytical term in the social sciences genre is a loanword from the humanities. The use of the term varies greatly within and between disciplines. This study attempts a metadisciplinary literature review of genre as a term found in a corpus of JSTOR articles. I cast a very wide net by including any document in English that includes the term genre in the title or abstract. The resulting thousands of documents are "read" with the assistance of a statistical topic model to classify documents into topics, that is, strata of common vocabulary. I then perform content analysis on a stratified sample of classified texts to compare their different uses of the term genre. In an examination of the benefits and hazards of such a distant reading approach, I outline a battery of diagnostics to examine the validity of the topic model from both quantitative and qualitative perspectives. Through a combination of machine distant reading and human close reading, I arrive at a schema of five theories of the term genre. In an argument for pandisciplinarity, I conclude with an analysis of the logical possibility of new metaconcepts of genre that satisfy the strictures of multiple disciplines.

Keywords

genre, disciplines, computational text analysis, topic modeling, content analysis, digital humanities, distant reading

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In a motivation of some of the arguments to follow, I take a metadisciplinary approach, which is to cast as wide a net as possible on the term genre. In so doing I hope to test the tacit cultural assumption that discipline-based decisions of relevance are valid, that is, that when we exclude arguments from other disciplines we remove distractions and focus on what is important. The alternative possibility is that we are wasting intellectual resources, because to exclude important work about our topic, even if it is codified in foreign terms, is to risk ignorance and redundancy. The topic is genre and how disciplinary boundaries form such that people using the same word nonetheless cannot communicate effectively. They draw on different paradigms, which is to say the term is not really the same term. What I hope to do is uncover the knowledge contexts surrounding the terms, and map these contexts in a way that enumerates the various communities of discourse and theories constituting the term.

3.1 Genre

I take genre as a candidate explicans for the ability of scholars to know what to read and what to avoid from the cultural archive. A theory of genre will benefit from a review of the literature, yet to do so would catch me in the conundrum of performing the phenomenon I wish to explain. The genre structure of sociology should guide me to a definition of genre, a statement that already presumes an ontological difference and morphological relation between disciplines and genres, namely that scholarly genres are not equivalent to scholarly disciplines and that the former are located within the later. I will begin with an unstudied attempt to tease out the relation of discipline and genre before turning to a more rigorous, even empirical, treatment of genre as a term in American scholarship.

Genre is a loanword from French. The origin of the French-Latin word “genre” and the English-German word “kind” both mean membership by inheritance of innate class characteristics, archaically by presumptive blood descent within a family, race, or nation. In common English it is restricted to mean a broad category of art, especially literature and music, and some but not all other cultural fields (e.g. baseball is not a genre of sports). As a term in scholarship, genre may be an observable phenomenon, a conceptual component of a theory, or a conflation of the two. In the social sciences genre is a specialty concept as in sociology, while in the humanities it is ubiquitous especially in cultural studies. Academics define and use the term differently between and within disciplines.

Figure **??** shows the count of mentions of the term genre in the Google Books Ngram database for English terms (Michel et al., 2011). The trend exhibits the typical take-off in publishing in the second half of the twentieth century. I apply change

point analysis, which detects significant differences in time series data (Matteson and James, 2013; James and Matteson, 2019), to the second difference of the trend, a measure of acceleration, to get clues as to whether the trend is a single process or whether there are inflection points. The first segment of the curve from 1899 to 1984 indicates a period of positive acceleration or quickening of the growth trend. On average in the first period the rate of change from one year to the next increased by a modest 13.3 occurrences a year. However, during the period from 1985 to 2008 the rate of change, though always steep, began to decline by an average of 238.3 occurrences a year. Like a projectile that is simultaneously climbing and falling, 1984 acts as launch point of precipitous yet unsustainable growth.

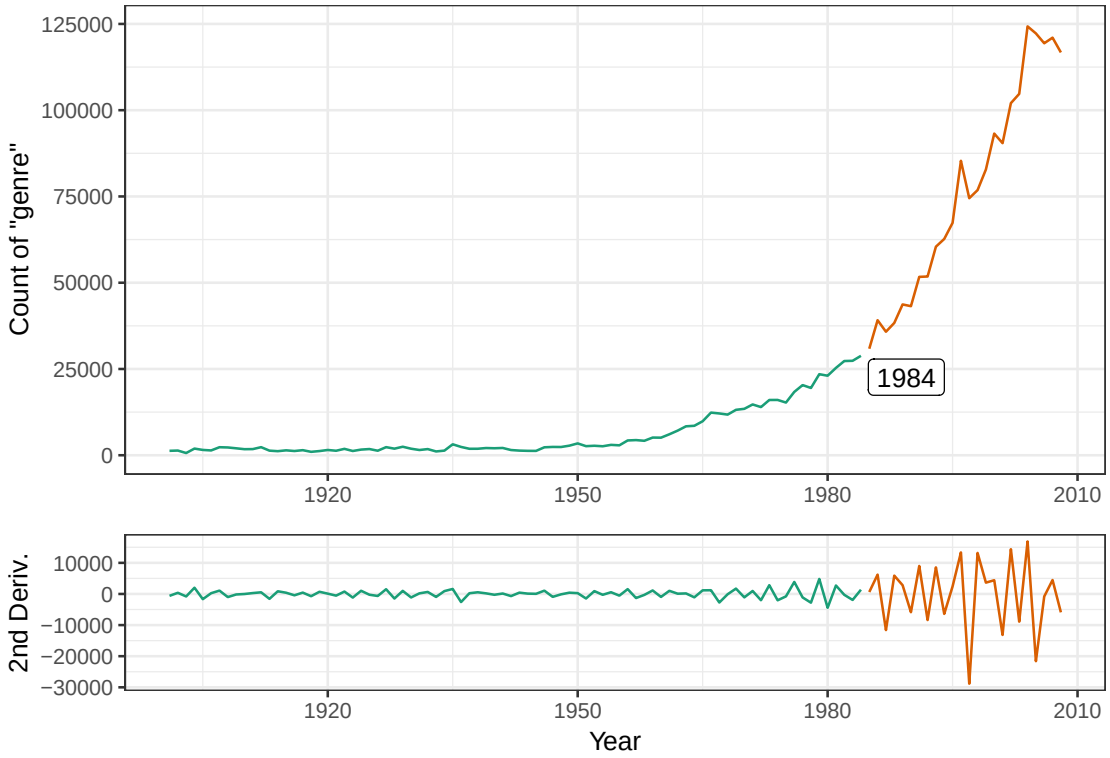


Figure 3.1 shows a similar trend but using relative frequencies instead of absolute counts. Here “genre” is plotted as its share of all terms in the corpus. This trend exhibits no inflection point at 1984 that is statistically significant, and visually the trend does appear the same on both sides. No other inflections points are detectable due likely to greater year over year variability in this series in the first half of the century, reducing confidence in any estimate of a change point. To interpret this difference in statistical significance between relative and absolute measures would indicate that interest in genre continued to grow even within a secular slow-down in the volume of texts that resembles the familiar S-shaped diffusion curve. Alternatively, on visual inspection of the relative curve it appears that indeed there is an inflection point, just one a

decade later in 1996. After this point the relative frequency seems to drop rapidly, a change that would no doubt be picked up statistically after a few more years of data and one that may in fact be located a few years earlier than the peak suggests. Together these trends describe a career to the term genre that has been strong for a century and that may now be in decline.

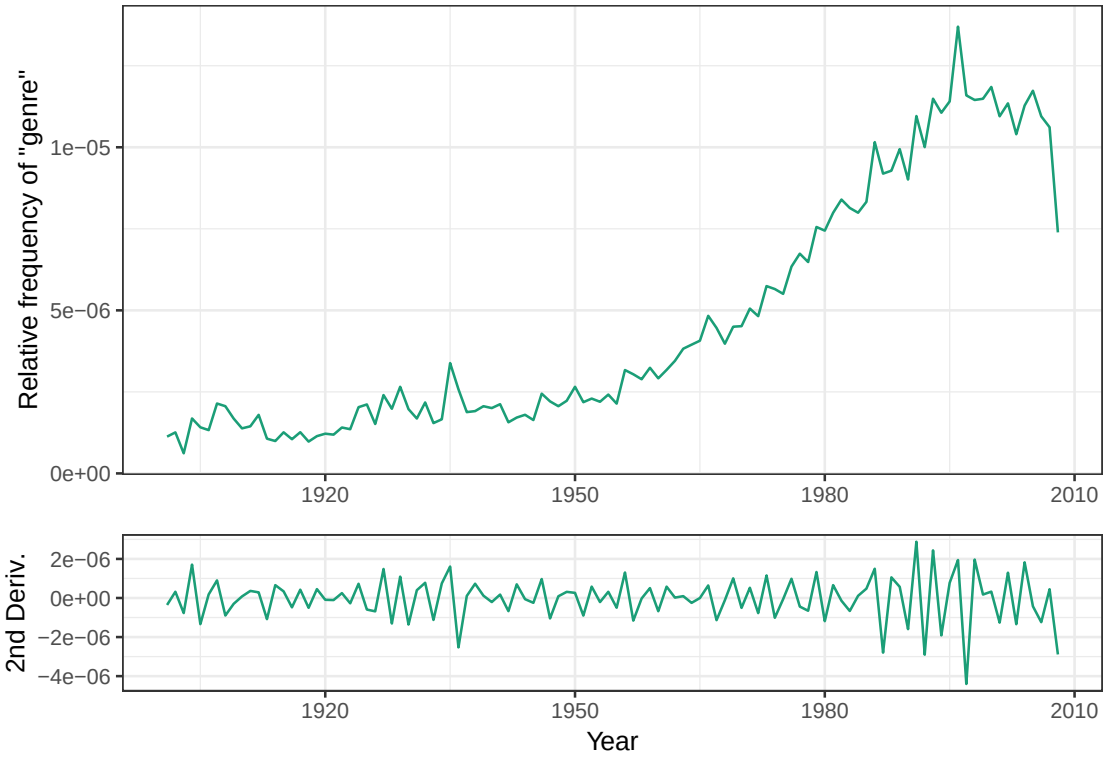


Figure 3.1: Relative frequency of term ”genre”, 1901-2008.

Figure 3.2 gives an indication of what things the term genre has been used to describe. It illustrates the frequency of terms appearing in the Google Books Ngram corpus as the third term in the trigrams beginning with “genre of” or “genres of” (Google, 2012). The size of the words is proportional to the total frequency of the trigram in the English corpus, which spans centuries from 1590 to 2008. The bias of the source–books–is clear in the outsized importance of “literature” and “writing” which are followed closely by “music”. The next ten largest nouns are poetry, discourse, fiction, art, autobiography, painting, film, romance, folklore, and history. Ranked within that series would be several adjectives as well: popular, science (fiction), historical, and literary. Each of these terms refers to a field of concrete cultural products, with the exception of “discourse” which is more abstract.

Figure 3.2: Wordcloud of third term in 3gram beginning with ”genre of”.

Most items toward the top of the list are less popular (to write about) art forms like television, dance, and theater. Toward the middle of the list begin to appear adaptations of the term from the cultural to the social context. These include practical fields like medicine and journalism, political areas like law, government, and crime, and social arenas like identity and protest.

3.2 Method

As I have said, the first consequence of eschewing disciplinary limitations is to bloat the size of the “literature” on genre, since no uses of the term would be excluded. An empirical approach to the standard academic convention of a literature review will help reign in the scale and complexity of the task. My aim, however, remains practical rather than scientific. The methods need to be good enough to yield results that offer something new above a traditional literature review relying on library search and disciplinary wisdom about what is important. This is not because a scientific approach is undesirable, it is that it is not yet demanded of “the literature”. Sociologists are not expected to take a sociological orientation toward the history of their fields. Rather the literature review serves the social purpose of taking a position in a field of cultural

production. It is a listing of a roster of political support and rivalry, and an advertisement to attract a desired audience.

To take an empirical approach to the literature review would be subversive were it not the first function of disciplinary genres to render atypical draws from the archive irrelevant. Disciplinary subfields, genres, are credentialed by secret sets of references, and most comers are held at the door. This in and of itself can be subversive of even more arbitrary club rules, namely those of educational pedigree, such that anyone willing to invest in a presentation of the genre definition will be granted access to the venues, if not the invisible colleges, of the subfield. To be admitted to the arena is no guarantee of achievement within it, but it is a start. Nevertheless, the scale of the archive will always supply entropy enough to create a deterrent of flotsam and jetsam around subfields composed of projects and persons who either never cracked the code or who willfully eschewed it.

3.2.1 Distant sampling

The research strategy here attempts to parry the entropic tendency of the archive by substituting human for machine limits. The methodological premise of a meta-analysis of genre is that the Gordian knot of the global cultural complexity of the archive can be cut by stratified sampling. I use a large digital archive of texts, JSTOR, to represent the whole of the academic archive. Though clearly a toy representing only a fraction of all networked scholarly produce, JSTOR is large enough to easily surpass individual cognition and compel the equivalent types of complexity reduction facing any researcher approaching the real archive via their local university library portal.

I use a simple term search of the keyword “genre” to define half of a sampling frame.[1] I could then take a simple random sample of texts, analyze how each uses the term genre, develop a classification scheme, and enumerate the different uses of the term. Unfortunately, a small sample in a statistical sense may be larger than a poor researcher can handle. 1,000 texts is not large statistically, but it is huge from a content analysis perspective. What’s worse, 1,000 texts may still exclude, by random chance, small subcultures of the term. Stratification within a more or less global sampling frame resolves this issue by delineating those subcultures so none would be left out.

Alas, the JSTOR digital archive lacks subject labels at the article level, though it does include them for book chapters and for journals. While not foolish, inheriting a journal label to the articles included within it may be a coarse approximation if within-journal content variation exceeds between-journal variation. We can use text analytic classification methods to cluster articles directly and discover latent groups of articles, and in so doing we can have an independent standard to

[1] TODO, I did not, but should take a random draw of the same size to serve as a control.

compare to the discipline labels given to journals. It is an open question whether such methods align with what we have discussed above as disciplinary and subdisciplinary groupings, for us whether regularities in vocabulary correspond to regularities in the meaning of the term genre. If they do not, then the study will only be a stop en route to a true census of the uses of the term genre, and the contribution will be to have interrogated the quality of the methods used, though this would be a small consolation indeed! Even so, for a new method to claim to be able to improve on conventional wisdom, I behoove myself to proceed methodically.

The choice in computational text analysis (CTA) about how to represent texts as data hinges on whether word order is preserved. The older and more tested approach is to not preserve word order. The name given to this "bag of words" format reminds one of its inelegance. A bag of words is a frequency table for each document counting up the number of times particular words are used, a representation that effectively reduces a text to its vocabulary. It is the analyst's crude operational decision to treat vocabularies as indicators of meaning, but social scientists conventionally insist on cross validation via qualitative analysis. While the ambitions of computational text analysis may start with a replacement of, for instance, the standard literature review, the conventional distrust, at least in sociology, of mathematical models of text makes CTA more of a sampling method than an analytic method. The study will culminate in a reading of texts, albeit one that is different than traditional qualitative analysis because the CTA researcher welcomes the introduction of interpretive bias from an understanding of the mathematical model before, during, or after the texts are read. In the game of "choose your influence", CTA is one choice while disciplinary wisdom is another.

There are two types of classification methods in text analysis, direct document clustering and topic modeling. Direct document clustering treats the bag of words as a vector space and calculates distance or similarity metrics between documents, which are then clustered. In a topic model, the relationship between documents is mediated by an unobserved but latently modeled representation of their content; documents are similar because they are formed from the same topics.

Whichever approach one takes, and both may be used, recall that the goal is to organize the texts into strata for the purpose of stratified sampling. We said that we wish to typify and enumerate the different uses of the term genre. By qualitative analysis, we could read every text in a simple random sample and come up with a theory of the use of genre in that text. The demerits of this approach are several (c.f. Nelson, 2017, 5). It would take longer than we want even for too small a sample. We are not humanists and have not been trained in text analysis (this will hound us no matter what). Fatigue will set in, and accuracy and consistency will suffer. We may limit our set of theories to spare us the agony of complexity.

It will be hard to reproduce our results. There may be path dependency with a different reading order producing different theories. On the upside, we would be more educated for it.

Instead, we will stratify the sample, and it is in the configuration of the strata that much of the work will be done. The strata impose upon our interpretation of the texts the assumption of sameness.

3.2.2 No cigar

The popular yet maligned distant reading approach taken by digital humanists (e.g. Moretti, 2005) is being taken up with gusto by social scientists who are less skeptical of quantitative methods (e.g. DiMaggio et al., 2013). Following Nelson (2017) I employ a quantitative analysis of texts not to replace human reading with machine reading but to support reproducibility in traditional qualitative content analysis. While CTA makes it possible to dispense with reading altogether, knowledge, understanding, and the cultural logics of arguments–especially their ontologies–are still only obtainable by reading primary texts, closely or not. The most radical interpretive CTA method would involve deep neural net supervised machine learning, which may be able to predict how a particular human reader would classify a text without their needing to read it, though this has never been demonstrated. What I gain from CTA is guidance in answering the question of what to read, and perhaps in what order to do so.

As we know, the question of what to read is answered institutionally for scholars already by way of canon, curriculum, word of mouth, and digital reference term search services. These are their own forms of distant reading, because they each make obsolete the archaic image, true of figures like Weber, of a scholar buried in library stacks reading everything they come across (and so it has been said of Weber, forgetting nothing).[2] These contemporary shortcuts are historically arbitrary, but what is important is first that they serve the function of reducing the overwhelming cognitive complexity of published scholarship, and second that they structure that reduction in the same way for all scholars. An arbitrary reduction needs to be consistent to act as an infrastructure for subdisciplinary scholarship, otherwise scholars would find themselves located in different literatures.

If distant reading is a criticism of close reading then it has a big hill to climb especially among humanists who are trained to deal very carefully with texts. In the social sciences a type of customary distant reading is that of ritual citations, those that have developed a meaning that may be oblique to their content or at odds with the intentions of the the original

[2] What a scandal it would be if Weber's lionizers discovered that he had only read text indices! Surely they would bury such a fact. But the point would remain that even if a scholar were able to consume an entire corpus, the sheer scale of contemporary publication is now beyond even a genius's capacity.

authors. A ritual citation is simply one that is cited but not read, but also one that is so often used that its socially acceptable usages are known from other secondary accounts. For all the lack of due diligence in the use of ritual citations, their socially understood meanings are better than the thoroughly perfunctory citation, those included because they were returned by a digital reference service and never read by anyone.

What are the social patterns of the traditional literature review are topics for the sociology of knowledge and science and for the information sciences. This is not the task of the current study. What we take from the traditional approach is the consequences of excluding large segments of intellectual history. What CTA makes possible for the first time is a nonarbitrary, inclusive analysis of *all* content in a digitized corpus. It will not necessarily be a good analysis, but what it will lack in quality it will make up for in coverage. A CTA approach to the literature review will at least make clear what lacuna would be left by the traditional approach. They also reduce the potential idiosyncrasy of a particular author's literature review because, unlike a personal reading, a CTA model can be communicated precisely.

Of course the cognitive limitation of how much any scholar can actually read and understand remains. There will be an exclusion mechanism no matter what, therefore a chief assumption of a CTA literature review is that corpus segmentation is both possible and that some reduced form of reading, some sampling procedure, can be said to be representative of the unread portion in each segment. These representative texts will be subjected to a close reading, but their interpretation will be generalized to unread documents. Hence I call this a "no cigar" approach to reading, as in "close but". If on the contrary to the assumption no two snowflakes are alike, then the enterprise of knowing more than we have before is fraught, and CTA becomes yet another arbitrary reducer.

What is worse, or perhaps better, is that there is reason to believe that idiosyncrasy itself is an historically variable feature of disciplines. If institutional isomorphism has proceeded to some high level in contemporary disciplines, then the assumption that reading the bellwether texts is as good as reading the entire herd may hold. If this is true, however, it raises as many questions about the process of institutionalization in cultural production as it answers about the potential to learn truer versions of intellectual history.

3.2.3 Topic Models

We have referred generically to computational text analysis, and now we can discuss the topic model as our technique of choice. There are many ways of estimating a topic model (e.g. the famous Latent Dirichlet Allocation (LDA) estimator)

but the model itself is simple. It is a latent variable model that decomposes a document-by-term matrix–in which every document is represented as a frequency distribution over every term appearing in the corpus–into two unobserved matrices:

- a topic-by-term matrix, and
- a document-by-topic matrix.

Topics are directly represented by they topic-by-term matrix. A topic is a probability distribution over a vocabulary. To draw on a topic means to choose vocabulary as a random draw from this distribution, where words with higher probabilities will be chosen more often. In the case of genres we might imagine a topic about film and a topic about music. Some words may be important (highly probable), to both topics, such as the word “genre”, while others would be distinct, such as the words “movie” (probable for film but improbable for music) and “band” (vice versa).

Note the usual distributional bait-and-switch of categorical statistical analysis, where observed count data are operationalized as the outcomes of unobserved probabilities. The probabilities are what will be estimated, not the counts. The importance of this will be explored in the sections on estimation and diagnostics, but suffice to say that the differences between probabilities and counts encapsulate many of the difficulties applied researchers encounter when using topic models.

Given topics as term distributions, a document can be represented not as a distribution over terms, but as a distribution over topics. The topic mediates the relationship between documents and terms. In order to generate diction for a document, all that need be understood is the ratio of topics out of which it is composed. This is sometimes explained as a generative mechanism; to ask what word will be chosen next in composing a document, one first samples from the document’s own topic distribution to decide which topic the word will be drawn from, and given that topic, one then samples from the topic’s word distribution to decide which word will be included in the document. A document’s topic probabilities also create the expectation of how many words are attributed to each topic. A document with topic probabilities .7 from music and .3 from film would be expected to be 70 percent about music and 30 percent about film, making for a parsimonious albeit reductive description of document content.

It is important not to overinterpret a topic model. To describe a topic model as “generative” implies that it explains how documents are written. Such a generative metaphor reveals the absurdity of a topic model as a representation of writing. Not to mention the fact that punctuation tends not to be represented (though it could be), the terms chosen would be in a random order incapable of making meaningful sentences. Hence it is best to avoid the generative metaphor as an explanation

of texts. If topic models touch on the generation of real, meaningful documents, it is only in a very limited sense. What the topic model really represents is how vocabularies are organized to condition an author's diction. A vocabulary can be thought of as an infrastructure of meaning more trivial than grammar or syntax and much more trivial than concepts or ideas. A topic is a simple list of words that is known or knowable across all authors in a field. Topics do not tell stories; authors tell stories in part by making diction choices that are conditioned by topics.

From a sense or meaning making perspective topics are trivial; this is because so little is known about what an author says by knowing the topic or even the term distribution of a document. What topics are useful for, however, is the segmentation or cartography of a corpus. Topics are really a global feature, perhaps a cultural feature, of a corpus of texts that is itself meaningfully selected. If indeed a field of texts is oriented to common if not always overlapping vocabularies, then topics can represent this well.

A topic model could be posited based on the domain knowledge of an expert, and this would be a form of estimation. The practical value of statistical topic modeling is that the unobserved topics can be induced, with a raft of statistical assumptions, directly from the observed document-by-term matrix to arrive at a model with the features just described. An estimated topic model will contain several other parameters filling in assumptions necessary to make it possible to identify the unobservable topic probabilities in each of the two matrices of the model. For instance, in LDA models the concentration parameter commonly called alpha makes an assumption about how many topics tend to comprise each document. Alpha values close to zero make it very likely that documents are composed of only one topic, while an alpha value greater than one increase the chance that a document will be decomposed into several topics. Alpha equal to one creates no tendency, so concentrated and diffuse mixtures are all equally likely to occur. It would behoove a researcher to make an informed decision about this parameter, yet software often sets an arbitrary default that the user may or may not be fully aware of.

3.2.3.1 Choosing K

Finally, topic models require the analyst to choose the number of topics K. The approach we take to guiding this decision is not to expect one correct specification of K but rather to see it as a changing resolution. A K=2 model usefully bifurcates the sample and is not simply wrong because it is too restrictive. As K increases we expect the samples to continue to divide as new parameter spaces become available to partition the sample. While this is not strictly a hierarchical design, since each

K model is fit independently, we should expect to see aspects of hierarchical topics as well as some degree of stability in the relationships among topics.

Between model cross-validation means that document and term groupings should be relatively stable as K increases. The document overlaps between, say, a three topic model and a four topic model should not be random. By graphing the document overlaps between pseudo hierarchically organized models, it should be clear which topics are the most stable and which are constituted partly by chance or by spurious association. An ensemble approach would then recommend itself; if the content of a topic is stable across different specifications of K, within limits, then we should have even more confidence in that topic.

When parameter space is limited the content with the strongest signal will come to define the topic, but the document by term vector will be contaminated with content that would be separated given more space. For sets of documents that are constituted by multiple true topics, we expect to see splitting of larger topics as the resolution increases to meet the real diversity. Hierarchy will reveal itself as topics with stronger topic signals subsume weaker ones until K reaches a point where there is enough space to separate them. On the other hand, in the classic trade-off between variance and bias, where K overshoots the true number of topics, we expect to see random splitting and possibly "dust bin" effects where spare topics allow larger topics to prune their weaker term associations. Indeed dust bins may appear even before the true K is reached. Where the term proportions explained by topics are very unequal, it may pay during estimation to treat a true smaller topic as a dust bin for a larger topic, because the optimization gains of clarifying a larger topic may be greater than the losses of confusing a smaller one.

Another interesting feature of this approach is that it shows when and how topics are able to appear given the parameter space constraints. We expect the most dominant topics, those that appear at low K and remain stable as K increases, to derive from vocabularies that are both distinctive and used often. The content with the strongest signal will be "FREX" terms, terms that are both frequent and exclusive (Bischof and Airoldi, 2012). Frequent means they have high counts in the overall corpus either due to occurrence across many texts or to very large counts in a few texts. Exclusivity (or monosemy, the opposite of polysemy) means that terms co-occur with an invariable set of additional terms. Exclusivity is related to the notion of anchor words that are maximally exclusive, appearing in only one topic, but likely very infrequent.The exclusivity of terms relates to the separability of topics (Arora et al., 2018), while the topic frequency of terms relates to the topic's contribution to explaining global corpus frequencies, that is, to maximizing model likelihood during estimation.

It should be possible to predict a priority for topic emergence as models increase parameter space for topics. First, we expect topic model estimators would be very tuned to picking out even a handful of texts written in a different language than the main corpus, as terms within those documents would be both frequent and exclusive. We should expect technical jargon to also send a strong signal for it's high exclusivity. Indeed, these special vocabularies are salient for both humans and machines for the same reason; they are easy to disassociate from the rest of the text. The priority, however, for the estimators will be to explain global term frequencies, so jargon will likely be behind frequent terms that appear across multiple topics, as in the case of polysemy or the more common case of simple language ambiguity. Trailing the pack and the last to emerge will be, as we have discussed, idiosyncrasy.

Let us remind ourselves of what badness means, because a bad model in a statistical sense may very well be the correct model for the analytical purpose of the researcher. A human reader with an interpretive goal in mind can be quite apt at scanning text content and ignoring what she finds to be irrelevant. Some of this seeming irrelevance has to do with the syntactic structure of language, while others a reader knows by experience to be elements of style and rhetoric in their field. The interpretive goal becomes like a flashlight that darkens much more content than it illuminates.

While human readers tend to make sense of only small portions of texts, the machine is not so lucky as to have the human capacity for selective ignorance. The topic model estimator sees and makes sense of everything at once. This is sometimes at cross purposes to the researcher's hope of complexity reduction, because in interpreting the model rather than the text she will be told by the model that something is important even if she would have easily ignored the same context in the natural setting. A topic model that is both correctly specified and accurately fit on a large corpus will likely have dozens or even hundreds of topics. Such a variegated classification scheme is likely to contain some topics that a reader would consider to be redundant, for instance, because they are about the same thing yet differ for an irrelevant stylistic vocabulary. Many others will simply be irrelevant to her research agenda. The task of sorting through the topics is supposed to be easier than sorting through the original texts, yet the researcher is sure to find many inscrutable lists of FREX terms in a that can only be understood with reference to classified articles.

In the case that a correct model of vocabulary clustering is actually too complicated to be helpful, the correct research decision may be to deliberately underspecify the model. We can imagine the real topics as guests standing in a line of priority, and the model is like a wedding with a limited number of tables. The guests with the strongest relations among them sit at the first table, the next strongest at the second and so on until all of the tables are full. In their munificence the

happy couple still lets the remaining guests in, and what can they do but pull up a chair at the tables where perhaps they already know one of the more honored guests. However, if an additional table, or several, were to be found, the crashers could look among themselves for close relationships, even perhaps peeling away a priority guest, to form a separate group. Prior to there being room, that group would be unrecognizably distributed among several tables. The group would not exist, but the individuals would, and they would find a seat somewhere.

Just as the arrival of wedding crashers at the tables does not alter the identity of the core group that constituted them to begin with, a model where K is set too low will serve to highlight those vocabularies that send the strongest signals, even if the tails of these topic distributions are contaminated by unidentified topics. From a frequency and exclusivity standpoint the unidentified topics are the less important ones. Smaller and less distinct groups will be occluded in an underspecified model, and whether these are substantively important is a theoretical decision.

Table 3.1: Content priority across frequency and exclusivity

exclusivity	frequency	
	low	high
low	4. idiosyncrasy	2. polysemy/ambiguity
high	3. jargon	1. foreign language

Indeed we may never expect idiosyncrasy to emerge as its own topic except in the limiting case. Presumably K can be set so high as to approach the saturation point of a topic for each document. In this event topics that would otherwise appear in common may alter to represent the uncommon parts of a document, and the topic would merely reproduce the term distribution of a particular document. Thus there is a transition from content in common to content idiosyncratic to groups of trivial size and to individual texts in the limiting case. The model is unable to ignore supposedly idiosyncratic content, and will thus find a way to classify it among topics in common, effectively distorting the term vector of those topics. There may be no objective point at which the content in common is neatly separable from the idiosyncratic content; indeed common content evolves only by idiosyncratic innovation. An ensemble approach allows us to observe how particular content moves among topics as parameter space opens up.

Finally, there may be hope that sparse model estimation techniques would ameliorate some of the considerations above. Sparse model regulation, such as those using the L1 or LASSO constraint, bias parameters downward and thus may set trivial regression coefficients nearer to zero. Such an approach may well fail to represent idiosyncrasy at all, which is either a benefit or a hazard. Such a biased model would, by effacing the idiosyncratic portions, yield topics representing only the

common portions of documents. This avoids what we have termed contamination at the cost of losing information that we may care about. Thus for sparse model techniques to be used responsibly document residuals would need to be calculated to help recover the unmodeled portions of the texts. The model diagnostics we explore below attempt to separate model parameters into common and idiosyncratic elements, the difference being whether the idiosyncrasy is located in the topic model or in the residuals.

3.2.3.2 Bias

Before documenting the data preparation below, it is important to keep in mind several sampling and modeling considerations that tend to be overlooked. First, idiosyncrasy is assumed to be unmodelable. A flaw of traditional topic models is that, at one level, all documents are generic. Originality exists only in novel admixtures of vocabularies held in common. Vocabularies that are limited to trivially small sets of works, be they idiosyncrasies of content or style, become sources of bias to topic model estimators. Because idiosyncratic vocabulary is by definition rare, it lacks both the mass of frequency and distribution across documents to be reliably picked up as a topic. Indeed, if each document were expected to contain some idiosyncrasy, then the number of topics needed to catch all of the idiosyncrasy would be equal to the number of texts in the corpus. Each document would then be a combination its own idiosyncratic topic (of which it would account for 100 percent of topic content) and a distribution over other topics held in common. The real number of topics would then be K+N where N is the number of texts and practically always much greater than K. Researchers would balk at including such a large set of extraneous topics, while estimators would both be strained by the greater parameters space and would collide with hyperparameters designed to militate against estimating topics distributed only over a single document.

The impracticality from a modeling perspective of representing idiosyncrasy coincides with the undertheorized tendency among researchers for extreme pruning of idiosyncrasy during data preparation. A more parsimonious modeling solution would be to allow a single extra topic designed to catch all idiosyncrasy. Yet this would tend to violate the assumptions behind construction of the other topics for two reasons, first because one topic would have significant distribution across all documents and second because terms within the topic would never be estimated together as they would really be a mixture of N uncorrelated subtopics.

Idiosyncrasy tends to be pruned in a desire to limit the length of the vocabulary to bring it within the bounds of computational power and the chances of a successful parameter optimization. Depending on the task, however, the

researcher may not be so concerned with performance, and may leave plenty of idiosyncrasy in the sample. What then is the effect on the topic estimation of such idiosyncrasy, since the idiosyncrasy must end up somewhere?

First, there will be a tendency to muddy the content of common topics with the particular idiosyncrasies of the documents that happen to draw on them. This in part explains the long, non-zero tails of topic by term distributions, which are usually filtered out during post-estimation and interpretation of the models. We would however expect them to corrupt the error structure of the topic they contaminate, leading to suboptimal estimates of the true terms in the topic.

Second, the document proportion of the contaminated topic will be inflated in the contaminating document. After all, the idiosyncrasy of the document was represented, erroneously, in the contaminated topic. Because of the length of the term vector it is not difficult to imagine the truly pathological case wherein the probability sum of the false portion of the topic is greater than that of the true portion. In this event, a document could be categorized within a topic due more to the false content than to the true content, especially if the idiosyncrasy was placed in topics randomly. Contrary to the effect of random error in an explanatory variable in ordinary least squares linear regression, which is to bias the regression coefficient downward, in a topic model the effect will be to bias the topic probability of a document upward.

DiMaggio et al. (2013) represent a typical albeit conservative approach to topic modeling as distant reading. Their data preparation of a newspaper corpus about U.S. arts policy in the 1980s and 1990s resulted in 54,982 unique terms and 7,598 documents (2013, 582). This incredible dimensionality in the term vector, which eliminated only stopwords and a few hand-picked terms and did no stemming, represents a very conservative approach to term filtering admitting to no performance based truncation. They chose a model with 12 topics. Thus in a strict interpretation of their 12-topic model, we are to believe that the extreme idiosyncrasy of news, with all of its historical specificity, is contained in a noise or junk topic rather than creating bias on the estimation of the signal topics. With such a huge term mass to classify and so few topics in which to do it, it is incredible to think that the algorithm would alight on a junk topic rather than using that spot for a signal topic. It is plausible that the noise (and so offensive a term to those reporters trying to say something new!) is distributed across signal topics rather than being safely tossed in the dust bin. To wit, their choice of a low alpha parameter of 0.1, which assumes that each document is generated from relatively few topics, makes it even less likely that the estimator would spend precious parameter space on a noise rather than on a signal topic.

DiMaggio et al. (2013) attempt to placate statistical criticism by substituting quantitative, statistical forms of validation for qualitative cross validation of topics. This may be more treacherous than the authors admit. Their analytical approach is:

1. Fit the topic model.
2. Sort the topic by term vectors in decreasing order.
    a. Split the fat head from the skinny tail.
    b. Interpret the terms in the fat head.
3. Sort the topic by document vectors in decreasing order.
    a. Split the fat head from the skinny tail.
    b. Classify those documents in the fat head according to 2.b.
4. Interpret the documents according to 3.b.

The sorting procedures are a typical low-hanging fruit use of the model. Even though the model is a much simpler ball of string than the original full text corpus, it is still a very complicated statistical equation with, in this case, 12 * 54,982 + 12 * 7,598 = 750,960 estimated parameters. Sorting the term and document vectors allows the analyst to proceed from an interpretation of the strongest signals toward the weakest, stopping when the author feels satisfied that the research question is addressed. The assumption here is that the strongest statistical signals are unbiased, that when parameters are converted to ranks, and the ranks are converted to truncated lists of words and documents, that those lists are correct.

The specter that I raised above applies to the document ranking more than to the term ranking. A formal feature of topic models is that each topic is composed of all terms in the corpus. Of course this is an artifact rather than an intention of the model, as the goal is to separate relevant from irrelevant terms in the constitution of topics. Similarly, all documents are distributions over all topics, but this is not (necessarily) the intention; again we expect an elbow in the sorted topic document vector in front of which are relevant and after which are irrelevant topics. Any concentration index, such as the Gini coefficient, calculated on the topic term and to a lesser extent the topic document vectors will show very high concentration, where most of the probability is owned by a few elements.

We can test for some of these expectations of bias. A document's topic assignment may be considered suspect if its term distribution from that topic derives from the low and long tail of the topic, rather than from the select high probability terms normally associated with the topic's meaning.

3.2.4 Qualitative Cross Validation

To be sure, topic model parameters may be biased by misspecification, and if we are being fair, by the gargantuan task we ask of them. In part because topic models, notwithstanding their decades of development, remain difficult to validate statistically, and in part because educated people scoff at the idea of machine reading, many researchers ultimately rely on qualitative interpretation to evaluate model quality. Goodness of fit means that topics pass a sniff test upon inspection. A list of words either does or does not inspire a theory of meaningful content, and this theory either is or is not confirmed upon inspection of document with a highly ranked topic probability.

The same scholars who promote qualitative cross validation (QCV) would presumably have bet on John Henry rather than the steam drill. The arguments against the machine, which excels only at recognition, is that it is a ham-fisted intruder into the delicacies of sensemaking, semantics, and interpretation. Meaning operates very differently from information namely by bringing grounding to the response to information. One example of grounding is spreading activation, that when information is presented to the mind by sensation, the mind responds by representing not only a construct of the stimulus but also a network of constructs adjacent in memory to the stimulus. Simply, humans see more than they perceive, but machines cannot.

That machines are dumb because they recognize rather than interpret is not entirely fair. In machine learning the analog to memory, be it treated as semantic grounding or anything else, is mathematical model representation, and the analog to learning is a Bayesian updating of old models with new data. A machine seeing new data with an old model can indeed see more than it perceives. At this moment in the era of computational social science, however, researchers train models for the first time on the data they wish to explain. It is theoretically possible to communicate and transport models from past to present researchers, however this is not done in practice for lack of infrastructure and more importantly because social scientists rarely study the same thing twice. Where data are ample it is possible to simulate a history of memory for the machine using hold out techniques where a model is trained on one sample of the data and applied to predict another sample. Where the goal is to maximize prediction, training and hold out samples are randomly selected. A different approach (e.g. Nay, 2017) involves selecting training and hold out as a process in time. This is a closer approximation to human memory, as humans always approach the present only armed with a memory of the past. In this sense a time ordered model training process may create the same kind of errors on new data that a social institution would.

As clever as the time sorted hold out strategy is, it is unlikely to outperform a supervised approach to model validation

wherein human judgements serve either as diagnostics or training materials for model fitting. Human culture is far too expansive to be modeled by a computer for no simpler reason than the data of human memory are always rapidly lost and what is retained is selected for arbitrary historical reasons. What makes the contest between John Henry and the steam drill interesting in the modern era is the social problem of cultural reproduction. Machines will outperform humans only where human history is made more accessible to machines than to humans, which may be a join function of the success of digital archiving coupled with the deterioration of human education.

In the case of topic models, some advocates for the machine go so far as to claim that the topic model actually recovers semantic context (DiMaggio et al., 2013, 578) or what we have called grounding. Semantic context is a more specialized notion than memory, and it refers to the human capacity for reproducing common meaning. In language viewed through a topic model a large collection of terms defines the topic while only a sample of these terms will be observed in a particular document. In this sense the topic model fills in missing information in the way that meaningful interpretation does. This notion rests on a very strong assumption, however, which is that information tacit in a particular case is explicit in a different case, indeed a quorum of different cases, and that the cases overlap enough to become included under the same topic. With big variation in document length topic models may take grounding, which is properly a community resource, arbitrarily from the longer documents within a corpus thus giving them undue influence over sensemaking. In real sociocultural interaction, a large, exogenous influx of novel term associations would not determine meaning at the margin. Real meaning has legitimacy enforced by interested actors, such that deviant term associations are negatively sanctioned. Topic models only learn from cultural expression and are ignorant of social processes that condition expression. If novel terms are associated in one text with a core of common terms found in many texts, they too will be added to the topic. This is a corruption of the grounding that would not occur in real life.

The estimation of grounding would seem to compete against the other feature of polysemy, that a term may appear in multiple topics each with a different context. How does the machine know that a particular term distribution (document) is a case of missing grounding within the same topic as another document, or is in fact a different topic with a different context? Of course the machine knows nothing other than how to maximize an objective function. Estimators are designed to start from a more or less arbitrary guess and update parameters in the direction of models that are more likely given the data. Indeed, it is the hyperparameter choices of the researcher that often decide which research approaches will win out. For example, the question of whether or not a topic model detects polysemy is operationalized as topic correlation and governed

by the choice of the sigma prior, which controls the diagonalization of the correlation matrix, where a constraint toward low topic correlations prohibits detection of polysemy. The current state of software discourages an understanding of how hyperparameter tuning relates to a particular research agenda, and this opacity to the method is a strong driver toward QCV.

Cheap computing does make grid searching across hyperparameter settings possible, if not cost effective, but until this approach is usefully automated it is safe to assume that models will be misspecified in an unknown way, that the model is tuned in a particular arbitrary theoretical direction that is unknown to the researcher. Why would one believe that QCV would inoculate against the hidden bias imposed by the model? To be clear, a biased model is one that will present a vocabulary that *does not* represent the text accurately. In the conventional use of topic models, the researcher is eager to use the topic as a lens that both arranges documents into relevant subsets (a particular draw from the archive) and primes her interpretation of the documents content by a suggestive list of terms. We wish to keep two forms of QVC error in mind.

The first is classification error. Continuous document by topic probabilities are interpreted categorically according to an explicit or tacit threshold of classification. Explicitly, one could analyze the global decay of topic probabilities and attempt to find natural empirical separations at threshold values. More commonly, the tacit satisficing criterion is met as one walks down the ranked list of documents and eventually decides that they have understood the topic. The error arises in the within-class generalization where classification quality has degraded in a continuous fashion (and past the point reached by our satisficed reader) yet such errors have been effaced by the hard classification rule. In short, by understanding the bellwethers, the researcher only partially understands the corpus and indeed only further mystifies the poorly classified stragglers.

It will help to visualize the statistical situation leading to this error. In the expected case of model misspecification, usually too few topics, we should also expect an urchin shaped quality distribution where on each topic spine are bellwether documents drawn out by their strong signal to be representative of the topic. As one descends the spine of each topic we will begin finding the poorly classified documents collected on the body of the urchin. These documents are representative of no topics, that is, equally representative of all or several topics. For a misspecified model, it is possible that a collection of these stragglers would be given a home in a model with an extra spine, that is, new parameter space for an extra topic. But without a topic to represent them, the analyst may make the mistake of a false generalization from bellwether to straggler documents. Such stragglers may even be halfway up the spine, assuring their classification but for the wrong reason: bellwether documents achieve their topic probability by virtue of words at the head of the sorted topic by term vector,

whereas stragglers achieve their lesser but still above threshold topic probabilities from the meaningless long tail of the topic by term vector. This long tail, we must recall, contains terms that may have trivially small topic probabilities when considered separately, but when considered together, because the term vector is so long, their cumulative probability of the false segment of the vector may rival in classification power that of the true segment.

The second is confirmation bias. Readers tend to skim and scan documents more quickly and less carefully when they are told what they are about ahead of time. It is natural for researchers to want to examine the document by term vectors of the topics in order to understand the results of the model and apply the findings to solve research problems. These lists may be very evocative of theoretical assumptions and practical expectations about the corpus, which has not normally been read ahead of time. Theories of the meaning of the term lists are very likely to establish confirmation bias in the reading of the texts. This means that documents that have been classified by a satisficing or threshold rule will be read differently with a theory of the topic in mind than they would have otherwise. Confirmation bias means that the analyst will have a tendency to focus on content that appears to conform to the topic theory while discounting content that contradicts it. Sometimes this will be warranted; after all, a feature of the model is the ability to classify documents into multiple topics. In the pathological case, however, the meaning of the document will be distorted to fit the theory of the topic. A model that causes the reader to misread a document is certainly not helpful, and the pull of confirmation bias tends to be strong even when one is aware of it.

Fortunately we may adjust our research strategy to avoid each of these errors. First, to ameliorate the effects of misclassification, a simple concentration metric such as the Gini coefficient applied to the vector will help discriminate between documents classified strongly into only a few topics (highly concentrated probabilities) from documents that are classified weakly into all (that is none) of the topics (unconcentrated probabilities). To assess a particular topic classification it should be possible to decompose the portion of a document's text that is estimated to derive from a particular topic. That portion can then be scored according to its weighted average rank of the terms actually contained in the document, with poorly classified texts having lower scores. The utility of this quality scoring is to shine a light on the yet to be correctly classified texts, which may give an indication of when it is warranted to increase the parameter space of the model, and which may substantively reveal the less dominant (perhaps dominated) vocabularies.

Second, it is a simple enough procedure to forestall interpretation of the topic by term vectors until after a direct inspection of documents grouped by their topic classification. Indeed, this may promote a more accurate theory of the topic since terms will be interpreted within context.

3.3 Data

The JSTOR Data for Research service allows researchers to download non-consumable versions of full text in very large samples up to 25,000 documents. We will use the JSTOR Data for Research service to download a bag-of-words text corpus for topic modeling. I take the following steps to develop a corpus:

1. Search dfr.jstor.org using the query `(ta:genr* OR ab:genr*) AND la:eng` and requesting 1grams.
2. To cull documents for which genre is not an important term, exclude documents containing fewer than five variants of the term genre (1grams matching the regular expression `^genr`: genre, genred, and genres).
3. Remove 1grams appearing fewer than three times, which often includes optical character recognition errors.
4. Remove 1grams shorter than three characters and longer than 25 characters, again often OCR errors but also stopwords that will be removed anyway.[3]
5. Remove 1grams longer than three characters that are all the same letter, often OCR errors but sometimes real, as in Roman numerals.
6. Compile baseline word counts for each document assuming that at this step the documents contain only valid terms, and no OCR errors.
7. Remove SMART stopwords.
8. Remove numbers.
9. Remove punctuation, except intraword hyphens.
10. Lemmatize or stem English words.
11. Remove lemma with fewer than three characters.
12. Aggregate 1grams defined by a single lemma and, for ease of interpretation, name the sum after the most common 1gram.
13. Remove terms appearing in fewer than 20 documents.
14. Remove documents that, after the above filters, have a word count of fewer than 500 words.
15. Remove documents that are identical in content to another document even if metadata differ, i.e. reprints.

The initial query returned 7,695 articles from 1,205 different journals, as well as 6,485 book chapters from 4,427 books.

[3]The Freudian "id" is an unfortunate casualty of this step, as well as some footnotes, endnotes, and captions containing small text where word boundaries were not detected during OCR and a series of words was concatenated.

After the above processing steps, the sample was reduced to 3,547 articles and 2,797 chapters, or 6,344 total texts.

It is fair to ask what is lost during the pre-processing of texts. Many are included in error due to JSTOR's internal translation of abstracts; where "genre" is the French translation of the English "kind" the text will be included even if the term genre does not actually appear in the English title or abstract. While I do not carefully look at the content of the excluded documents, assuming they were not texts that made important use of the term genre, I do retain some information about what components of a text were lost of those documents that were not cut. This is a measure I call idiosyncrasy, or the proportion of terms in a document eliminated during pre-processing. I call it idiosyncrasy because the pre-processing condition was that terms would be eliminated if they did not appear in at least 20 other texts. Texts that lost a large volume of words to this filter are drawing on a vocabulary that almost no other texts use. It would not be surprising if these were ethnographic or content analytic studies of non English materials.

Figure **??** shows the right-skewed distribution of idiosyncrasy. The median text lost about one tenth (10.19 percent) of its words, while 90 percent of texts are within two tenths, and outliers begin at about three tenths as can be seen in the boxplot. The 153 (2.41 percent of) texts above three tenths vary across a range as wide as the rest of the distribution. The most idiosyncratic text, at 60.4 percent of its vocabulary lost, is Welsh's "Editorial: The Genre Revival".[4] The article, from the journal *Hebrew Studies*, is a single page introduction in English to a 12 page essay reprinted in the original Hebrew. By page count alone we would expect the idiosyncrasy to be 12/13 or 92.3 percent, which also illustrates how terms that are not in the Roman alphabet may be discarded as OCR errors even prior to the idiosyncrasy measurement.

[4] www.jstor.org/stable/10.2307/27909026

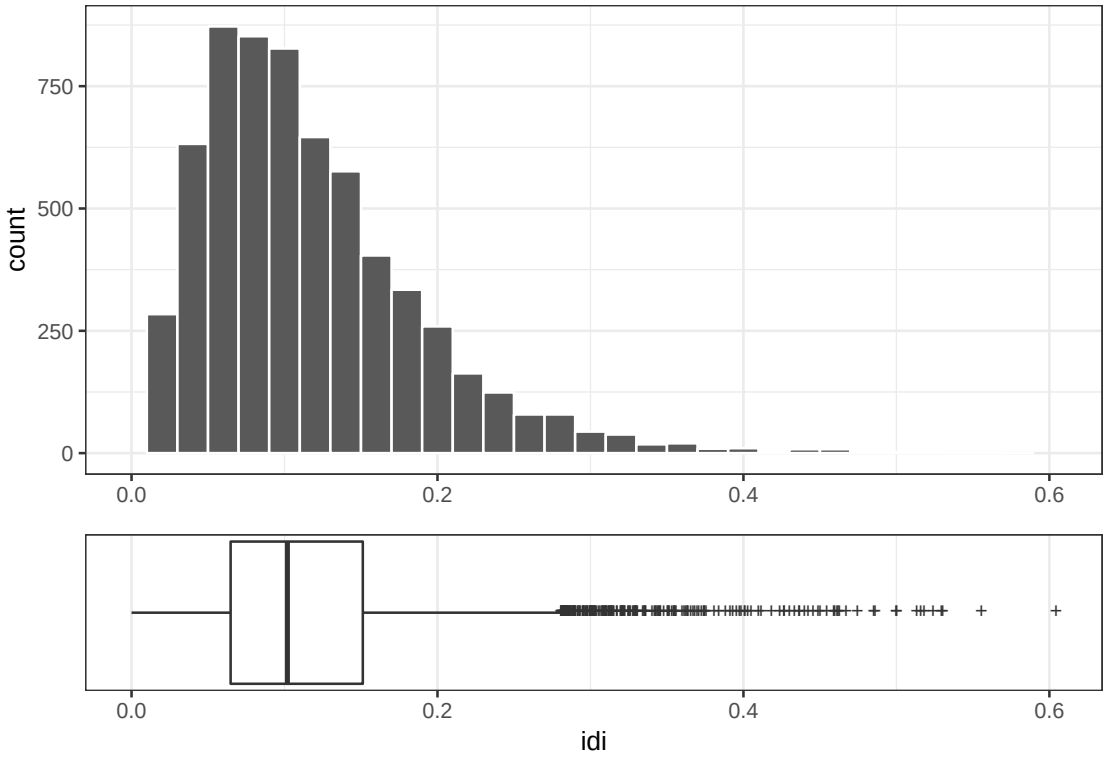


Figure **??** shows the logarithm of the count of the term genre as a proportion of the total term count of a text. This distribution is much more highly skewed but contains fewer outliers. In the median text a genre variant accounted for about 6 in 1,000 terms, while at the 90th percentile the rate is 27 in 1,000. 44 texts (0.69 percent) are outliers where one in ten or more words is a genre variant. The text with the largest genre proportion, at 35.7 percent of its words, is Welsh's "Editorial: The Genre Revival"[5], a single page introduction in a special issue of *Literature/Film Quarterly* on genres.

[5]www.jstor.org/stable/10.2307/43795866

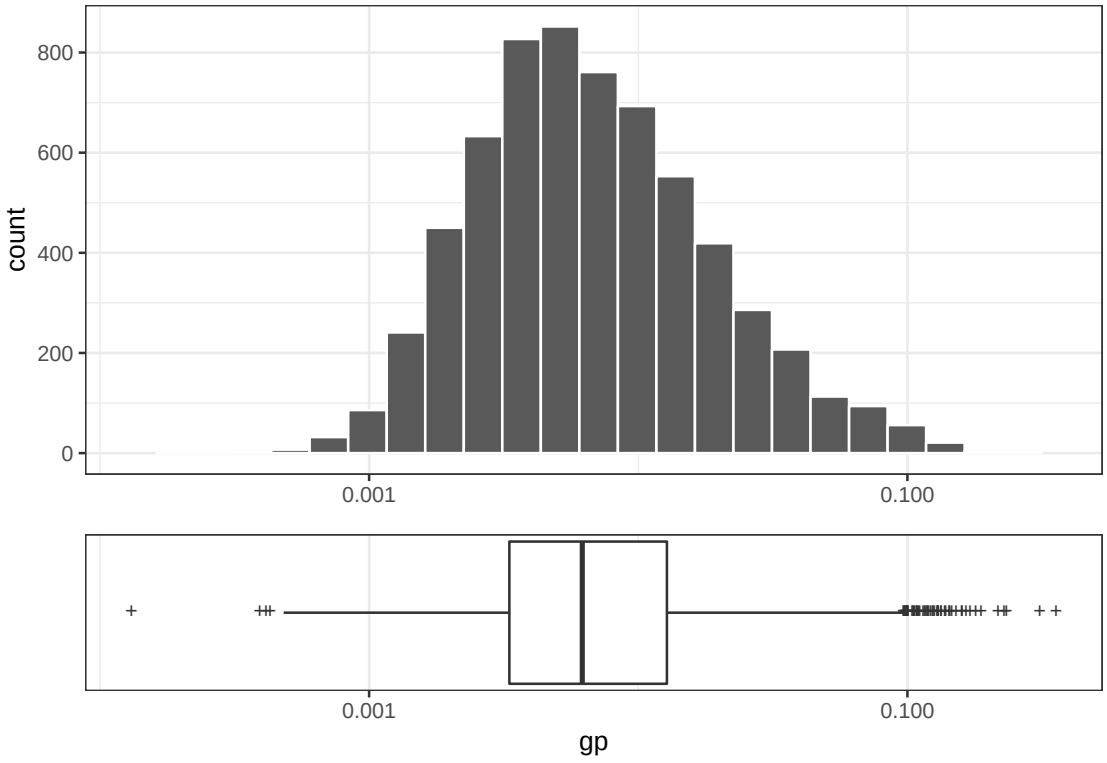


Table 3.2: Subject Distribution of Texts

Subject	N Percent	W Percent	N Rank	W Rank
Language & Literature	20.29	26.96	1	1
Humanities	13.45	11.5	2	2
History	8.77	8.56	3	3
Social Sciences	7.19	5.46	4	7
Area Studies	5.57	3.55	5	6
Sociology	4.72	5.57	6	4
Film Studies	4.02	6.09	7	8
Music	3.83	4.84	8	5
Arts	3.65	3.33	9	9
Education	2.89	2.39	10	11
Religion	2.64	3.06	11	10
Anthropology	2.06	1.87	12	13
Art & Art History	1.95	2.17	13	12
Asian Studies	1.77	1.18	14	15
Performing Arts	1.55	1.71	15	17
Linguistics	1.46	1.2	16	16
Philosophy	1.2	1.24	17	14
Middle East Studies	1.02	0.65	18	19
Political Science	1	0.88	19	21
Other	10.98	7.79		
Total	100.02	100.01		

Table 3.2 enumerates the subject labels each text inherits from its parent book or journal. JSTOR categorizes the volume

rather than each item of its contents, and volumes may bear multiple labels. The count (N) of discrete labels as a percentage is listed first and the table is sorted by that figure. In addition, to prevent double counting of texts bearing multiple labels, each label is given a weight (W) that is the inverse of the number of labels given to the text. The top three, Language & Literature, Humanities, and History, are the same in each case, while Sociology, Music, and Area Studies are ranked higher by weight than by count, an indication that Social Sciences frequently co-occurs with other labels and is therefore down-weighted. This makes sense as Social Sciences, like Humanities and Arts, is a meta subject.

"Subject" is the name given by JSTOR as a description of content, yet they also refer to "discipline", which as mentioned above is a description of conditioning social structures. This is not a mere mincing of words; the argument is that content and condition are related but not equivalent, that is, that *some* cultural formations (topics) will span social boundaries. These rankings, especially the lopsided proportion allocated to Language & Literature, provide expectations as to the number and content of topics, under the assumption that there is less within discipline than between discipline variation in vocabulary. Of course the goal is not to merely recover these discipline categories which are already given. Rather, the aim is to drill down to regularities of speech as indicators of a freely variable cultural dimension that is conditioned but not entirely controlled by social structure.

3.4 Estimation

I will I use the `stm` package in R to estimate a series of topic models (Roberts et al., 2013, 2018). The structural topic model (STM) is a variation on the correlated topic model (CTM) that allows for direct estimation of how covariates affect topic formation. The CTM was an early modification of the initial latent Dirichlet allocation (LDA) estimator, which tended to create topics that were statistically independent of each other and which therefore made it difficult to model documents as composed of multiple topics, a feature which has become central to the usefulness of topic models for applied research (Blei and Lafferty, 2007). It will be helpful to understand the complexity of the CTM before complicating it further, thus for the sake of simplicity we use the `stm` package to fit CTMs without leveraging the additional feature of covariate modeling.

To briefly explain the difference, the STM builds on the CTM by modeling the effect of document level covariates on topics in two different ways. First, covariates may affect topic prevalence. For example, including a dummy variable for the JSTOR discipline label Social Science interacted across all topic by document probabilities would provide a parameter measuring the degree to which social science texts contribute terms more or less frequently to that topic than do non social

science texts. For example, a binary category between social sciences and humanities interacted with a topic about music might show that social science texts are ten percent less prevalent in the music topic than are humanities texts. Second, covariates may affect topic content. Here the terms of a document inherit the covariate assigned to their document of origin. A social science dummy interacted across all topic by term probabilities provides a parameter measuring the degree to which a term of a particular covariate origin is more or less likely to contribute to a topic. In practice, content models help construct two different term rankings for the same topic, two because estimation on the high dimensional term vector space is intractable for all but the simplest binary covariate. In the same social science versus humanities binary, the content model would show how the vocabulary of social science texts differs from the vocabulary of humanities texts when talking about the same topic, music. In a subsequent chapter we will find occasion to use these more powerful features of the STM.

Because there are so many parameters CTM models are difficult to estimate, but the core approach is the familiar maximum likelihood framework. Estimators attempt to discover the parameters for the unobserved portions of the model that are most likely given the observed portions, the document by term counts. The estimator used in the stm package is a version of expectation maximization (EM) in which some parameters of the model are set arbitrarily, for instance randomly, in order to reduce the likelihood function to something tractable that can be maximized. The outcomes to each step of this expectation (guessing) and maximization (solving) procedure are then fed into another iteration. In practice each step of guessing leads to a smaller change in the parameters, and the model is said to have converged when the changes fall below a predetermined threshold.

The parameter space of topic models is far too complex to be able to write solvable likelihood equations and even for EM estimators to guess at them with consistent and accurate results, so topic models frequently include a raft of simplifying hyperparameters to reduce the dimensionality of the problem. It is not within the present scope to discuss these hyperparameters unless they are exogenous and can be set in ways that are practically meaningful for applied research problems. We have already discussed two of these, the alpha and sigma priors, which let us control the level of mixture of topics within documents and the correlation of topics respectively. We trust that others that are endogenous to model estimation lead to sensible results.

Hyperparameters aside, it is also necessary to initialize the substantive parameters of the model for the first EM step. The choice of model initialization is substantively meaningful and under the user's control in the stm package. For example, the CTM model may be initialized with the values of an LDA model where topics are uncorrelated; in this situation EM

would step the topic by document probabilities toward a more correlated outcome in which certain topics appear together frequently, if this model is more likely given the data.

The initialization we will use is called spectral initialization, which is related to the concept of anchor words discussed above. A spectral model considers only the square term by term matrix where each column and row refers to the number of times a particular word co-occurs within any document with every other word in the vocabulary. A dimensionality reduction technique such as principle component analysis or matrix factorization can be used to represent each term in a number of dimensions equal to the desired number of topics. This can in turn be used to initialize the topic by term matrix of the model. Finally, the usually much simpler topic by document matrix can converge quickly using EM on the basis of the good guess supplied by the spectral model.

Because the vocabulary vector tends to be very long it is not trivial even for spectral methods to reduce the term by term matrix to the number of topics without additional assumptions. Arora et al. (2018) have shown that assuming the existence of anchor words makes the decomposition fast and efficient while retaining the feature of a single determinate solution (Roberts, 2016). An anchor word is one whose probability is one for one topic and zero for all others. In the space of the solution the anchor words become the farthest corners of the multidimensional cloud of terms, and a convex hull drawn through them will contain all other terms. If the anchors are treated as singularly representing their entire topic, the position of every other term can be represented as a linear combination of the positions of all the anchors. The linear weights of the anchors then become the topic probabilities of the words, such that the closer a term is to an anchor the higher its probability from the anchor's topic and the lower the probability for all other anchors' topics. An anchor for each topic must be anointed so that its vector can be set to the assumed maximum sparsity, and the criterion for doing so is to find words with the above mentioned maximum frequency and exclusivity, words that always appear only given a particular set of other words. Even if the anchor word assumption is not strictly valid, using an anchor based spectral initialization in combination with the EM estimator may relax the assumption of sparsity (monosemy) and allow some distribution of erstwhile anchor words (polysemy) among topics.

Above we commented that sparse model techniques like L1 regularization could help clarify topics by setting more coefficients to zero. Such techniques create biased models in that they are less likely given the data, but the hope is that in the case of topic models it is the irrelevant terms of a topic or topics of a document that will be biased downward, in essence making regularization a kind of filter on the idiosyncratic portions of the corpus. Unfortunately, this desirable filter may

not be the actual effect of regularization. Sparse model techniques tend to bias downward the coefficients of terms that are highly correlated with other terms that themselves have a stronger association with the outcome. By assigning the portion of variance explained that overlaps among correlated predictors to the stronger term, it resolves an intractable ambiguity in an arbitrary way. In this situation L1 regularization may, in the topic by term matrix, occlude important and relevant terms rather than prune irrelevant ones, such as idiosyncratic or suppressed topic terms. This may actually make it harder to interpret topics without helping resolve topic corruption.

In the document by topic matrix L1 regularization may be more helpful by leading to topic concentration, which creates an effect similar to setting the alpha concentration parameter of the Dirichlet distribution in LDA below one. Like a short blanket that cannot keep the head and feet warm at once, regularization may also offset the goal of modeling topic correlation introduced by the CTM. There is no statistical guide out of this morass. The impractical solution is to fit models under multiple assumptions and compare the results by QCV. For a model that is already as complicated to interpret as the topic model, this would be a steep climb for most researchers. The normal remedy is liberal use of George Box's assertion that "all [models] are wrong" (DiMaggio et al., 2013, 582), which may not satisfy those hoping that topic models can shed light on the more easily occluded corners of intellectual history.

Notwithstanding the deep inventory of research decisions we have mentioned, will begin with the conventional hyperparameter assumption of the number of topics K. We fit nine models in sequence from K = 2 to K = 10 in order to use the development of topics through the K space as context for the interpretation of the focal ten topic model. We set the sigma prior to zero to allow for the free estimation of document by topic correlations, which can be set as high as one to mitigate the CTM. We use spectral initialization, which we recall relies on the anchor words assumption to facilitate a determinate solution the topic by term matrix that is then updated to find a more likely within document topic mixture. In spectral initialization there is no alpha concentration parameter as in LDA, and because we do not use L1 regularization we create no preference during estimation for sparse, concentrated document by topic distributions. These choices favor a less biased and more saturated model.

To set up QCV prior to model inspection, we use the document by topic matrix of the focal ten topic model to establish a sampling frame for the creation of test comparisons. These comparisons are designed to establish the presumptive substantive validity of the head of the document by topic probabilities without consideration of pathologies arising from tail-based classification errors. In these "sniff tests", which are explained in greater detail below, I ask myself to recover

model classifications of documents by inspecting selected documents without prior knowledge of topic by term content. While this is an admittedly seat-of-the-pants goodness of fit test, if I cannot make sense of topic separation then there is a more serious problem with the core deliverable of the topic model. Passing these tests is a necessary check before getting into more subtle model interpretation concerns.

3.5 Diagnostics

Having fit nine models sequentially from K = 2 to K = 10, we alight on the final as the focal model given that we assume that at ten topics we have still underspecified K. In this section I implement the several approaches to validating topic quality mentioned above. Some diagnostics use measures calculated on the first eight models to contextualize the ninth, while others are performed only on the focal model. These are necessary guides to interpreting topic models as a form of analysis whose final results are almost guaranteed to be misspecified. Diagnostic procedures help to avoid mistakes in interpreting a bad model. If all models are wrong, then it behooves us to always interpret model results in the context of diagnostics. We divide the diagnostics into two sections, lower tail probabilities and topic graphs.

3.5.1 Lower tail probabilities

First are diagnostics that each attempt to make sense of the problem of false, or at least unhelpful, probabilities often found in the lower tail of the document or term distributions.

- Ghost probabilities are terms that are predicted to be but are not actually in documents.
- Lower tail probabilities are terms that are beyond a substantive threshold of relevance.
- Junk threshold refers to the problem of estimating where the relevance cutoff is.

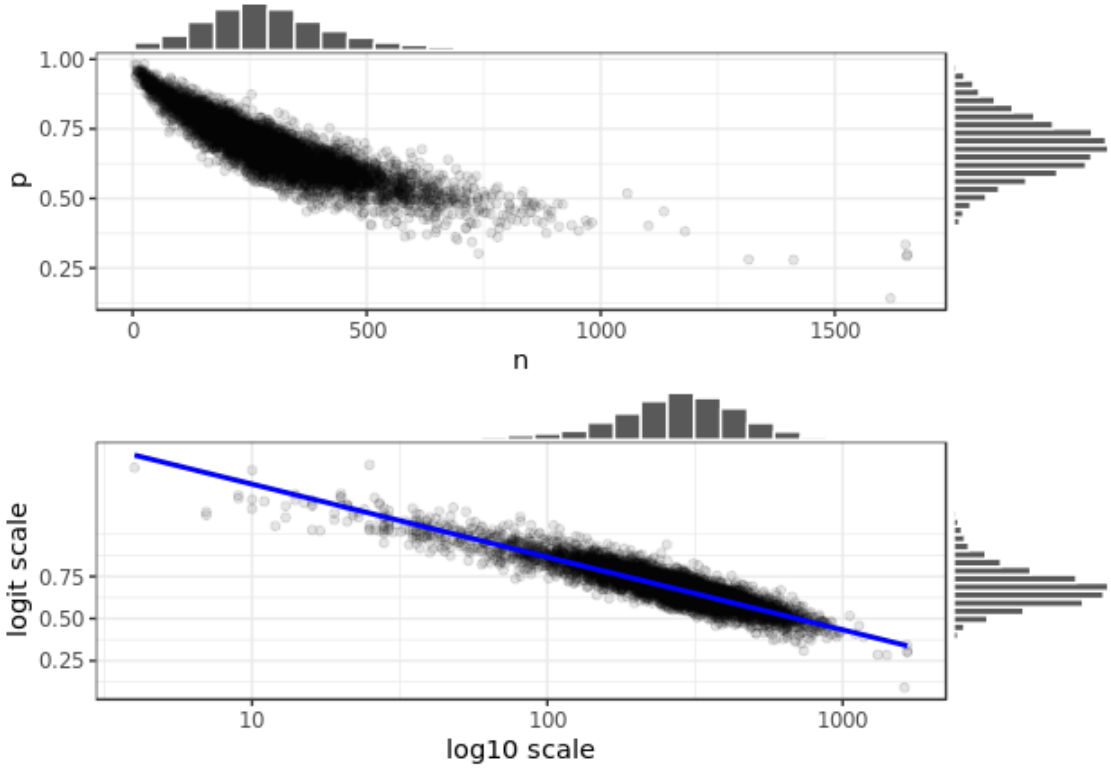
3.5.1.1 Ghost probability

Ghost probabilities are terms that are expected to be but are not actually present in a document. By the logic of the topic model these occur because documents draw on only partially overlapping vocabularies; those parts of the vocabulary that do not overlap will still be assigned to the topic and will be present only in some documents. These may well include idiosyncratic terms, in which case they represent a bad fit. If they are taken as valid then they imply that if a document were to be written again, or to continue to be written, then eventually these terms would show up. Indeed we expect the

proportion of ghost terms to be higher the shorter the document, even when the topic in which it is classified is well behaved. In the spreading activation theory briefly mentioned above, to the extent that topics can be thought of as a meaningful grounding that helps to control both the generation and interpretation of texts, then it is possible that the reading of a document containing only a portion of the topic will elicit or bring close to the mind terms that are not actually present. If the grounding is expected to be corrupted, for instance with the idiosyncrasies of very long documents, then ghost terms are a source of bias. So ghost terms are either a feature or a bug depending on how the topic model is itself reified.

The sum of ghost term probabilities by document ranges from only a few (14 percent) to almost all (98 percent) of the words predicted to be in a text. The mean and median are 68 percent and the distribution is very close to being normally distributed notwithstanding its bounding between zero and one. Figure **??** shows that, predictably, the proportion of ghost terms is strongly associated with document length. Predicting the log-odds of the probability makes for a better fit for the smallest documents (as illustrated), but for the sake of simplicity in the bulk of documents between 100 and 1,000 words in length, the association of the untransformed probability with the log_{10} of document length is linear, with a ten percent increase in length associated with a one-third (0.346) decline in the ghost probability.

In a topic model every document is predicted to be a distribution across the entire corpus. The fewer the number of words in the text, the more it will be predicted to contain words not appearing in the original. From the model perspective a small text, like any small sample, will be expected to have high variance across multiple draws. This implies that the particular instantiation of the text is arbitrary. Another way to say this is that the grounding of smaller texts is much more important than for larger texts, since there are many more blanks to be filled in. The uncertainty around small texts from a statistical perspective inverts the usual sense that a reader has that a smaller portion of text is easier, not harder, to understand, or from the writer's perspective, that brevity is the soul of wit. Of course such ease would derive from the quality of the reader's own grounding; short texts never seen before may be difficult for both human and machine alike to classify because they lack the length to disambiguate the proper grounding. In any event readers using a topic model to understand short texts should question whether the model's best guess is indeed the proper semantic context for interpretation.



A document's ghost probability is related to the notion of residuals that would help assess overall model goodness of fit. A document's per term residual can be calculated as the observed minus the predicted document term probability, a document's overall residual the sum of the squares of the same. These residuals differ from the ghost probabilities in that they also include the gap in prediction for the terms that do appear in the original. Either can be used for diagnostic purposes. The ghost probabilities draw attention to more absurd prediction errors, while the residuals are more statistically precise. Table 3.3 shows the results of two separate linear regressions which help to rank topics according to each of these goodness of fit measures while controlling for the powerful effect of document length, as well as the other topics. In each, the higher the ranking the more documents within a topic are affected by poor fit. The results are not consistent between the fit measures. For the ghost probabilities model, the more a document is composed from topics 8, 2, 3, 5, and 1 the more likely it is to be predicted to contain terms it does not actually contain, while documents composed from topics 4, 9 and 6 are more likely to have their terms accurately predicted. For the residuals model, only topic 1 is expected to have a poorer fit, while drawing from topics 7, 4, 9, and 8 are all expected to improve document fit. The only topics for which the direction of effect is in agreement between the models is topic 1 contributing to bad fit, topics 4 and 9 contributing to good fit, and topic 10 being neutral.

Table 3.3: Logit of document by topic probability predicting A. logit of ghost probability or B. residual, controlling for log10 of document length

Rank	A. Topic	Ghost p Coef.	B. Topic	Residual Coef.
First	8	0.0498	1	0.0142
Second	2	0.0391	10†	-0.0002
Third	3	0.0349	3†	-0.0018
Fourth	5	0.0216	6†	-0.0073
Fifth	1	0.0176	5†	-0.0087
Sixth	7†	0.0054	2†	-0.0091
Seventh	10†	-0.0030	8	-0.0141
Eighth	6	-0.0177	9	-0.0221
Ninth	9	-0.0278	4	-0.0245
Tenth	4	-0.0324	7	-0.0295

† not significant at $p < .001$
Outcomes normalized to make ceofficents comparable.

3.5.1.2 Junk terms

Researchers who use topic models usually have a substantive expectation that there is a transition along the sorted vectors of both document and term probabilities between true and false classifications. Unfortunately the model knows no such transition, but interpretations almost always treat the mathematical feature that all topics are distributions across all words and all documents are distributions across all topics as a methodological artifact rather than a desirable result. As we have mentioned, the satisficing behavior of descending the ranked list until the researcher feels she has learned something may not be ideal. The problem is that the ranking used by satisficers may itself be biased due to the cumulative effect of lower tail probabilities.

A junk term is one that is common but unconcentrated or evenly classified across all topics. This is the model's way of saying that it belongs nowhere, which is to say everywhere. If such a term is truly evenly distributed across topics and documents then the biases would balance out. However we do not expect language to work this way; what is more common is that junk terms are parts of suppressed topics, which would emerge at a higher K, and that these topics are concentrated in regions of the corpus. If this is true, they will bias upward fitted topics that are correlated with the suppressed topic. If the suppressed topic stood in a hierarchical relationship to one topic this would not be a concern because in effect the child topic could be considered to be partially constitutive of the parent topic at a lower resolution of K. However in the expected case of more freely variable topics, unfitted topics will bias upward the topics with which they are correlated.

Some back of the envelope calculations can illustrate the pitfalls of junk terms. For argument's sake we can suppose

a problematic junk coefficient to be a function of the length of the global vocabulary vector such that the bias it might introduce to a topic would appear in a summation of some large portion of the global vector. Substantively, a topic ought to be characterized by several dozen or perhaps a few hundred terms, and because this is a feature of language and cognition we would expect it to be invariant to the size of the global vocabulary. However, as the global vocabulary grows the effect of junk terms as a source of bias increases. In our case we retained 8,390 terms in the global vocabulary vector. If conservatively we say that a topic is described by as many as 500 terms, then the unused portion of the global vector would be 1 - (500 / 8,390) or 94 percent of it.

Now we can consider how large a bias would need to be to be problematic. A bias of five percent or a proportion of 0.05 could be more than enough to for instance change a within-document topic ranking. What then is the sum of the lower tail probabilities (LTP), less than the94th percentile, of each of the topic by term vectors in our K = 10 model? Table 3.4 shows that the lower tail of the distribution ranges from one quarter to one third of the total topic probability. These are hardly insignificant portions of the classificatory power of the topics, but in order for the junk vector to bias a particular document's topic classification it would need to contain a large number of these terms, the largest of these lower tail terms being on the order of four hundredths of a percent. In the especially problematic case it would also not contain terms in the head of the distribution.

Table 3.4: Sum of topic by term probabilities below 94th percentile.

k	LTP	Max.
2	0.326	0.000436
3	0.317	0.000492
8	0.317	0.000434
5	0.307	0.000421
7	0.277	0.000381
10	0.258	0.000383
4	0.253	0.000390
1	0.252	0.000436
6	0.241	0.000398
9	0.239	0.000400

Table 3.5 illustrates the LTP problem for a document that we expect to be poorly classified, that is, that has a large portion of its explained words deriving from a topic's lower tail. The document in question, a chapter from Mason and McCruden's "Reading the Epistle to the Hebrews", is derived entirely from topic 2, which we may surmise is about

religion.[6] Here nearly a third of the terms explained by topic two come from the lower tail. If we assume that these terms are representative of topics other than religion, then we must conclude that the topic assignment of this document is biased dramatically upward, that rather than being 100 percent about religion, it is in fact 66 percent about religion, and the remainder is unexplained. In this case the corrected estimate does not alter the topic ranking since there is no topic mixture to confuse.

Table 3.5: Lower tail diagnostic for Mason and McCruden's "Reading the Epistle to the Hebrews"

Topic	Topic Proportion	N Terms Explained	LTP	N from Lower Tail	N from Upper Tail
2	0.999	298.597	0.325	97.130	201.466
9	0.001	0.168	0.000	0.000	0.168
1	0.000	0.058	0.000	0.000	0.058
10	0.000	0.052	0.000	0.000	0.052
7	0.000	0.047	0.000	0.000	0.047
4	0.000	0.031	0.000	0.000	0.031
8	0.000	0.023	0.000	0.000	0.023
6	0.000	0.016	0.000	0.000	0.016
3	0.000	0.008	0.000	0.000	0.008
5	0.000	0.001	0.000	0.000	0.001

If the terms in the lower tail are on the contrary about religion, then the document may in fact be correctly classified. Figure 3.3 shows the lower tail terms from topic 2 that are actually present in the text alongside those that are expected to be but are note present. When sorted by the expected proportion, most of the terms do not appear to be highly relevant to religion, though some–like bishop, ritual, homilies, and hell–certainly are. When sorting by those terms that are actually in the text–such as Levi, eschatological, and messiah–the religious meaning is much more clear. These results suggest that the 500 term threshold may be too low for this topic, that it has a very long list of relevant vocabulary. It is interesting to note that the term ranking by original document frequency is more suggestive of religious content, while the predicted frequency, of messiah for instance, actually dilutes the term ranking. This is an indication of imperfect fit, as a term like messiah was predicted to be less important to the text than it actually is.

[6] www.jstor.org/stable/10.2307/j.ctt1bhkpdr.8

Show 10 entries Search:

Term	Frequency	Expected Topic Proportion	Expected Topic Frequency
All	All	All	All
fall	0	0.000435	0.00
ways	6	0.000434	0.00261
political	0	0.000434	0.00
callimachus	0	0.000434	0.00
preserved	13	0.000430	0.00559
characteristics	0	0.000429	0.00
promise	0	0.000429	0.00
bishop	0	0.000429	0.00
hope	0	0.000428	0.00
birth	0	0.000424	0.00

Showing 1 to 10 of 4,066 entries Previous 1 2 3 4 5 ... 407 Next

Figure 3.3: Terms from Mason and McCruden's "Reading the Epistle to the Hebrews" that are expected to derive from topic 2

While we have already inspected the summary ranking of topics in terms of a few measures of goodness of fit, it is helpful to observe the within topic distributions of LTP, which will make the level of overlap among topics more clear. First we will inspect the primary topic classification, as it is common for researchers to reduce the document by topic probability matrix to the primary classification. Then we will look at each topic considering all LTPs at once, not just that of the primary topic.

Figure 3.4 plots the distribution of a document's primary topic classification, the topic with the highest document by topic probability for each document, over the document LTP ranking. In other words, every document is put in a line starting with the highest LTP and ending with the lowest LTP. The documents are then labeled with their main topic classification, and a histogram is drawn for each topic according to counts in bins of 200 along this line. This design mimics the satisficing behavior of the conventional reader during QVC. Topics clustered toward the head (left) of the line are composed of poorly fit documents, and those toward the tail (right) are composed of well fit documents. The plot shows that some topics are cleanly separated, namely topics 2, 5, 3, and 8 at the head from topics 9, 6, and 1 at the tail, with topics 7,

10, and 4 in the middle.

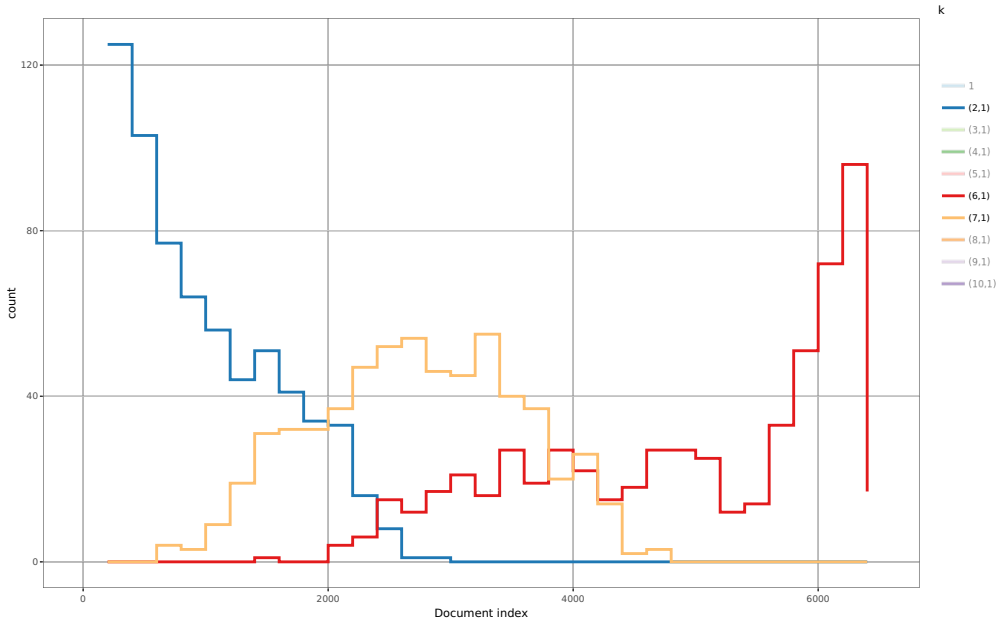


Figure 3.4: Documents ranked by sum of lower tail probabilities by primary topic classification

For a different view of the problem taking all topic LTPs into account, Figure 3.5 shows the document distribution by topic of the LTPs. Rather than looking at only the primary topic, here we separate each document into its ten topic components, thus each document is counted ten times, once for each of its topic LTPs. The logarithmic scale helps us see a fairly even separation, at p = 0.00219, between the portion of the corpus for which LTPs are and are not a serious consideration. Below the sag between the two modes the LTPs are vanishingly small and of no practical concern. Toward the upper mode, however, we are concerned that the LTPs may be a source of classification bias. This empirical separation visible on the log scale is lower than the p = .05 standard that we considered above to be practically problematic, which covers only the right hand tail of the upper mode.

When looking at the LTP distribution for all document by topic pairs we should expect an imbalance in favor of the upper mode, simply because for every well classified document a few topics will be concentrated in the head (low LTP) and the rest will be concentrated in the tail (high LTP). Poorly classified documents will be drawn from the tails of most topics. Here the lower mode accounts for 52 percent of document by topic LTPs, so the distribution is more evenly split than we

would expect with strong document classification. This can be visually confirmed by the nearly balanced shape of the black series, which shows the distribution of all 10 * 6344 LTPs.

When comparing LTP distribution among individual topics there are clear differences. Some topics have a much higher proportion of problematic upper mode LTPs than others. For example, for topic 4 62 percent of documents are poorly classified, while the same for topic 8 is 34. Overall, topics 3, 8, and 6 have lower than average LTPs, topics 4, 9, and 7 have higher than average LTPs, and topics 1 and 10 are close to the average. Topics 2 and 5 stand out by being more dramatically split between the two modes, with most of their documents having low LTPs but a few having some of the highest in the sample.

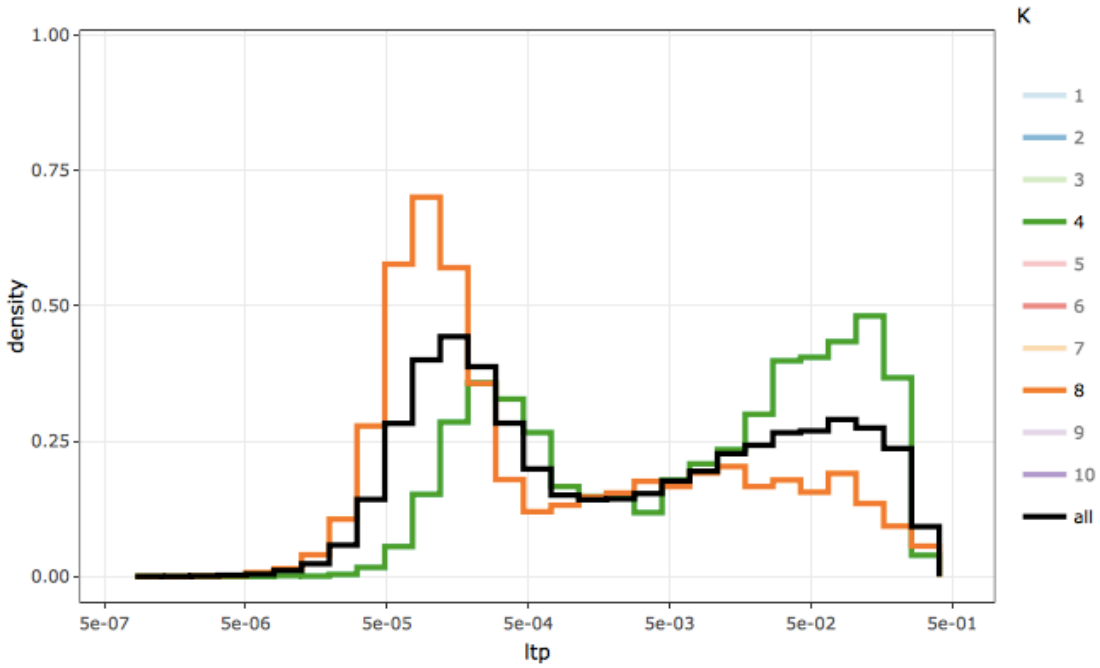
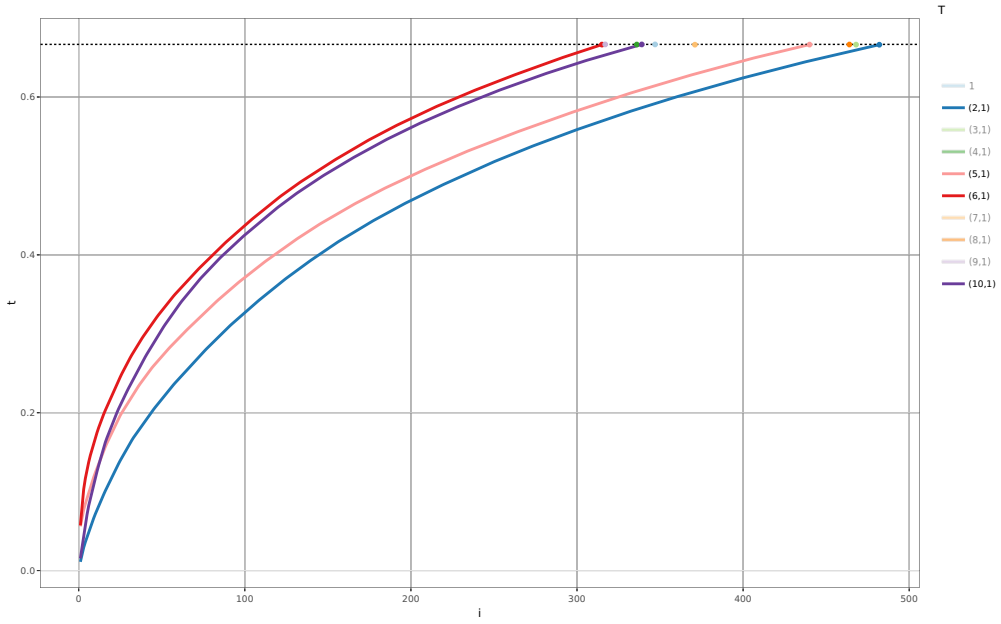


Figure 3.5: Document distribution of sum of lower tail probabilities below 94th percentile by topic, log_{10} scale

Finally, the LTP distributions explored above are based on the arbitrary cutoff at an index of 500, which we will recall was chosen to divide the topic by term vectors into true and false segments. To show that topics actually vary in the length of their relevant term lists, we can hold a particular LTP proportion constant and see how many terms it takes to reach that threshold for each topic. Figure **??** shows the cumulative proportion of the sorted term list for each topic up to an LTP cutoff of one third, or an upper head probability of two thirds. This cutoff is close to the maximum LTP at a constant index of 500, and indeed we can confirm graphically what was said above that the topic accounting for the maximum LTP is topic

2. Topics that reach the threshold early tend to have a more concentrated term vector, that is, have fewer terms accounting for the same amount of total probability.

Topic 6 reaches the threshold first at an index of 315, which is a considerably shorter list than 500. Topic 6 also starts with the highest curve, meaning that it can be summarized by a short list of high probability terms. Starting high does not necessarily mean a topic will finish early, as evidenced by topic 10, which starts as high as topic 6 but grows more slowly and finishes late. The reverse is also possible, as in the case of topic 10 that starts low and finishes early. Topics can therefore cross each other in the explanatory power of their term lists. Overall the topics are divided into a faster (topics 6, 9, 4, 10, 1, and 7) and a slower (topics 2, 3, 8, and 5) group.



While there is no substantive reason to prefer topics with concentrated term vectors, researchers tend to favor them because they are more cognitively tractable. It is hard for analysts to make sense of hundreds of terms; the more a topic can be adequately summarized by a short list the more easily it is to reify. These diagnostic plots help to identify the topics which may require additional attention to their lower ranked terms.

3.5.1.3 Zero threshhold

Whereas junk terms are spread evenly as a function of uncertainty, terms that are more confidently placed in a few topics are just as confidently excluded from other topics. It is natural to expect a term that is known to not belong in a particular topic to be set to zero. However in order to prevent the estimation of negative probability values, the quantity estimated is a transformation of the probability that approaches but cannot meet or pass a zero limit. In the STM model this transformation is the logarithm which is infinite when transforming a probability of zero. When these estimates are exponentiated to recover their associated probability, they will be vanishingly small, and some may even be returned as zero due to machine limits on the representation of small numbers. These pseudo zero coefficients are no practical bother as they are not big enough to sum, even in large numbers, to a significant probability. A pseudo zero coefficient will be a large negative number on the logarithm scale, whereas a junk coefficient, a small but nontrivial probability, will be a smaller negative number.

Zero predictions would make the strict delineation between relevant and irrelevant terms or documents easy even if it would still be an overly inclusive standard. It will be helpful to find a natural breakpoint to establish when model predictions are no longer relevant. It turns out that an empirical threshold is obvious in the case of documents but not in the case of terms.

Figure 3.6 plots the progression of modal separation of probabilities at growing levels of K. The modes are most visible in the log-odds of the probability. When K is less than 5 the distribution has three modes. In the upper mode are nearly perfectly classified documents, which suggests counterintuitively that at low Ks it is actually easier for the model to perfectly separate some documents. This high mode is mirrored at K=2 by a low mode of the same density, because for every document probability that is approximately one in one topic there must be a probability of approximately zero in the other topic. As K increases the imbalance grows as one implies K - 1 zeroes. But what is more stark is the vanishing of perfect classifications as K increases, to the extent that mode in the middle accounting for the bulk of the distribution is already below .5 even at K = 3. This implies that mixtures are indeed the normal outcome for document classification when the model allows it.

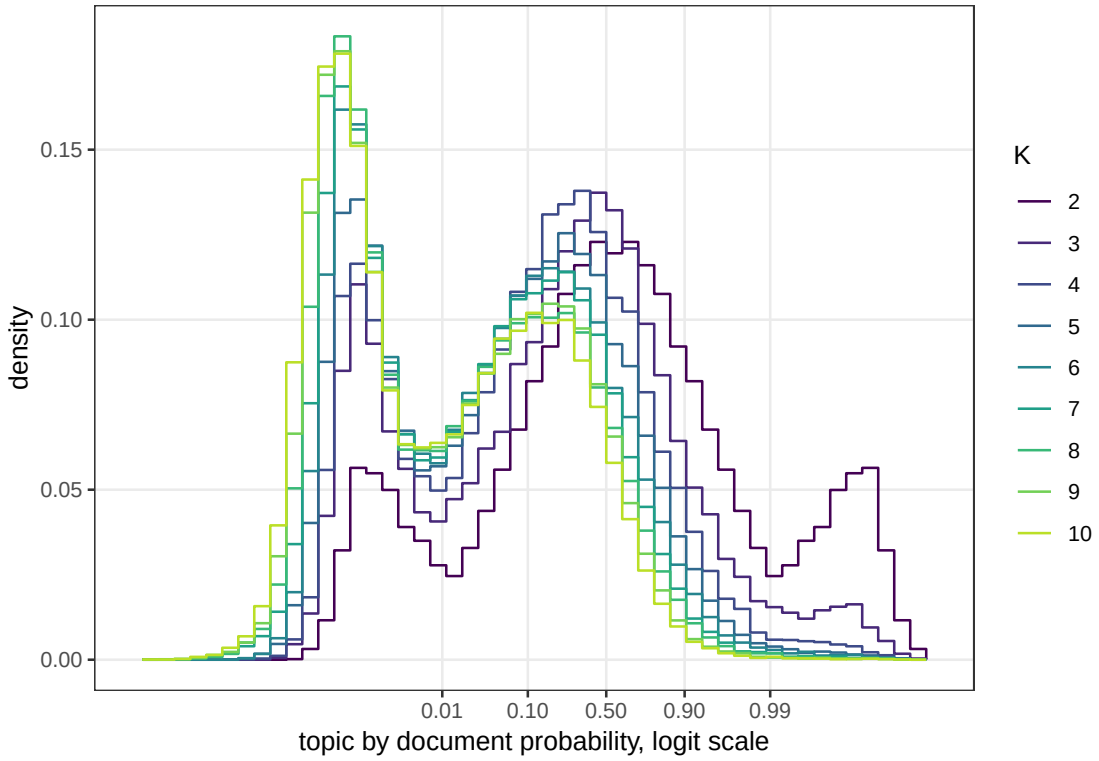
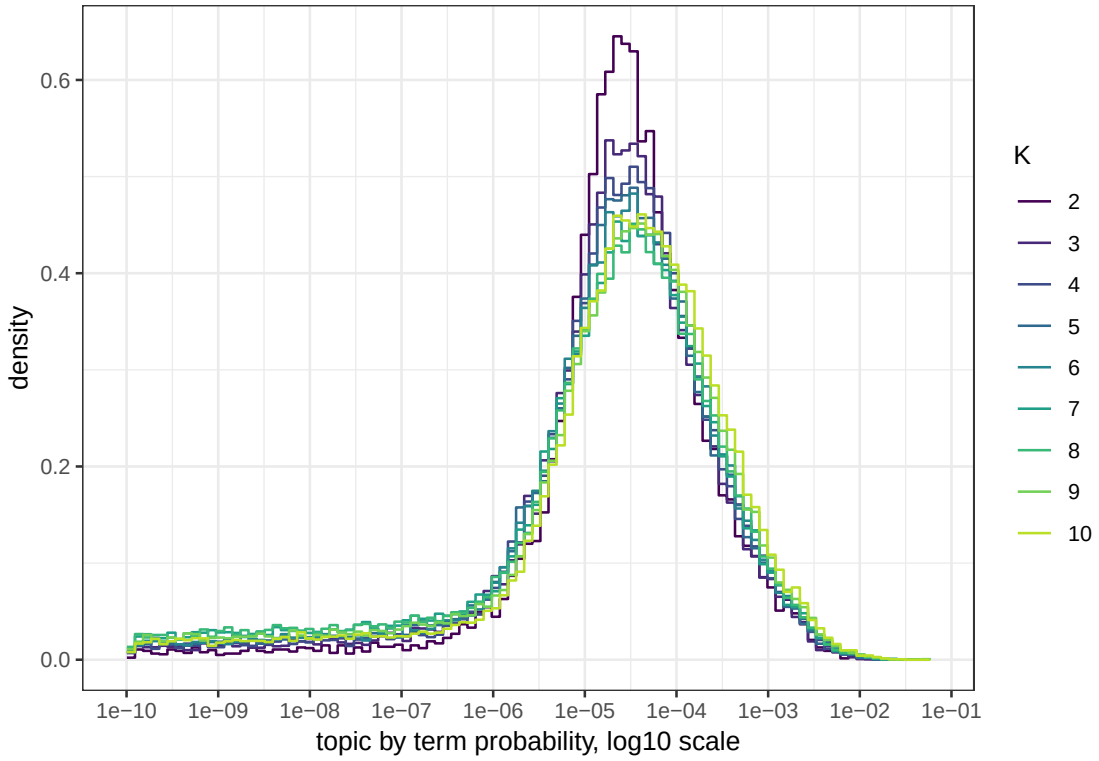


Figure 3.6: As K increases so does separation among junk (lower mode), weak (central mode), and strong (upper mode) topic by document probabilities, logit scale

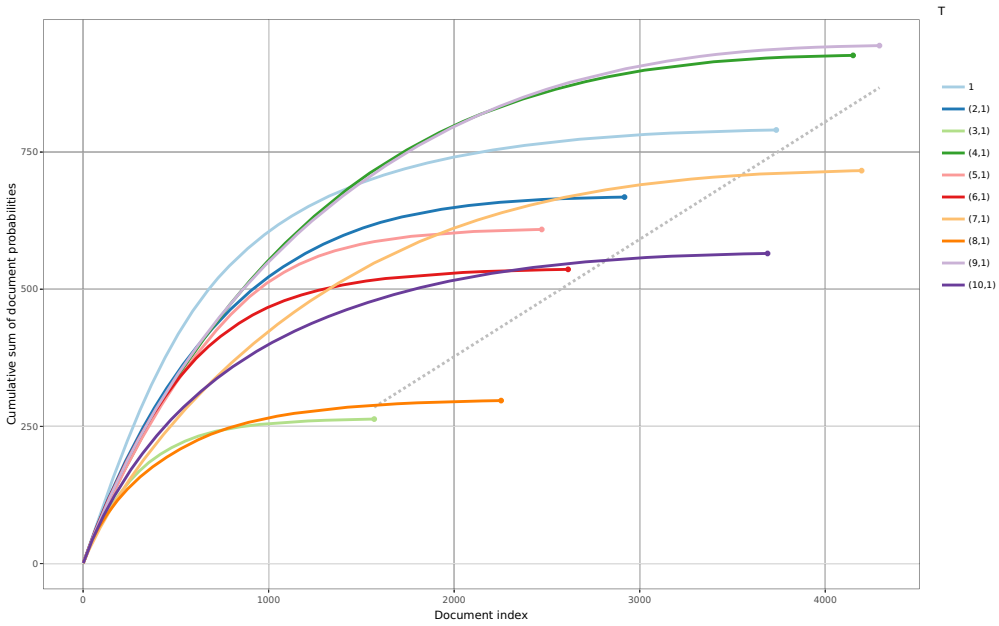
Similarly, Figure **??** shows the topic probability distribution but for terms rather than documents. Here there is no neat separation of modes between zero predictions and substantive ones. At each K there is a single mode at a very low probability of less than 1 in 10,000. In the figure the body around the mode appears to account for more of the distribution than is actually the case, as the graph is truncated at 1e-10. Not shown are the expansive left hand tails of vanishing probabilities. The portion of the distribution to the left of an arbitrary point of 1e-6 at the left base of the mode is 10.2 percent at K = 2 and 47.7 percent at K = 10. Similar to the balancing of ones and zeroes above, this fattening left tail implies that as K increases and more terms find a home in a particular topic (as the right tail thickens) the more those same terms are excluded from the other topics (the left tail thickens at a faster rate). It is worth noting that from the model perspective there are many terms that are not in the long left tail that contribute to document classification for a topic but whose probabilities are nonetheless so small that researchers are likely to dismiss them as unimportant. Within the model, a term with a probability of 1 in 1,000,000 would count as a substantive term belonging to the body of the distribution.



We can use the modal separation as a natural break in the log-odds of the document by topic probabilities to assist us in an enumeration of the number of documents relevant to each topic. Figure **??** shows the cumulative distribution of within topic document probabilities truncated at a threshold of 0.005298, the bottom of the trough between the middle and lower modes of the K = 10 distribution. Here we see each distribution rise at a certain rate and flatten off until hitting the point after which all probabilities are pseudo zero, the point approximately equal to the topic's share of corpus documents. The linear trend of the endpoints (dotted line) makes sense given that portions of documents are counted on the y and whole documents are counted on the x.

Substantively may suspect whether documents near the endpoints are indeed relevant to the topics, which implies an overcounting of relevance and a different threshold earlier in the trend perhaps nearer the elbow of each curve. It may be more useful to compare the relative landing points as well as the trajectories of the curves. The steeper the curve at the beginning, the more the topic contains strongly classified documents. Curves that grow more slowly are more likely to be in mixtures with other topics, and those that slow rapidly and come to their endpoint sooner simply represent a smaller segment of the corpus. Inspecting the first 500 documents shows four separate trajectory clusters, which do not merely reproduce the ultimate topic sizes. The low group contains topics 3 and 8. These are the smallest overall topics by document count,

yet inspecting the first 50 documents in each curve reveals that topic 8 starts with stronger document classifications than most topics but declines in rank by virtue of representing fewer documents overall. The next group contains topics 7 and 10, which start with lower classification strengths than most topics but also maintain their momentum to eventually land in the middle of the distribution. Topic 7 especially has a low trajectory but does better at maintaining it, which may indicate that it is rarely a star but commonly a supporting actor in document mixtures. The third trajectory group–topics 6, 5, 2, 4, and 9 by final count–starts in a bundle of strong classification before diverging rapidly at about index 700 as they approach their endpoints. Finally on a trend of its own is topic 1, which sustains strong classifications longer than any other topic.



These document trajectories trends provide a view of topic dominance that is different than the usual ranking of topics by their total corpus term share. The corpus term share effaces differences in document size as well as the the fact that rankings change depending on where one looks along the cumulative distributions. In this model the ranking by median document probability in the first 300 ordered documents provides a better view of classification strength among the sets of documents that researchers are much more likely to focus on during QCV. Table 3.6 shows that by this document share criterion topics 1, 2, and 6 are much more highly ranked.

Table 3.6: Topic Rankings by Share of Corpus Explained

Rank	Topic	Corpus Share	Topic	m300
First	9	0.1438	1	0.914
Second	4	0.1409	2	0.7786
Third	1	0.1253	6	0.7593
Fourth	7	0.119	9	0.7576
Fifth	2	0.1057	4	0.7363
Sixth	5	0.0973	5	0.7279
Seventh	10	0.0871	10	0.638
Eighth	6	0.0848	7	0.5905
Ninth	3	0.0495	3	0.5585
Tenth	8	0.0465	8	0.519

3.5.2 Topic Graphs

Where above we concentrated on individual terms and documents, here we take several approaches to graphing topics directly.

- A concentration plot organizes topics according to how focused they are in particular regions of the document and term vectors.
- A QCV confusion network graphs how easily a naive reader can separate topics.
- A topic descent graph contextualizes topic emergence as K increases across models.

3.5.2.1 Concentration

Though it was possible to observe concentration during a consideration of junk vectors, now we will measure concentration directly. Figure 3.7 shows the topic distribution of the Gini coefficient, a measure between zero and one where larger values indicate higher concentration, separately within documents and within terms. The document distribution has a more normal, the term distribution a more uniform shape. For documents, a mixture of a handful of topics is the norm at a median of 0.754. On the right of the distribution a small but not insubstantial number of documents are highly concentrated, which is to say classified in only one topic, while on the left is a longer tail of multivocal, or more likely poorly fit, documents composed of several topics. For the term distribution there is a wide range of concentrations of roughly equal size, that may reflect the right-to-left gradation from monosemy to polysemy and ultimately to topic irrelevance. The exceptions to uniformity are the discontinuous jump on the right of anchorlike terms that fall within one topic alone and the long left tail of guesswork, likely lower frequency terms that the model classified everywhere and nowhere.

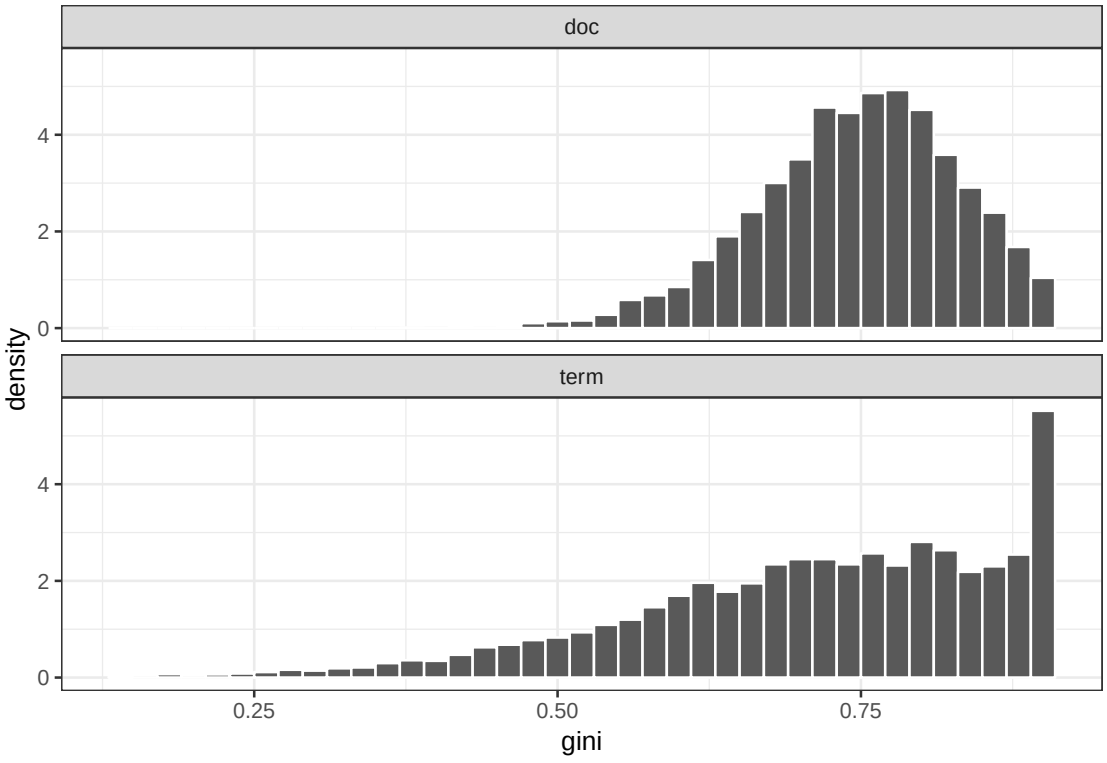
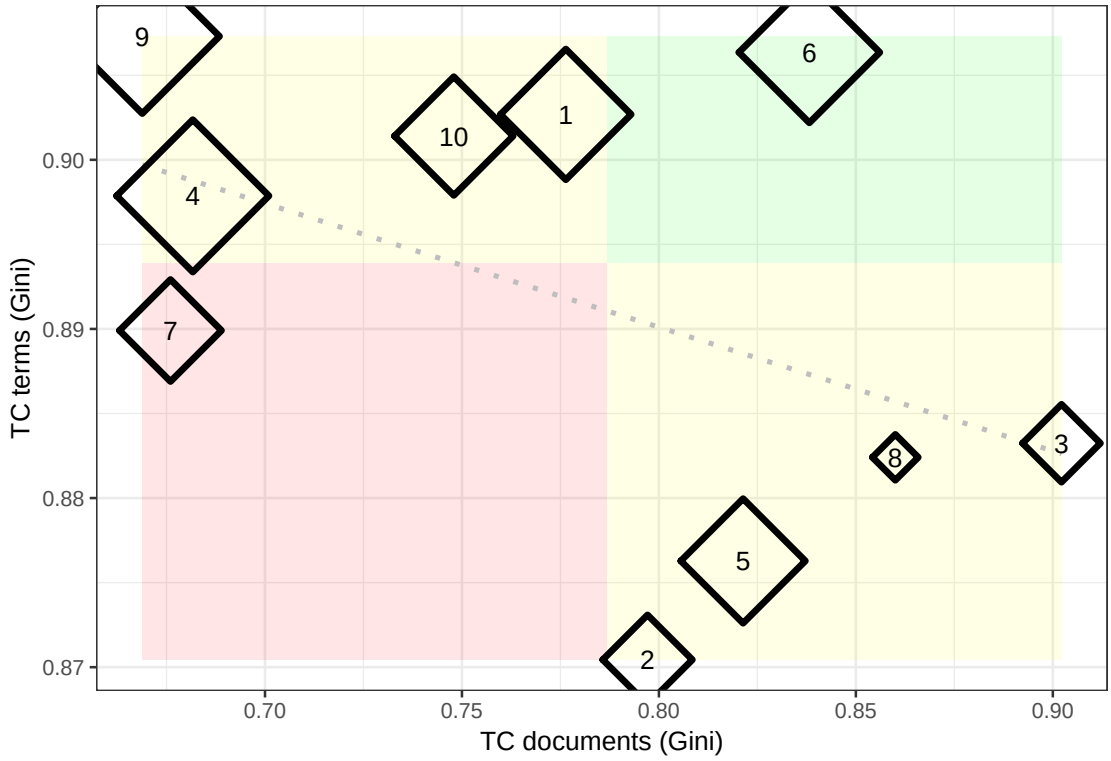


Figure 3.7: Concentration of topic probabilities within A. documents and B. terms

The concentration idea can be flipped to apply to documents within topics and terms within topics, and doing so provides useful dimensions along which to organize topics. The document within topic Gini measures whether the total document space taken up by the topic is spread evenly or not, holding constant the size of both documents and topics. The term within topic Gini on the other hand holds topic size constant but not term frequency, which is desirable in that minor documents are more worthy of equal treatment than minor terms. A high term within topic Gini represents what we noticed above that some topics more than others can be well described by a relatively short list of important terms. Figure **??** plots topics along each of these concentrations. It is divided into four regions split at the median of each axis. In the green quadrant are topics that are highly concentrated in both documents and terms, in the red quadrant are topics that are relatively diffuse on each dimension, and in the yellow are topics that are concentrated in one but not the other.



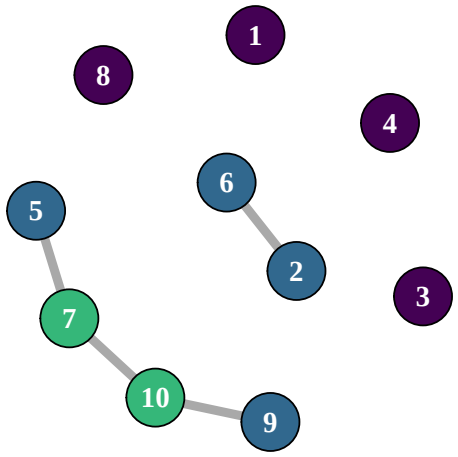
The concentrations are inversely related such that almost all topics fall in the yellow quadrants. Indeed only two topics, 6 and 7, fall in the same half of each distribution. This pattern is partially driven by size, share of corpus term frequencies, which is proportional to the area of the black diamonds. Topics composed of fewer terms have less power to fill up documents and therefore may naturally be more concentrated in documents. Topic 6 shares the desirable quality of describing a shorter list of documents and being described by a shorter list of terms. Topic 7 on the other hand is, notwithstanding being among the smaller topics, spread out among many documents while having a diffuse (though not the most diffuse) term list. A group of the smaller topics (2, 3, and 8) and one larger topic 5 are concentrated in documents and not terms, while the remaining topics 1, 4, and 10 are concentrated in terms but not documents. Topic 9 stands out as being both the most concentrated in terms and least concentrated in documents. Though it effaces the difference between the yellow quadrants, we collapse these two dimensions into one by normalizing and averaging each and assigning an overall concentration rank to each topic.

3.5.2.2 Blind QCV

Contrary to the conventional approach of inspecting the topic by term matrix first, I performed a blind QCV sorting test in which I tried to recover the model classification without prior knowledge of topic content. This test allows me to interpret topic content from whole texts rather than from the decomposed topic by term matrix and gives an opportunity to assess document classification quality prior to developing a bias about what topic contents mean. It is important to do this as soon after a model is fit as possible–but after one is confident that the model won't need to be refit!–so that other work requiring topic interpretation is not delayed and does not interfere with validation.

For each topic I created a list with 45 documents to supply five comparison cases for each of the other nine topics. These lists were the conventional document by topic rankings sorted in decreasing order of topic probability. For each of the 45 unordered topic pairs I removed five articles at random from the document list of each topic and combined them to create a new randomly shuffled set of ten containing documents from both topics. The validation task was simply to inspect each document and attempt to recover the topic groupings, the logic being that the better the document classification the easier the sorting. Difficulty was measured by the chi squared probability of the manual classification against the true classification. An additional metric of difficulty, the amount of time required to complete the task, was gathered as well but not used.

Each of the 45 sorting tasks was completed as quickly as possible, which in practice meant skimming the first page of each document. If this was enough to suggest the correct groupings the task would be finished. If the status of some documents was unclear then a closer inspection of the text would be necessary. Never was a document read closely, so topic content is still what can be gleaned from a cursory skimming of the text. Each document appeared only once within a particular topic's list to avoid the bias of knowing how a document had already been classified in a previous task. However, because a document could have appeared twice or more if it was ranked in the top 45 documents of more than one topic, some documents were seen twice. In these cases the bias would serve to confuse rather than clarify since the classification would be different between two instances of the same article.



Among the 45 different sorting tasks only two outcomes were observed. 41 tasks were performed perfectly (p = 0.0114), while in 4 tasks one error was made, which is to say two documents were misclassified (p = 0.2059). Figure **??** visualizes the pairwise outcomes as a confusion network. Topics that are disconnected were sorted perfectly, while topics that are connected were confused. The graph reveals some variation in topic confusion, as two were confused twice, four were confused once, and the remaining four were never confused.

It is not actually clear whether topic confusion is a function of document misclassification or my lack of familiarity with topic content. An added benefit of this procedure is that it begins to establish a theory of each topic by a direct inspection of bellwether texts, and this growing familiarity decreases the task difficulty over the course of the testing. In either event the results of this diagnostic provide an additional basis for understanding interpretive difficulties later.

3.5.2.3 Topic descent

All topic models are mixture models in that they treat the observed document by term frequencies as the outcome of multiple topics mixing together in different proportions within documents. Whereas the flat approach treats *documents* as mixtures, a hierarchical topic model also treats *topics* as mixtures of other topics. Here topics are mixtures of ancestor nodes

in a tree network of topics. A hierarchical model could, for instance, obviate the procedure of removing common language syntax words such as articles and prepositions because it could represent these as a root node of all topics, indicating that all vocabularies appear in a partial mixture of a language's basic syntax. A flat model retaining syntax would burden the estimator with learning that syntax terms should be distributed evenly across all topics. More substantively, a hierarchical model applied to scholarship may help pick out fields that have various empirical studies that are nonetheless united by common theory terms or argumentative style words. Because substance in its detail can easily swamp framing terminology by sheer frequency, flat topic model estimators will tend to rends apart fields where novelty is a virtue and classify them by their minutia rather than by their themes.

Models and software for hierarchical models have been developed (Teh et al., 2006; Roberts, 2015), but they are not yet in common use by social scientists. Here we use a pseudo hierarchical model in which we fit separate models at increasing levels of K, and we then do postestimation to measure the document level overlap among topics between adjacent levels of K. We refer to this as topic descent, and it shows how document classification evolves as K increases.

Because a topic descent graph represents relationships only between K-adjacent models, it is an ensemble of bimodal graphs:

$$G = \{(V_{(2,3)}, E_{(2,3)}), (V_{(3,4)}, E_{(3,4)}), ...(V_{(K-1,K)}, E_{(K-1,K)})\}$$

, where each subgraph is a vertex set composed of topics from model k and its adjacent model $k+1$ from the minimal two topic model $V_{(2,3)}$ up to one less than the maximal model K, here $V_{(9,10)}$.

$$V_k \in \{(T_{(k,1)}, ...T_{(k,n)}), (T_{(k+1,1)}, ...T_{(k+1,n)})\}$$

As bimodal graphs they allow edges only between topics of adjacent models, that is topic overlaps within models or between models that are two more more steps apart are not represented. For each pairwise combination of between model topics, we calculate their overlap as the sum over all documents of the joint probabilities that a term from a particular document would come from each topic simultaneously. The document by topic probabilities are represented by Greek letter theta, θ.

$$E_{(k,k+1)} = \sum_{d=1}^{n} \theta_{k,d} * \theta_{k+1,d}$$

This per pair per document joint probability is the expected portion of a document that would be simultaneously explained by a topic from model k and a topic from model k + 1. For example, document one has a probability of .5 from topic 1 of model k = 2 and a probability of .9 from topic 1 of model k = 3. The expected probability that the models predict the same portion of document 1 is the joint probability .5 * .9 = .45. It is the chance that the different models make the same prediction for that document. The sum of this joint probability across all documents is the total document share that the two topics can be expected to simultaneously explain if they were statistically independent. Note that this measure is willfully ignorant of the actual term overlap between the two topics and is therefore a conservative estimate. Knowing the term content may allow us to say that in fact all of the first topic is contained in the the second, in which case the overlap would be .5 rather than .45.

Figure 3.8 shows the results visualized as a Sankey diagram. Each stratum contains topics from a single model, and flows between nodes are the predicted document share overlaps between topics in adjacent strata. For clarity only the largest (blue) and second largest (red) flows are visualized, though the graph layout was calculated using all edges, and the remainder can be inferred from the edgeless space of each topic. Here we will refer to topics of the final K = 10 model by number only, like topic 8, but when referring to topics of ancestor models we will apply the model prefix, e.g. topic 4 from model k = 7 will be topic 7k4. By following the main blue flow between each level it is possible to see topic lineages that extend with continuity through several K transitions. These lineages have different depths, ranging from the longest of eight generations leading to topic 2 to the shortest of one generation leading to topic 9.

Four flow patterns are evident. *One to one* (1-1) and *one to many* (1-m) flows are common at early strata where large topics either do or do not split when an additional K slot is made available. Note that each bimodal graph in the ensemble is complete in that each topic connects to each other topic in the adjacent model. The classification of a flow between *one* and *many* is a function of the concentration of flows leading into and out of a topic. *Many* refers to a set of relatively even flows, whereas *one* refers to a single dominant flow. For example, in the flows around model k = 3, the trunk of topic 3k1 splits into two boughs (1-m), whereas the trunk of topic 3k2 remains intact (1-1). *Many to one* (m-1) flows are especially interesting, as they identify topics that had previously been distributed as junk among several topics at the preceding stratum but that flow together when space is available. These flows form the first generation of a new lineage, as in topics 5k4, 7k7, and 9k9. Finally *many to many* flows describe topics that are formed from many sources but are then immediately disbanded. This is harder to observe here where most edges are not displayed, but an example is 8k4 which draws from many topics and is then

split in two. The instability of such topics suggests a lack of validity.[7]

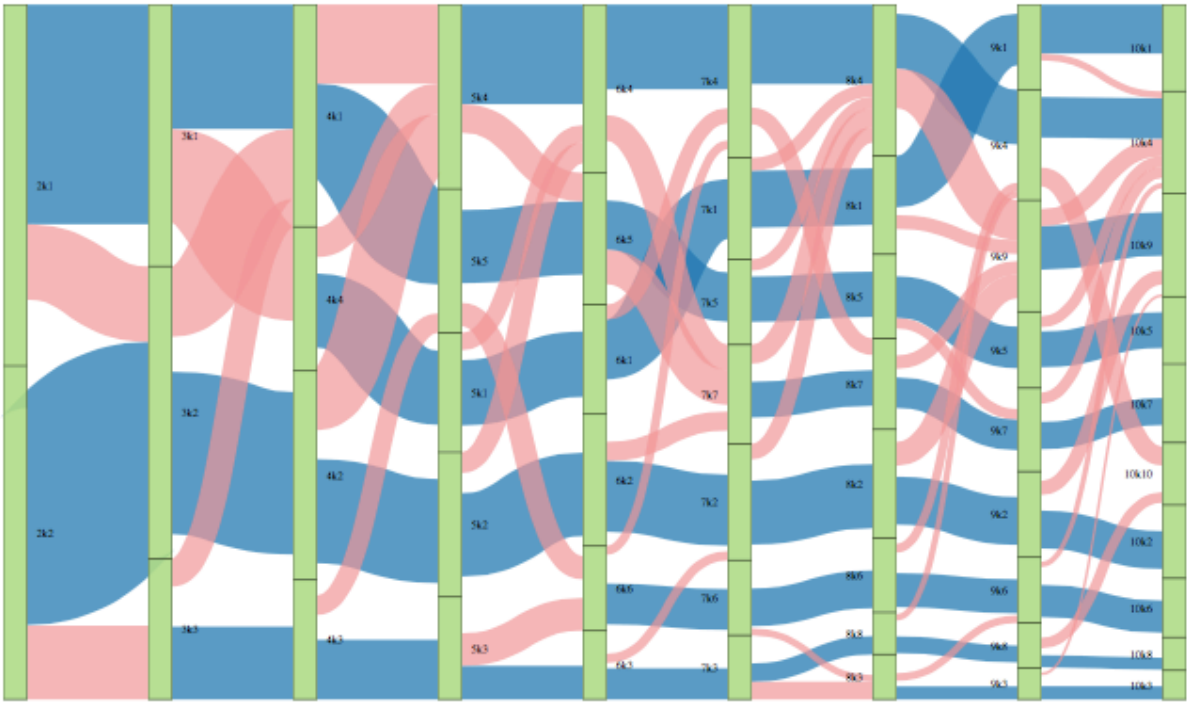


Figure 3.8: Sankey diagram of document overlap between topic models of increasing values of K.

The assumption that the depth of a topic's lineage is an indicator of the strength of its statistical signal implies stability in both the term and document list for each stratum of the lineage. The truth is mixed. The longer the lineage the more churn one would expect in term rankings as its meaning develops toward a more refined vocabulary. Refinement here means that portions of term frequencies are regrouped when a k slot becomes available and the smaller portion is pieced out of the lineage. Figure **??** shows the top 40 terms by probability for the topic 2 lineage. It is clear that there is a gradual reversal of two main term clusters. Early in the lineage it is driven by terms relevant to literary studies such as work, text, form, narrative, book, poem, and author. Certain of these, like literature, narrative, and history, decline gradually. Others, like text, poem and author, maintain their status. Unmistakably terms relevant to religion climb in prominence, with god appropriately rising to take the mantle of topic 2. Interpreting topic 2 in the context of its lineage suggests that in this corpus the study of religion is a subfield of literary studies. This has face validity given the importance of studying texts for both fields. It would be more difficult to perceive this relationship between literature and religion taking the conventional

[7]TODO: Find a concentration measure that corrects for small sample bias to help cluster nodes in these four categories.

approach of using only the lateral topics within the k = 10 model as context.

3.5.3 Summary

Above we explored ten different features of topics that may affect their substantive interpretation. We predict that documents from topics with the following features may be poorly classified, that is, their substantive content may contradict their topic driven content label. In general, topics may be considered less valid:

Term level indicators:

- **Lower tail probabilities**: The higher the topic proportion of terms below the topic by term junk threshold.
- **Term index LTP**: The higher the number of terms required to reach the LTP threshold.

Document level indicators:

- **Ghost probabilities**: The higher the average document proportion of ghost terms within a topic.
- **Residuals**: The higher the document differences between the predicted and observed term probabilities.
- **Document Primary Class LTP**: The higher the document proportions of terms below the topic by term junk threshold by primary topic class.
- **Document Total Class LTP**: The higher the document proportions of terms below the topic by term junk threshold by all topic classes.
- **Mean belwether classification strength**: The lower the document probability of the first 300 documents of topic.

Topic level indicators:

- **Concentration**: The lower the Gini coefficient topic term and document probabilities
- **QCV Confusion**: The higher the difficulty of blind document sorting.
- **Lineage depth**: The lower the number of ancestors in the topic descent lineage.

Table 3.7 shows the topic rankings for each of these indicators as well as a summary of all rankings. The highest quality topic is 6, which is usually in the top three ranks, its exceptions being higher residuals, a shorter lineage, and some QCV confusion. The lowest quality topic is 2, its exceptions being the deepest lineage and strong bellwether classification strength. Topics 6, 9, 1, and 4 may be separated as a group of higher quality than the rest.

Table 3.7: Summary of Diagnostic Ranks

Rank	ktl	cut	ghst	res	pltp	altp	m300	gini	conf	ldp	Summary	Rank Mean	Rank Variance
First	9	6	4	7	9	3	1	6	3	2	6	3.5	5.4
Second	6	9	9	4	6	8	2	3	8	8	9	4.2	9.1
Third	1	4	6	9	1	6	6	1	4	5	1	4.5	6.1
Fourth	4	10	10	8	4	2	9	10	1	1	4	4.5	7.4
Fifth	10	1	7	2	10	5	4	8	9	4	8	5.8	10.4
Sixth	7	7	1	5	7	1	5	9	5	6	3	6.3	12
Seventh	5	5	5	6	8	10	10	5	6	7	5	6.3	2.5
Eighth	8	8	3	3	3	7	7	4	2	3	10	6.4	5.4
Ninth	3	3	2	10	5	9	3	7	10	9	7	6.6	6.3
Tenth	2	2	8	1	2	4	8	2	7	10	2	6.9	12.8

3.6 Topic interpretation

At long last and armored with a diagnostic assessment of the topics, it is appropriate to interpret the model content of topics. We have three exhibits to assist us in topic interpretation. First are journal topic associations. Second are notes taken above during blind QCV of bellwether texts, which usually amount to gut reactions to the front matter of articles. Finally we will inspect the topic by term lists directly. We will initialize each topic interpretation by inspecting journals and bellwethers, and then we will elaborate the content using the model lists, being sure to note instances of polysemy.

3.6.1 Journals

A good place to begin is to ask whether we have done more than merely reproduce a categorical scheme we already had access to. If topics are entirely predicted by journals, then they may not be very valuable as guides to scholarship, though confirming this would be an argument against the importance of interdisciplinarity. Figure 3.9 shows the relationship between topics and journals when documents are assigned to their primary topic classification. Each journal is scored by the standardized χ^2 residuals from a test of categorical association between a table of topics by journal document counts. The standardized residuals can be interpreted as t-scores on a normal distribution; they represent the distance between observed and predicted table frequencies in standard errors from what would be expected if the dimensions were independent. Roughly, scores with a standardized residual higher than two are worth noting, and the higher the residual the stronger the association. Rather than sort through all 874 discrete journals for each topic, I report only the top ten highest residuals.

Show 10 entries Search:

Topic	Journal	Residual
All	All	All
4	Science Fiction Studies	19.09
4	Callaloo	5.37
4	Journal of the Fantastic in the Arts	5.3
4	MELUS	4.73
4	Biography	4.63
4	Russian History	4.16
4	Studies in East European Thought	4.16
4	Latin American Perspectives	4.11
4	Research in African Literatures	3.46
4	American Literary History	3.39

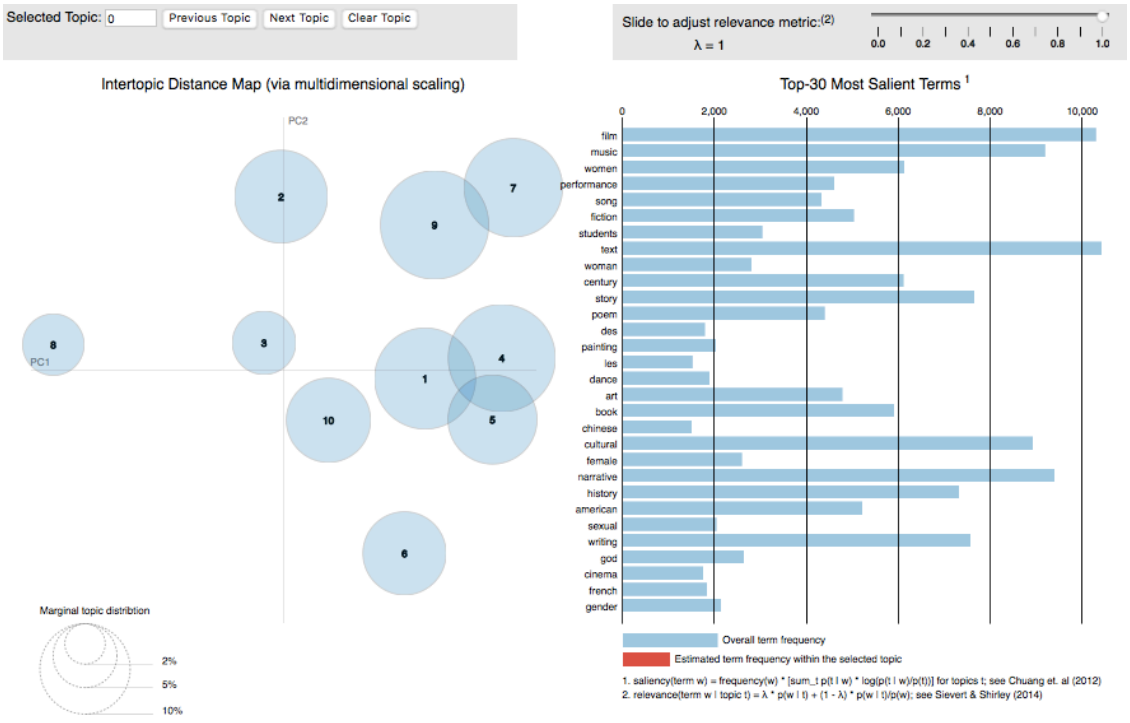
Showing 1 to 10 of 100 entries Previous 1 2 3 4 5 ... 10 Next

Figure 3.9: Journal Topic Associations

3.6.2 Belwether texts

Recall that the inspection of bellwethers occurred in the context of a shuffled list coming from two topics. Notes were taken to record the rationale that was the basis for splitting the texts into two groups. Over the course of the 45 separate tasks, themselves shuffled randomly, the rationales for each topic set in and the sorting task became easier. Below we characterize each topic based on an inspection of the journals with which they are associated and the blind QCV notes.

3.6.3 Terms



The topic by term matrix is unwieldy; Figure **??** provides a browser generated by the `LDAvis` package that helps display topic associations and term lists. In the left panel a multidimensional scaling technique is used to reduce the term vector two two dimensions. The area of topic bubbles is proportional to the topic's share of total corpus frequency, and shorter distances between topics indicate similarity in term content. In the right panel terms are displayed as bars with their topic frequency (red) as a share of their corpus frequency (blue). This list may be sorted by several scoring techniques that operationalize the notion of exclusivity in different ways.

First, when no topics are selected, the list is sorted by a score called saliency. Saliency is a measure of how informative a word is for guessing the topic from which it comes. Terms that are both very frequent and very exclusive rise to the top of this list, and indeed the most salient term "film" is very frequent and is an anchor term for topic 5. Recall that anchor terms are found in one and no other topics. It is rare to be frequent and an anchor; it is more common that terms are frequent but salient by virtue of being totally absent from some if not all other topics. For example, the term "text" is common and found in almost every topic, but is totally absent from topics 5 (film) and 6 (music), which makes sense if text, film, and music are simply different terms for what is a singular object orientation of each topic. The few true anchor terms on this list are film (5), les (8), chinese (3), sexual (7), and cinema (5 again!). Anchor terms for the remaining topics are too infrequent to show

up as globally salient, but they include literacy (1), biblical (2), utopia (4), musicians (6), hamlet (9), and painter (10).

Second, when a topic is selected its terms can be ranked by a score called relevance (Sievert and Shirley, 2014, 66). Relevance is a balanced sum of the overall frequency of a term and its lift, which is its topic frequency as a proportion of its corpus frequency. The weighting parameter lambda (λ) sets the balance of the sum. When lambda is one terms are sorted in the classic order of their topic probability. When lambda is zero terms are sorted by their exclusivity to the topic regardless of how infrequent they are (practically, a setting just above zero allows anchor terms, which all have equal rank and a topic proportion of one, to be sorted by their frequency). Setting lambda to zero will put all anchor terms at the top, and empirically it turns out the anchor list is often quite long. Practically, setting lambda to 0.5 tends to nominate a handful of terms important to the focal topic as well as others, highlighting cases of polysemy, ambiguity, or true pantopical relevance.

Recall that goodness of fit during estimation makes reference only to a topic's ability to explain global corpus frequencies. While relevance and salience are interesting postestimation techniques, estimation was not designed to form topics that maximize them. Nonetheless, to the extent that anchor words are highly relevant, the use of anchor words to initialize estimation does allow these particularly relevant terms to impact model results. Though we did not describe the model method of choosing anchor terms, the ultimate choice remains apparent in the final model as an artifact. Anchor terms are identifiable as the only terms for which the fitted log of the probability is -1000, the arbitrary minimum, for the nine topics for which the term is *not* the anchor.

3.6.4 Dossiers

Below we assemble the several source of topic interpretation to create a dossier on each topic, and finally establish for each a theory of topic meaning. Recall that until this point we have been reticent to describe such theories for fear of the confirmation bias they will exert on close readings of texts. These biases are inevitable and the goal is to exert some control over their formation rather than to presume we may approach texts from an unbiased vantage point. Thus we expect that in the writing of dossiers we will at this stage solidify the confirmation bias that will inform the subsequent "close, but" readings of texts. We table the problem of seriation and proceed in numerical order to aid in later referencing. Each dossier was written by first completing the initial characterization from journals, then layering on bellwether considerations, and finally by inspecting topic term list. For concision we present all of the results for each topic in one paragraph.

3.6.4.1 Topic 1, *students*

Topic 1 refers to what I above called the "abstract" sense of genres of discourse. The leading journals are different; the first *Discourse Studies* is general while the second *Research in the Teaching of English* seems to apply the notion of discourse to the particular professional domains of education and literacy. During QCV the importance of discourse was never noticed, and it was almost entirely taken to be about teaching and pedagogy especially with respect to writing. A few articles dealt with technical writing in business rather than in education contexts. From the term lists the model anchor "remake" is not expected, and in fact we might have expected it to occur in topic 5. The bulk of the terms are related to education. Not only "discourse" but "writing", "reading", and "text" share considerable overlap with other topics, and may help place topic 1 in a central location on the topic map.

Table 3.8: Topic 1 Terms

lambda	Terms
	model anchor: remake
0.01	literacy, students, classroom, data, grade, curriculum, learners, textbooks, pedagogy, courses
0.5	students, research, writing, study, teachers, genre, language, discourse, learning, information
1	genre, writing, students, text, study, language, research, discourse, social, reading

3.6.4.2 Topic 2, *god*

Topic 2, which above we interpreted as religious studies, is here led by the journal *Quaderni di Studi Arabi*, which is dedicated to the culture and history of Arab civilization. While that scope may include religion we would expect it to extend far beyond it. While there are certainly more explicitly religious journals among the list, there are also journals dedicated to antiquity. This helps broaden our understanding of the topic, which is more about the history of Abrahamic civilization than about religion narrowly. We should also resist a western centric notion of religion, as we are bound to discover important religious themes in topic 3. During QCV this was often labeled as "biblical" with occasional reference to Islam or the Quran or Hellenism. Indeed the most relevant term "ibn" means "son of" in Arabic names. The model anchor "Twain" seems fairly oblique to the topic although Mark Twain may have spoke frequently of god. The term lists remind us that underlying biases in publishing, here the over representation of Christian topics, can be reproduced with a naive focus on high frequency terms.

Table 3.9: Topic 2 Terms

lambda	Terms
	model anchor: twain
0.01	ibn, biblical, jesus, prophet, arabic, hebrew, testament, ovid, virgil, persian
0.5	god, christian, der, und, arabic, jewish, die, greek, islamic, ibn
1	god, text, poem, tradition, poet, der, christian, book, die, und

3.6.4.3 Topic 3, *chinese*

Topic 3 includes several pan Asian studies journals as well as journals focusing on Japan and China. Like topic 8 the signal in likely due to language and cultural content and perhaps more simply geographical terminology like state names. Unlike topic 8 they were not drawn into the sample because of a coincidental meanings of "genre" in French. During QCV a specifically historical thrust was apparent especially with reference to Chinese imperial dynasties. Interestingly Hittite civilization appeared more than once, which is geographically closer to the content of topic 2 but nonetheless categorized separately. Several references were made to the Song dynasty, which poses a true polysemy and disambiguation challenge with respect to topic 6.[8] The terms contain many more proper nouns, place and person names, than other topics, and raise the importance of Japanese and Korean topics that were not as apparent in the bellwethers.

Table 3.10: Topic 3 Terms

lambda	Terms
	model anchor: shuo
0.01	chinese, china, shi, korean, wang, buddhist, zhang, tokyo, liu, shu
0.5	chinese, japanese, china, japan, korean, shi, hong, wang, liu, han
1	chinese, text, japanese, china, song, line, time, japan, century, work

3.6.4.4 Topic 4, *fiction*

Topic 4 is almost exclusively concentrated in the journal *Science Fiction Studies*, with a smattering of weaker associations across a diverse set of journals. This suggests a fairly narrow focus, not even of fiction but a subgenre of it. During QCV the topic was difficult to disentangle, though ultimately it was not confused with any other topic. It was often noted to be fiction or science fiction, but as often it included the analysis of cultures of utopianism or futurism, often applied in nonfiction settings, for instance, to study historical narratives in support of political racism and in various locations like the American

[8] Only challenging due to the preprocessing decision to convert all terms to lower case. Had "Song" and "song" been left separate, disambiguation would not have been a problem. The model estimates that 14 percent of instances of song are from topic 3 and 82 percent are from topic 6.

west, the USSR, and post colonial Africa. Inspecting the term lists seems to efface the prominence of science fiction in favor of a political and historical terminology, though the model choice of Asimov for an anchor is a helpful reminder of the journal origin of the topic. The mixing of fiction and nonfiction topics may be a symptom of poor fit, or there may be a real elective affinity intersecting on utopianism.

Table 3.11: Topic 4 Terms

lambda	Terms
	model anchor: asimov
0.01	utopia, utopian, postcolonial, slavery, douglass, dystopian, suvin, soviet, stalin, genocide
0.5	fiction, political, science, history, american, cultural, narrative, story, world, national
1	fiction, political, narrative, cultural, history, story, world, american, social, science

3.6.4.5 Topic 5, *film*

Topic 5 is very well represented among a variety of journals dedicated to film and cinema. We wonder if the quantity of journals is reflective of industry support. Mixed with film articles were several related to television and one related to video games, perhaps sharing terms in common to the description of U.S. industrial entertainment media. The horror genre appeared to be over represented. We may speculate that subtopics with more exclusive vocabulary, even if they are a minority of cases, may come to be more representative of a topic than one would expect. Indeed the term lists reveal "Dracula" to be the model anchor and "zombie" and "horror" to be highly relevant, whereas "noir" is the only other subgenre term showing up in the top ten lists. While it is possible that horror is actually over represented in film scholarship, the model behavior suggests that it merely has a more distinctive vocabulary. Topic 5 was confused once with 7, perhaps due to the importance of storytelling to each.

Table 3.12: Topic 5 Terms

lambda	Terms
	model anchor: dracula
0.01	film, cinema, movie, hollywood, shot, cinematic, lms, filmmakers, camera, zombie
0.5	film, cinema, movie, television, hollywood, game, horror, shot, noir, director
1	film, genre, cinema, movie, american, audience, character, time, show, production

3.6.4.6 Topic 6, *music*

Topic 6 has several strong journals led by *Popular Music*, and interestingly *Asian Theatre Journal*. Farther down the list are discipline specific journals. The music topic was obvious and noted to be sorted with particular ease during QCV but was actually confused once with topic 2. The model anchor "jin" is probably a reference to the Jin dynasty in China, which indicates a curious segregation of the historical relevance of music in a presumably theater context from the rest of topic 3, where the model assumes that the term Jin is *never* discussed. Similarly, it is telling that the term "Indonesian" can be understood by its placement as an exclusive term in a music category to never be relevant to another topic. We might expect historical geographies to be relevant in all of their cultural dimensions, but at least with reference to the term genre there is considerable topic segregation.

Table 3.13: Topic 6 Terms

lambda	Terms
	model anchor: jin
0.01	music, dance, musicians, jazz, singer, rap, drum, hop, hip, indonesian
0.5	music, performance, song, dance, singing, musicians, singer, folk, record, band
1	music, performance, song, cultural, dance, popular, genre, play, tradition, record

3.6.4.7 Topic 7, *women*

Topic 7, like 4, is concentrated in one journal, *Marvels and Tales* which is about folklore, yet the second journal *Culture, Health & Sexuality* could not seem more different. Two other journals relate to women's studies, and several other journals relate specifically to British folklore. During QCV this topic was misunderstood as two different topics, one about folklore and one about gender and sexuality often with reference to youth and family. This may help explain why topic 7 was confused twice, once with 5 and once with 10. It is possible that the importance of family and gender in folk tales, for instance Arthurian tales of chivalry, allows folklore to be merged with modern gender studies. The model anchor "Archie" likely relates to problematic gender assumptions in the comic book series. The term lists otherwise describe a topic that is unequivocally about gender and sexuality, with queer topics showing up as highly relevant. Only one hint of folklore, Gawain, is observable in the top ten lists. Farther down the list especially at lambda = 0.5 are terms specific to family relationships, "husband" for instance being an anchor word.

Table 3.14: Topic 7 Terms

lambda	Terms
	model anchor: archie
0.01	sexual, feminine, heroine, husband, queer, lesbian, homosexuality, heterosexual, maternal, gawain
0.5	women, woman, female, sexual, gender, male, love, mother, men, tale
1	women, story, woman, narrative, female, love, men, sexual, gender, male

3.6.4.8 Topic 8, *les*

Topic 8 is seemingly related to French and music studies but is led by the biology journal *Crustaceana* and includes *Botanical Review*. This collection is likely united by the appearance of many French language terms, caught in the initial sample definition of the common French term "genre", which after all is a French loanword translating to "kind" but in the native tongue referring to much more than culture. Indeed genre also has the more special meaning "genus" which explains the appearance of life science journals. These errors should be removed from the sample but they provide an instructive challenge, or perhaps an easy win, for the topic model estimator. Unfortunately removing texts by the topic score may actually eliminate substantive texts that happen to deal with French language content but are relevant to genre studies, so removal by journal is more appropriate. During QCV several articles related to orchestral music, one of which was in Italian not French, and Gregorian chants appeared. It was noted that English language articles had the term genre included in a French translation of their abstracts, an in this case nuisance feature of the JSTOR search not disabled by a specific filtering by language. The term list is populated with not only French but also Spanish and Italian stopwords. Topic 8 is so different that it forms its own axis in the scaled topic map.

Table 3.15: Topic 8 Terms

lambda	Terms
	model anchor: epiphany
0.01	les, del, qui, une, pour, una, motet, madrid, chanson, tout
0.5	les, des, del, paris, french, est, spanish, qui, une, france
1	les, des, french, paris, spanish, del, est, text, work, century

3.6.4.9 Topic 9, *genre*

Topic 9 has one leading journal (*New Literary History*) like 7 and 4, but there is a clear "language and literature" trend among even the more weakly associated journals. It is interesting that the second journal *L'Esprit Créateur* is a French

language journal; we may anticipate some overlap with the French language topic 8 that may suppress its prominence here. Also our limited glimpse at topic 2 to illustrate topic descent above revealed the importance of poetry, and topic 9 includes *Victorian Poetry*. If the term poem is indeed important to topic 9, then it is a caveat against interpreting a term important across multiple topics as exhibiting polysemy, since here it would clearly have the same meaning just in different substantive contexts. During QCV it was sometimes hard to sort, and sometimes treated as separate literary theory and philosophy topics. It is possible that elements of style, such as a stilted or abstract diction, cause these areas to merge. Indeed the likely derogatory model anchor "simplified" may reveal that high minded bickering is characteristic of style more than content! As with topic 7, the error of positing two topics to describe one leads to a higher confusion rate with other topics. More than any other topic the relevant terms are the names of important figures usually real and sometimes imagined. The frequent terms suggest literature, and the relevant terms suggest philosophy. Either the two fields are erroneously merged or literary theory merely draws heavily on philosophy.

Table 3.16: Topic 9 Terms

lambda	Terms
	model anchor: simplified
0.01	hamlet, hegel, yeats, derrida, schlegel, pushkin, dostoevsky, nietzsche, kant, sonata
0.5	genre, poem, poetry, form, literary, nature, theory, poetic, critical, tragedy
1	genre, form, work, literary, poem, poetry, nature, text, critical, narrative

3.6.4.10 Topic 10, *painting*

Topic 10 is distributed among several journals about art, including a couple of Renaissance studies journals. During QCV this was easy to separate and was labeled painting, as in "Dutch genre painting". Topic 10 was confused twice, once with 7 and once with 9. The term lists suggest painting but also book publishing and place names specific to the British isles, whereas bellwethers much more strongly evoked Belgium and the Netherlands. The confusion stems from the reader seeing two topics, the British novel on one hand and painting on the other, where in the model they are collapsed, perhaps due to the prominence of London in both art dealing and book publishing.

Table 3.17: Topic 10 Terms

lambda	Terms
	model anchor: rosenberg
0.01	painting, irish, painter, dickens, wilkie, scottish, scotland, portraiture, canvas, gaelic
0.5	painting, letter, art, century, book, published, print, london, artists, england
1	century, book, work, art, painting, letter, history, published, london, english

3.7 Topic clusters

Having posited a nominal theory of each topic by inspection of journals, bellwether texts, and the topic by term matrix, we have not yet established what documents are about. Because the topic model is a mixture model we have at best understood what the potential for document composition is, not what their compositions actually are. Understanding the patterns of topic mixtures, or topic clustering, within documents is the last necessary analysis at a global level before proceeding with a stratification of the corpus for purposes of reading. Here we take two approaches to document clustering, first by hierarchical clustering of the distances between documents calculated directly from the document by topic matrix, and second by network community detection.

Agglomerative hierarchical clustering works by first calculating the euclidean distance between points in an n-dimensional space, either as documents in a vector space of topics or as topics in a vector space of documents. The data are naturally scaled to sum to one in the document dimension; before calculating topic distances they are rescaled to sum to one in the topic dimension, thus in each model unit size is held constant (document term length and topic share of corpus term frequency). Given these distances, clustering proceeds by assigning every point to its own cluster and then by merging pairs of clusters that are nearest each other in this space. Clusters have an ambiguous location based on the location of the individuals within them, and different methods of locating them for subsequent merges are possible. Here we use the maximum distance method, where the outer edges of two clusters define their distance, which helps to contain variations in cluster volume. Figure 3.10 shows the document by topic matrix as a heat map which serves as an ensemble of the two clustering models encoded in the seriation of their elements, one of the rows (documents) and another of the columns (topics). Each hierarchical clustering model is represented as a dendrogram with the height indicating the distances at which merges occur. The leaves of the trees are seriated to minimize the squared distances of the lines they draw, which results in the “least ink on the page” drawing of the tree. Within the condition of a one dimensional sequence, elements that are closer in their vector space are sequenced more closely together.

Within the grid is displayed the actual document by term matrix with probabilities coded as shading from p = 0, white, to p = 1, black. The darkest stripes represent those unmixed documents uniquely classified in a topic, and it can be noticed that everywhere to the left or right of the darkest stripes is very pale shading. Because rows sum to one, where shading in a column is gray, it must be complemented by shading in another column, hence the gray regions represent the mixed documents. The blue traces within columns plot the associated probabilities, with the dashed line indicating p = 0.5. The dendrogram on the left represents the clustering of documents and is shaded to reduce the clutter and draw the eye toward merges at higher distances. Note that the darkest stripes are associated with the lowest, earliest merges; these are the documents (the spines of the urchin) that "stepped" as far away from the pack in a single direction as possible, thereby landing very close to each other and very far from the rest.

At the higher levels of document clustering we may observe the unmixed documents being merged with mixtures in which the same topic is the dominant component, either in majority or plurality. A gray band above a dark band will be a cluster mixed in a different configuration than the gray area below a band, sometimes from the same secondary topic but in a different ratio and other times from a different topic altogether. For instance the spine of topic 4 is flanked below by texts with clusters of various mixtures in which 4 has a slight majority, including prominently topics 10, 7, and 9 but almost all other topics in separate groups save topic 3. Flanked above the spine topic 4 is mixed again with 9 and 7 but this time without taking a majority share.

The ensemble also helps to correct artifacts of the linear ordering of each dimension. For example, though topics 6 and 1 are adjacent columns, their spines are as far apart as possible in the row dimension. The merger of topic 6 into the cluster containing topics 7, 4, 9, 10, 2, and 1 is done at a relatively long distance and could be due to the space between 6 and any of the other members.

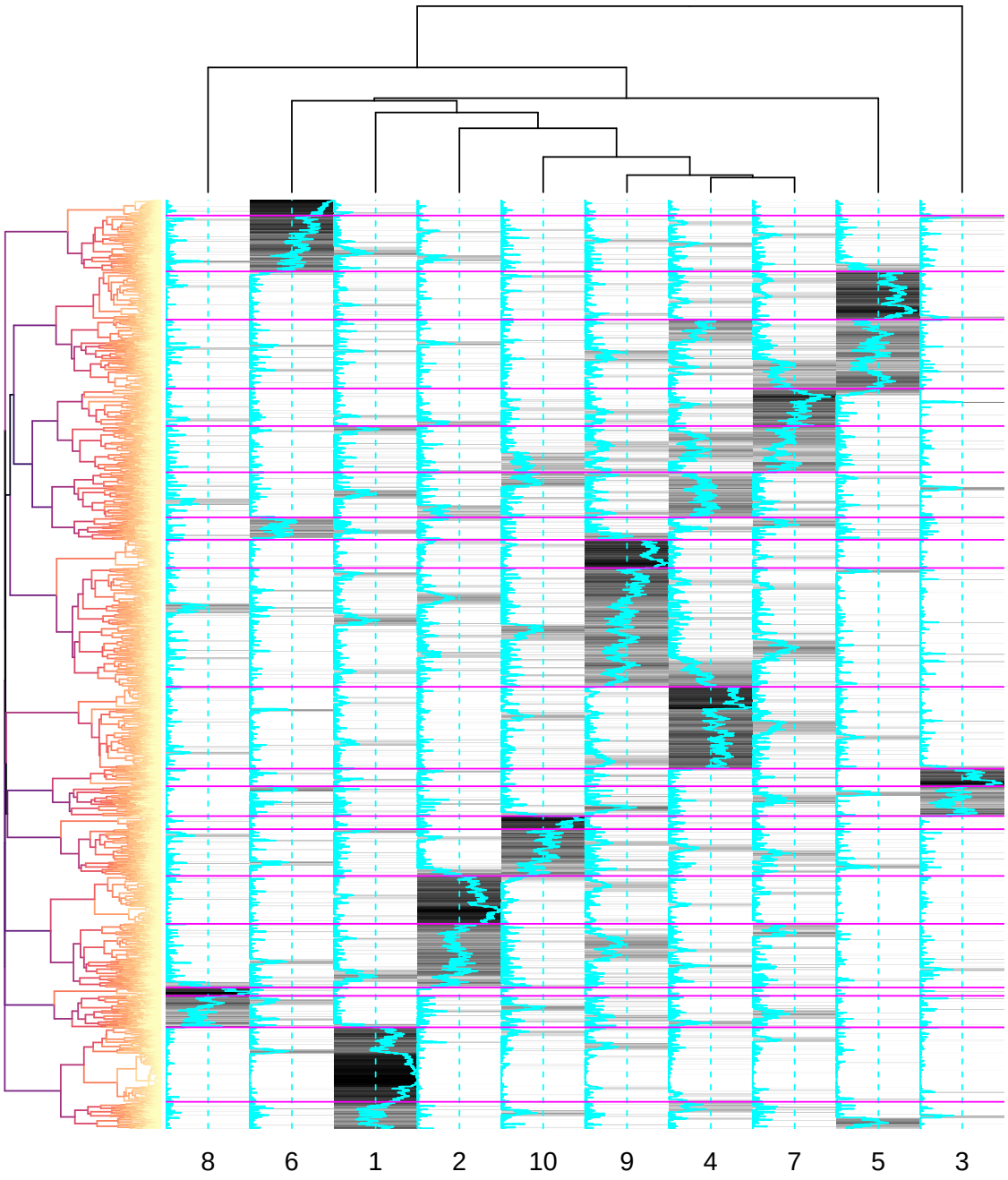


Figure 3.10: Heatmap by optimal leaf sorting of documents (rows) and topics (columns)

A serial ordering is not a great fit to data that can be found in almost any mixture, however it does reflect the human limitation that one must read one thing at a time. As a seriation technique for reading the ensemble hierarchical clustering model suggests a reading order of starting on a spine to read bellwether texts, then choosing clusters on the flanks to survey the combinations in which the focal topic is the majority player. One would then move to a different spine and repeat the

technique. The order of spines can be taken from the height of their leaves, starting low and working up to higher mergers. This would begin the reading order with the topics that are most closely related. In this case the lowest fork contains topics 4 and 7, though in a survey around every spine the relationships to almost all other topics would be addressed.

On the high side of the topic tree the most distant merges occur with topics 8 and 3. Interestingly, whereas topic 8, French language, was highly distinct looking only at terms, when looking at documents topic 3 is the most distinct. This makes sense under the theory that it is the translated abstracts that are being pieced out by topic 8, and that the rest of the documents if they are English must be composed of other topics. Indeed the spine of topic 8 is very short and the majority of its trace is below $p = 0.5$ and mixing with a variety of other topics. By comparison topic 3, pan Asian culture, mixes mainly with topics 7 (gender), 9 (literature), and 6 (music). A slice of 3 mixes with 5 (film); because we presume 5 to be relevant to modern times it may show that the content is not always necessarily about distant history as was gleaned by the bellwether review.

Almost every cluster has some activity away from its spine, but these tend to be minority players related to the spine of a different cluster. Given this pattern, in which not only combination but proportion matters, there may well be more strata than there are pairwise combinations of topics. Assuming a modest five texts per stratum, a lower limit of 45 topic pairs, and an upper limit of 90 to double that so that each topic may be in a minor and major position, then we would expect to read between 225 and 450 texts to be able to make a claim to have understood the remaining 5,894 to 6,119.

This seriation method would fail only in the case of truly unconcentrated clusters that are adjacent to no spine. The simplest version would be three way relationships meaning that then even more strata would be warranted. This scenario appears to occur three times in this data set. The most important instance fills the space between the spines of 9 and 7 where a middling cluster of topic 4 is mixed in a variety of combinations. It happens again between 2 and 8 adjacent to the spine of 2 but a separate cluster, and finally again between 9 and 4 adjacent but separate from 9. Thankfully the same model allows this possible lacuna to be noticed and filled without worrying too much about the combinatorics of three way interactions.

Though it may be an arbitrary simplification, a feature of the hierarchical model is that we may choose a cut point to split the dendrogram into a desirable number of groups. By trial and error 21 groups splits the tree into a major and minor cluster for each topic, where the major component is the spine with probabilities close to one and the minor are the different mixtures in which the topic is usually dominant. The 21st slot accommodates an additional disjoint minor cluster for topic 6. The boundaries of these groups are indicated by magenta lines in the figure. Next we will discuss how to use these clusters

for stratified sampling.

3.8 Reading strata

Table 3.18 provides a numerical summary of Figure 3.10 replacing documents with their clusters and tabulating the number of documents in which a topic is dominant. The rows and columns are in the same order as the figure. Treating these 21 clusters as sampling strata is a more manageable research design than the above mentioned 45 to 90 pairwise strata and reflect the empirical reality that three way combinations are rare and that not all pairwise combinations are important. They also narrow us to a research question that is either diagnostic or substantive depending on what the qualitative content of texts holds. The substantive question is, how does the content of a topic change when discussed in isolation versus in combination? The diagnostic question is, what happens to the content of a topic when the when its documents are not well explained by the available topic context.

The difference is that the former assumes topic validity, whereas the latter make a different assumption about topic bias than we have previously discussed. In our diagnostics we were concerned that the low but nonzero probability terms of a topic by term vector represent sources of error and bias, for instance, due to idiosyncrasy. This was the body of the urchin. The problem with this kind of bias was that a generalization from the spine to body may be inappropriate because documents in the body actually represent classification errors and should not necessarily be understood to belong to the same class as their spines. Depending on the researcher's goals this body bias may not have been too damning. If the topics that are learned are internally valid, and it is easy to identify the documents that they validly explain, then at least the researcher can claim to have understood some important portion of the corpus even if there remains a substantial unexplained portion.

Now we consider that it may also be possible that the spines are the bias inducing portions of the corpus. The logic here is that a text should never be categorized as nearly 100 percent derived from a topic, because this implies that it is 100 percent generic, that is, totally lacking in idiosyncrasy. What may be more likely is that those strongly classified documents are the ones that happen to not share any overlap with the other *available* topics. Since they must be 100 percent classified, in order for them to be classified anywhere the estimator may choose to distort the term vector to make special dispensation for these weird texts. This would imply that the texts that contain a mixture of a topic, rather than those wholly derivative of a topic, reflect the more valid portion of the term vector. If this kind of bias is indeed operative, then it poses a problem to the researcher, who will base her interpretation of a topic on the less valid portion of its texts.

Our stratification approach will allow us to adjudicate the question of validity by way of QCV. Each topic is represented by at least two strata, one mixed and one unmixed. We may compare the content of the unmixed texts to the topic portions of the mixed texts and assess whether they indeed reflect the same content. If they do, then the estimation is unbiased in at least this respect. If they are substantially different, and the unmixed documents appear less topic relevant than the mixed, then we have found a particular sort of bias due to underspecification of K.

Table 3.18: Document Clusters by Percentage Primary Topic Classification

Cluster	8	6	1	2	10	9	4	7	5	3	Total	N
6		100									100	108
6.1		97		1					2		100	382
5									100		100	329
5.1			1	1		1	12	11	74		100	471
7								99	1		100	256
7.1			5		9	3	21	62			100	316
4.1			6	3	12	4	71			4	100	308
6.2		52	5	5		20	7	11			100	153
9						100					100	193
9.1	1		2		3	77	10	6			99	812
4		1					99				100	559
3										100	100	120
3.1		9			2	10		6	6	65	98	204
10					100						100	89
10.1		2	1	8	86	1		1	2		101	320
2				100							100	327
2.1	3		5	82		6		3			99	435
8	100										100	57
8.1	73	3	5	1	8	2	2	6			100	215
1			100								100	509
1.1			77		1		4		18	1	101	181

Given the linear ordering of rows and columns, three seriation approaches are possible. *Inside out* would proceed from the lowest to the highest leaves when assessing topic relatedness, the lowest in this case being 4 and 7, and would emphasize the most interdependent topics first. Conversely *outside in* would start with the most independent topics. Finally, the easiest *playlist* seriation would simply be to read in the order given choosing either the top or bottom as a starting point.

We may now reflect on the guidance offered by Table 3.7, where topics 6 and 9 had the best and topics 2 and 7 the worst performance across a battery of diagnostics. The clustering results bear the diagnostics out only in one respect. If good diagnostic performance meant a strong signal then it makes sense that topic 6 is

Figure 3.11 illustrates the use of these clusters as strata for a sampling approach to mastering a corpus defined by the term genre. The clusters are seriated in playlist order from left to right beginning with

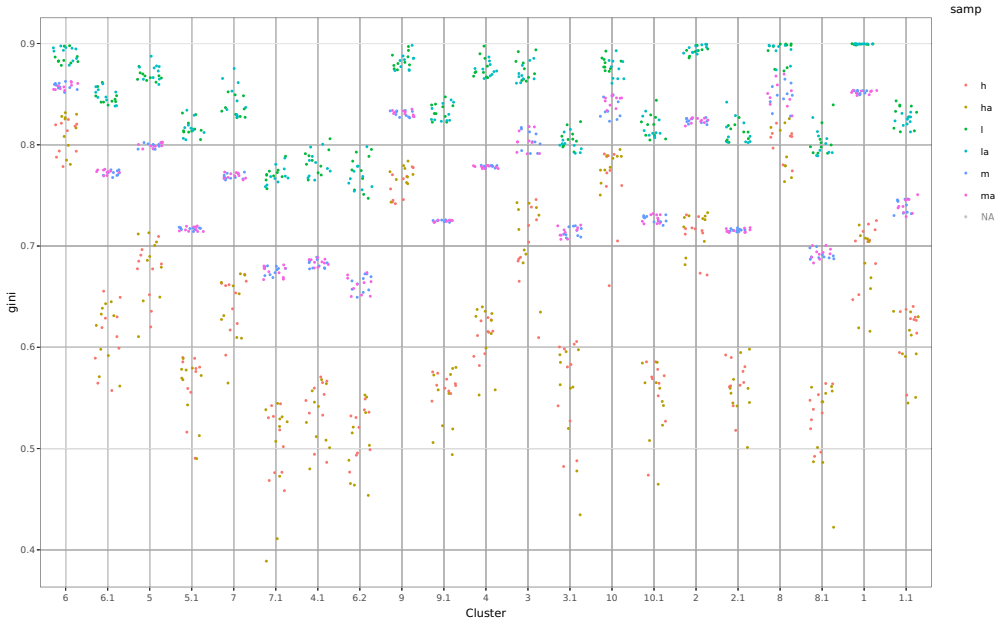


Figure 3.11: Reading Strata and Sampled Texts.

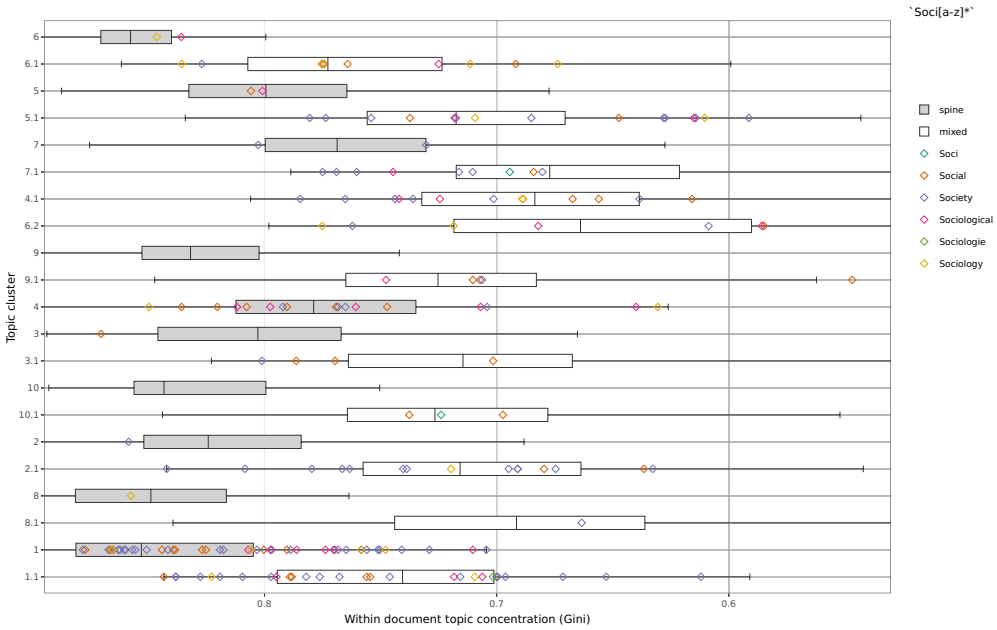


Figure 3.12: Topic locations of sociology texts (n = 182)

3.8.1 Document composition

3.9 Discussion

The first point concerns the urchin. Above we posited that it is in the spines of the urchin that the essence of topics is found, and it is the body that contains the idiosyncrasy. This is true for the good version of a bad model, but it is likely that topic model estimators actually find a different, worse version of a bad model. Consider the status of horror in the film topic. Horror was a subgenre of film and it was ranked very highly on the film topic, indeed horror articles were the bellwethers. The reason was that the topic came to most strongly associated with the component of it with the most distinctive vocabulary. Drama, for example, which uses a less fantastic and more relateable vocabulary, is drawn down the spine where it can mingle with the topics to which it is connected. Why should the weirdest component of a topic be treated as its most essential? This is a trend that all underspecified topic models will exhibit.

It is likely a mistake, however, to interpret the topic only with respect to its weirdest component. Weirdness here is not idiosyncrasy, because weirdness is something common and recognizable, whereas idiosyncrasy is individual and invisible.

Chapter 4

Vocabularies of Anthropology and Sociology, 1888-1922

Abstract

Knowledge development of journals in sociology and anthropology is measured as the change in topic prevalence over time.

Keywords

sociology of knowledge, topic modeling, history of social science

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4.1 Knowledge Development

What were the ideas that predominated in the social sciences at their formation as professions in the postbellum United States? What was the course of their development over a generation of scholarship? In this study I will answer these questions inductively through a reading of the original journals in each discipline. Though the goal is substantive, the methodological challenges of consuming a large quantity of text will feature importantly in the story that unfolds. Along the way I will demonstrate the usefulness of the computational *distant reading* that is being explored in the humanities and how it can be combined with traditional textual analysis for social science purposes. While controversial in humanistic circles that

emphasize the primacy of the reader's novel interpretive work when consuming text, distant reading fits comfortably within a social science epistemology that aims to achieve an objective description of intellectual history Indeed, computational methods offer a useful backstop to the idiosyncrasy of a particular person's reading of history.

Computational textual analysis promises to automate a particular slice of what hermeneutic methods accomplish. Hermeneutics claims that through historical methods it is possible to reconstruct the interpretive context of texts such that they can be understood in the same way that contemporary historical actors understood them. Establishing such context is a laudable yet arduous feat of historical research to uncover the social and intellectual milieu of a particular text. This is the gold standard approach, but one that restricts the field to specialists with the training and resources necessary for the undertaking.

Computers cannot study history in this way. What they can do, however, is mine source material for limited kinds of contexts. The kind I am concerned with below are the *historical vocabularies* that writers used to construct texts in historical time. Vocabularies are glyphs without grammar; they do not mean anything, but nothing meaningful can be said without them in the present or in the past. They are the mediated form of language, and in communicating with each other historical actors leave traces that survive perfectly in time so long as texts themselves survive.

While computers cannot read meaning in texts, and can barely recognize it, they are almost as good as humans at recognizing the glyphs of texts, and vocabularies are nothing but glyphs. What computers lack in smarts, they make up in speed and memory. The quantitative scale of their recognition makes for a qualitative shift because vocabularies can be enumerated across immense corpora of texts. Immense, at least, by human standards as there are limits to even computer memory and speed. Yet such enumeration of texts into objective historical categories; this is a profound resource for the intellectual historian. That one could begin a reading with such context would be a transformative research tool. Vocabulary enumeration, by which I mean simply the counting and classifying of texts according to the vocabularies they contain, invites a population studies approach to intellectual history. Where sense-making is driven by comparisons, a reader's arbitrary combination of texts is guaranteed to lead to anachronism. But if we can know that texts are relevant to each other without knowing why, we have done some small amount of hermeneutic work by supplying texts as historically correct context to each other.

And even going so far as abandoning the project of reading texts in a historically correct way, vocabulary enumeration can still lend objectivity to a novel construction, a productive anachronism, of textual meaning. Because vocabularies,

the problems solved by computers, are mathematically, algorithmically, or stochastically determined, they may provide an immutable description of corpora that, like a map, enables individual and collective exploration within a common framework. Such maps may become the parameters of interpretive methods, which we may use to surface and control some of our subjectivity.

This at least is the rationale for what follows. I begin with a discussion of intellectual history of two social sciences, anthropology and sociology, in the United States. I take a coarse view of national history as the history of wars because of their downstream effects on government activity and institutional investments. The first period is between the end of the American Revolution (1783) and the end of the American Civil War (1865) and is the national context for the origin of U.S. anthropology. The second period is after the Civil War until the end of World War I (1918) and is the context for the origin of U.S. sociology and of modern U.S. higher education generally. Wars of territorial expansion are waged regularly during both periods against native peoples and rival colonial empires, and social research was always recruited to solve attendant problems of population and to provide rationales for the relationships with and understandings of conquered or would-be conquered people.

I use intellectual histories of anthropology to characterize the antebellum period, and the same for the postbellum period including sociology. The most important journals in each field date from the postbellum period, and the appearance of each is implicated in the project of professionalization for each discipline. The 1920s marked the end of war with the last of the militating American Indian tribes, and a reckoning with the darkest sides of industrialization laid bare by WWI. Social research had by this time completed a shift from colonial to industrial problems and enjoyed a golden decade of development as a profession, punctuated by the next great historical crisis in the Great Depression. With the 1920s begins the adolescence of social research, which is beyond the present scope. This study is of its childhood, which ends with the Great War. I however draw the study out until 1922 because it is the end of the public domain in U.S. copyright, to aid in the reproducibility of the analysis and so that all readers may recover the texts in question without difficulty.

4.2 Social Science Journals

The journals within social science cover five different subdisciplines.

Table 4.1: JSTOR Social Sciences Journal Counts

Subdiscipline	N	Pct	Labeled	LPct
Archaeology	256	27.9	115	12.6
Political Science	219	23.9	183	20
Education	192	21	170	18.6
Sociology	160	17.5	145	15.8
Anthropology	46	5	89	9.7
Population Studies	22	2.4	27	2.9
Geography	18	2	32	3.5
Transportation Studies	3	0.3	7	0.8
Total	916	100	768	83.8

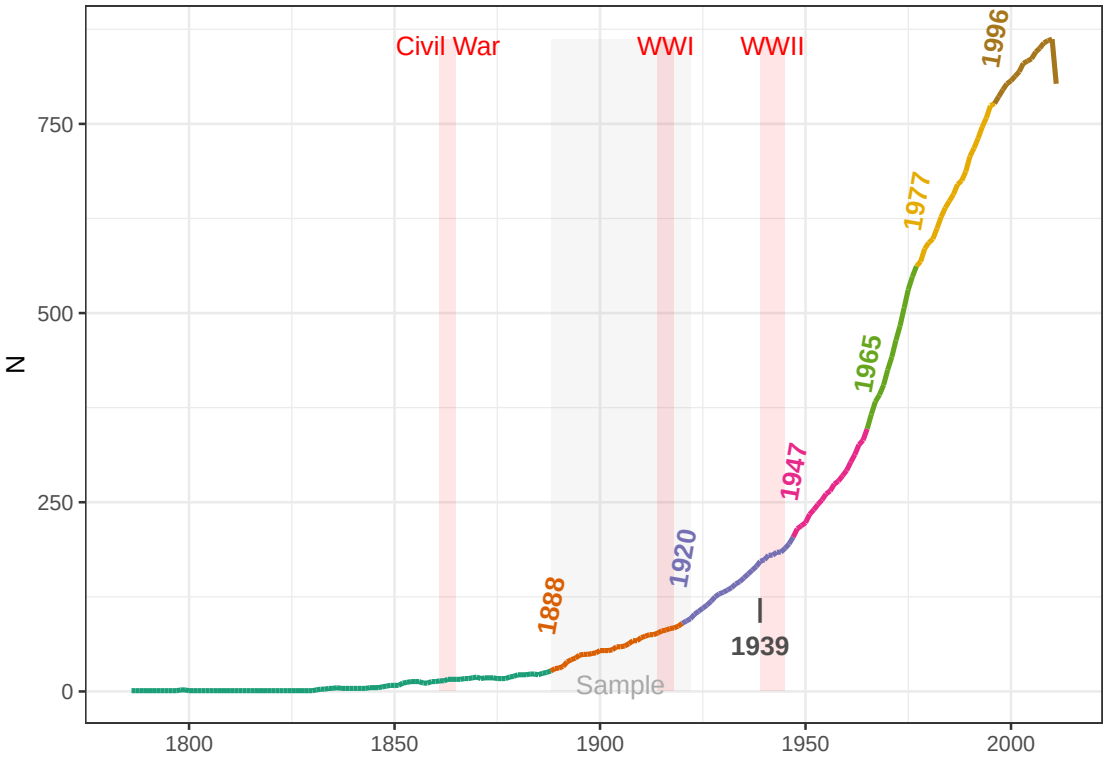

Figure 4.1: Periods in the Growth of the Number of Social Science Journals in the JSTOR Archive

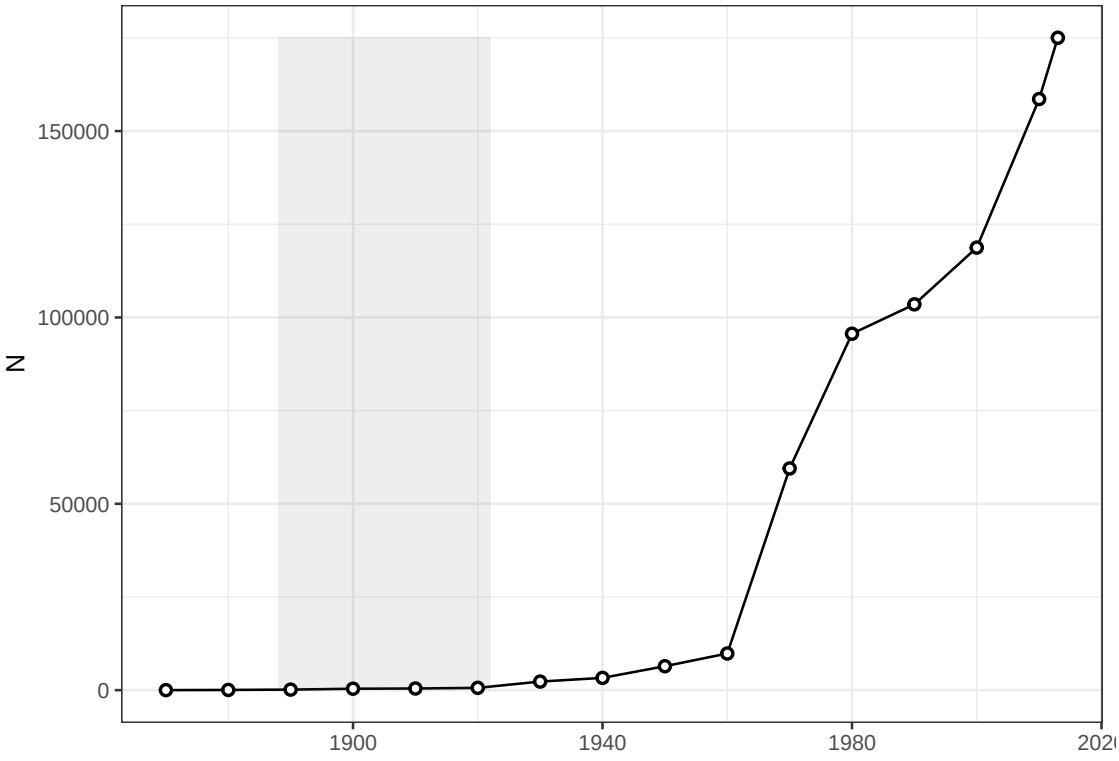

Figure 4.2: Decennial growth in number of PhD degrees conferred in the U.S.

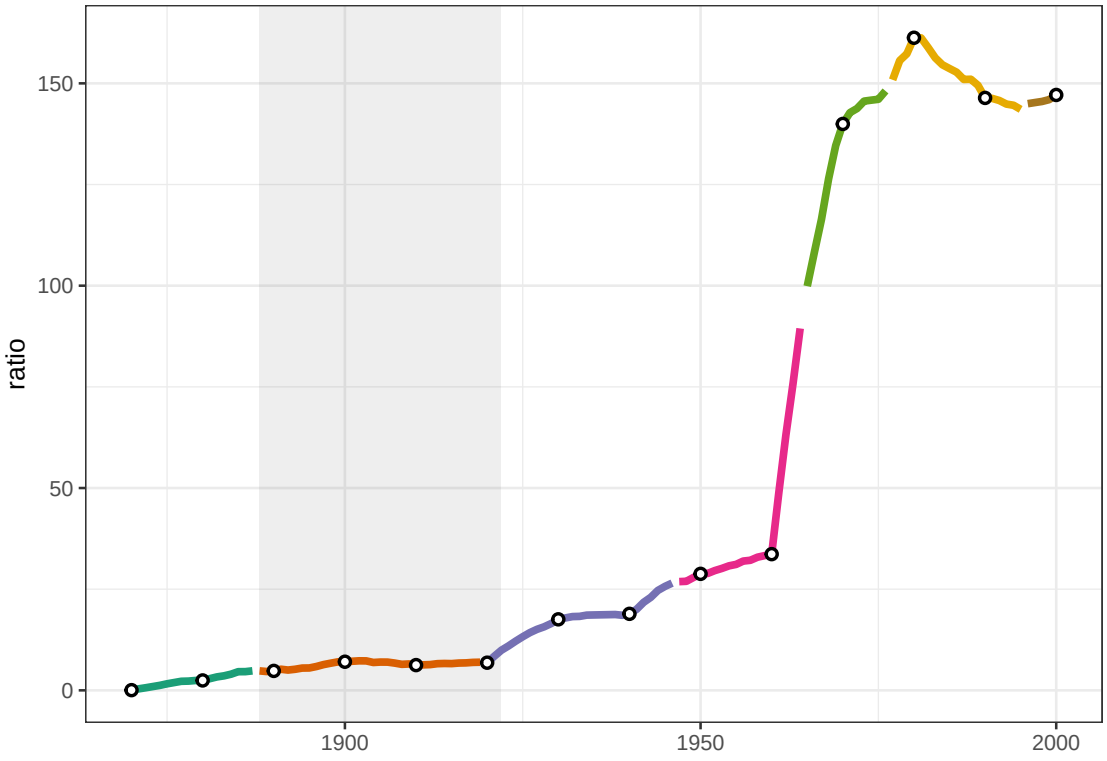

Figure 4.3: Number of PhDs conferred in the United States per Social Science Journal

This period represents one of stable growth, as the size of the field grows with the number of players on it. Between 1888 and 1922 there tended to be about seven new PhD's in the U.S. for every social science journal even as each population grew year over year. These growth patterns begin to diverge around 1920 as a decades long acceleration of personnel begins, relatively slowly between 1920 and 1960 at an average acceleration rate of 22 PhDs per journal per year, and then quite precipitously in the 1960s at an average acceleration rate of 121.

4.3 Topics $\stackrel{?}{=}$ Ideas

The strategy of the study occurs in four steps.

1. Sort text into categories of similar vocabulary.
2. Describe the vocabularies that define category membership.
3. Describe vocabulary prevalence across time and discipline.
4. Validate category contents by a traditional qualitative reading of texts.

I will spend considerable effort on solving the problem presented by step 1, as here everything depends on the computational methods employed. Steps 2 and 3 are straightforward given a successful mathematical model of texts. Step 4 is seldom attempted, and may be the hardest of all, because it is here that machine and human learning must be integrated. If I am successful, if through these steps I may operationalize the notion of cultural meaning or cultural logic as conformity to vocabularies, then I believe a new horizon of intellectual scholarship is possible. If on the other hand I find that machine-learned vocabularies do not correspond to human-learned understandings of the texts drawing on those vocabularies, then the discovery will be negative, that distant reading is not a scientific, historical, or hermeneutic method, but rather a toy at worst and a best new humanistic method of reading texts de novo.

The mathematical tool I will rely on in step 1 is called topic modeling, which refers to a variety of computational approaches to text data that blur the distinction between qualitative and quantitative analysis. The topic model paints a lexicographic picture of texts, analogous to the demographic picture gained by a civil census survey of cities and towns. To a topic model, texts are merely collections of terms (usually words) that are counted to create the so-called "bag of words" description of a text. In the same way that a census reduces communities to counts of the names of people who live in them, topic modeling reduces texts to the frequency of word choices in texts, to their diction or vocabulary. Just as a census of people fails to capture the nuanced interactivity of human settlements found in their culture, politics, and economic activity, the topic model washes away the meanings and intentions behind the words that are enumerated.

A population census would not be very helpful were it only a count of the names of respondents, and of course the really helpful data derive from the demographic and economic survey attached to the name. Text data do not usually come with such a collection of rich covariates, yet nevertheless topic models promise to discern helpful patterns from counts alone. The trick behind the estimation of a topic model is that it attempts to learn the demographic information (topics) without asking, by merely looking at how the names alone (terms) are distributed across geographies of interest (texts). If it can keep its promise, a topic model applied to census data might recover the cultural patterns latent in the distribution of names. It might, for instance, learn different groupings of names that in turn correspond to markers like age, race, national origin, or gender, so long as membership in those categories was related to geography. It might, for instance, successfully separate a category of Hmong names out from among the names of all people living in St. Paul because the non-Hmong names appeared in other regions where no Hmong names appeared.

To call the category of names "Hmong" requires an interpretation of the model, which by itself is just lists of names.

This is the work of step 2, and requires a little bit of shoe leather by trying to make sense of what a list of names refers to. Here reading texts is like a census taker knocking on a door, and a topic model's latent analysis saves on this effort. Sometimes bringing domain knowledge to bear on the list itself will suggest a category label, but often choosing a small sample of texts as exemplars of the category. Still this requires much less shoe leather than a traditional qualitative analysis in which each text is studied directly. Of course the census is much more informative because it asks about demographic categories directly thereby avoiding the need for a latent analysis. In domains where rich covariates are not yet available or are prohibitively expensive to acquire, latent analysis provides promising clues of patterns that already exist. What is even more interesting, and something that might surprise even census analysts, is when latent categories do not correspond to known survey items. In either event the power of topic modeling for inductive analysis is to reveal structure in how names hang together that was hidden.

Even without conducting the second labeling step, in step 3 it will already be possible from the output of the model to inspect the distribution of topics across available covariates, especially time. These are the patterns that will help validate the topic models against what is already known about intellectual history. For instance, the power of institutional and generational change may well be apparent in the historical distribution of topics. This step leads naturally into step 4 by suggesting anomalies that can only be explained by a closer look at the texts, the chore that the entire preceding analysis punts on. In step 4 we learn either that our understanding of history was wrong, or that our topic model was wrong, and there may be no method other than one's judgement to decide.

In the next section, before we delve into the statistical and computational nuances of topic models, I will spend some time developing a few themes to help organize the blending of quantitative and qualitative methods invited by topic modeling in particular and computational text analysis generally.

4.4 Prior Work

4.5 Information

Understanding differences in the ontological status of the "topic" concept is a good way to begin to understand how this method of analysis is used by researchers.

Analysts have conceptualized the use of topic models in very different ways. Some researchers treat topics as useful for

a particular purpose and not as true descriptions of real phenomena. Topics as information enhances the ability to search for relevant documents or statistical trends in otherwise unwieldy corpora as a time-saving alternative to manually reading large collections. (Boyd-Graber et al., 2017) Empirical problems, used as demonstrations of statistical techniques, have included

This is the "needle and haystack" approach favored by computer and information scientists who tend not to be interested in theoretical interpretations beyond the statistical definitions of topics.

4.6 Meaning

Other researchers instead grant topics ontological status, and these can be divided into three types. Most ambitiously, topics may be treated as representing categories of thought. Latent semantic structure latent semantic structure (**?**)

4.7 Communication

representational style (Grimmer, 2016) frame (DiMaggio et al., 2013)

4.8 Full-Text

Computational text analysis requires that text corpora be transformed from a human to a machine readable format. Several efforts to digitize paper archives have made historical research designs possible, notably the Google Books project, HathiTrust, and ITHAKA JSTOR archive. Digital storage devices like the portable document format (PDF) have also enabled texts to be represented in both a digital version and as a reasonable facsimile of paper originals. Reasonable, we should say, for most sociological purposes, put not for other historical questions where materiality of culture is important. (Schreibman, 2014, 149)

Digital archives make research into the production of culture difficult, precisely because they misrepresent several aspects of the means of production. Because researchers should be mindful that digitization of texts abstracts some qualities of texts and renders many others invisible. The importance of physical space and material qualities of libraries is illegible when working with digital archives, while the verbal content of texts is highlighted. We must keep in mind that we are not viewing what historical actors saw. Digital texts are almost perfectly fungible, while, variability in historical texts. We are liable, for instance, to underestimate the search costs to locate texts, and the fungibility of texts themselves.

There are reasons, however, to believe that digital text archives provide not just a useful but an historically valid abstraction from the material texts. If we want to understand how an individual scholar understood a particular text, better to have her personal copy, margin notes and all. Yet how would that scholar have treated the text as a cultural item? She would abstract her own copy to a format credibly held in common, the more antiseptically clean version that we see in digital archives. These are the ghosts of the texts, so to speak, but they are what would be left when all idiosyncrasies were removed, the version that one would assume colleagues thought of when declaring that text publicly.

This is by way of saying that the texts I compile below are not the same that were read by the historical actors under consideration. They are the texts that historical actors would assume their contemporaries were reading, that is, the sanitized, fungible, original published form of the text. By getting at these texts, we are getting at the real historical infrastructure for scholarly communication.

The optical character recognition that computers require in order to store text digitally depends critically on the hard work of creating quality scans of journal archives. JSTOR has done a commendable job of this. Next we will describe what the JSTOR archive has to offer.

4.9 Data

Every record for every journal was downloaded manually, including front and back matter, articles, and book reviews.

4.10 Sampling

Table 4.2: Filtering due to Data Management

step	doc	pag	par	sen	tok	ter	lem
imported	100	100	100				
cleaned	99.27	98.21	67.51				
tokenized	99.27	98.21	67.51	100	100	100	
preprocessed	99.27	98.01	67.35	91.38	42.21	35.74	100
sampled	1.84	1.56	1.17	1.43	0.62	4.95	20.86
100							

4.11 Units of Analysis

Conventionally researchers feed entire documents into the construction of term frequencies. This method treats any term in a document as being related to any other term by the same degree. The goal of any topic mixture model algorithm is to sift these terms into different topic categories basically by looking for clues across documents; a topic can be "seen" in a particular document to the extent that other documents include that topic and *other* topics different from the focal article, so that the intersection of terms reveals the topic. But a much simpler assumption to reduce the attendant noise within a document is to merely feed lower level syntactic structures–paragraphs and sentences–to the algorithm. We will see that doing so greatly improves the usefulness of discovered topics.

The irony of this approach is that while topics become more clear as documents become shorter, the assignment of any particular shorter document to a topic is murkier due to the smaller word count.

Long documents will contribute more text to the corpus, but this is fair as they make up more of the population of text. Thus a simple random sample will allow better descriptive statistics. I sampled at the paragraph level because.

4.12 Topics

The modeling objective is twofold, to sort text into categories of similarity, and to describe the qualitative content that defines the category membership. In this way we may operationalize the notion of cultural meaning or cultural logic as the rules of category classification. reduce expressions as instances of a latent category of expression.

4.12.1 How many topics?

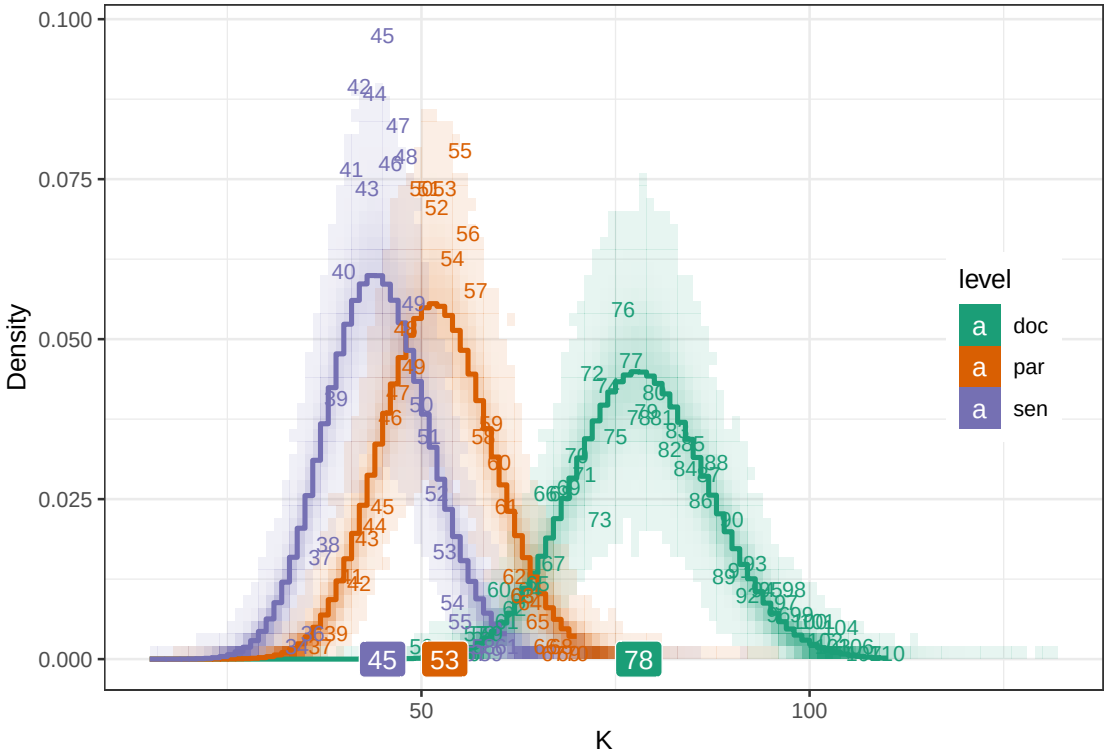

Figure 4.4: Distribution of K by convex hull

Table 4.3: Kurtosis Permutation Test

level	e	se	l99	u99	P(e ≦ 0)
doc	-0.0932	0.1149	-0.3682	0.2252	0.7948
par	-0.1125	0.1206	-0.3999	0.2185	0.8257
sen	0.0118	0.2304	-0.5078	0.6471	0.4973

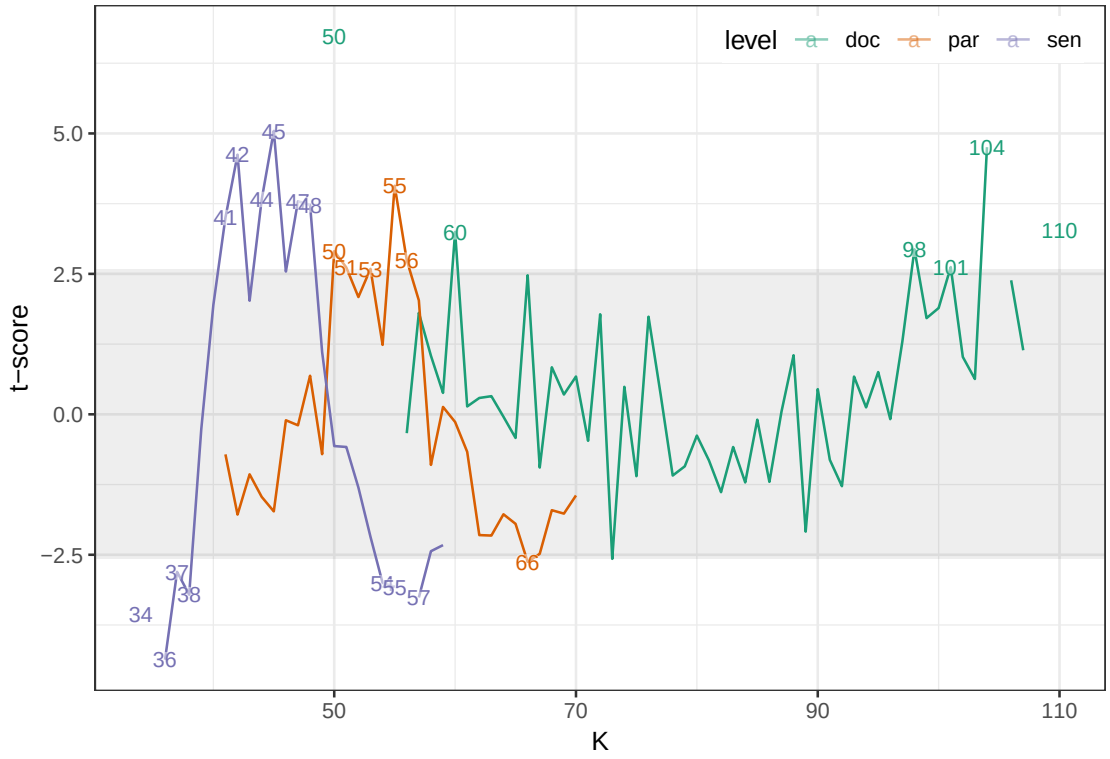

Figure 4.5: Significant Counts of K

4.13 Model selection

4.14 The Social Science Citation Landscape, 1900-1940

Abstract

Knowledge mapping of academic journals promotes the conservation of intellectual history and stimulates discovery of underexplored intellectual opportunities. Treated as a large network community detection problem, I demonstrate how to apply the clique percolation method to map two kinds of recorded knowledge: citations and full text. The features of generated maps are explained, and interpretive methods including visualization are presented. We use American social science scholarship in the first third of the 20th century prior to U.S. entry into World War II as a case, and describe how the intellectual landscape of four separate social science disciplines developed.

Keywords

citations, k-clique communities, community detection, landscape

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If knowledge is power then scholar must be a powerful class. But what kind of power is knowledge and in what way do scholars wield it? Is knowledge powerful a utility, like water or electricity, to drive a tool and accomplish a task? Is it an asymmetry of information, like a stock tip or the combination to a safe, that gives one a leg up on her competition? Is knowledge like the power of an authority, like a governor, a military commander, or clergyman, to compel the loyalty and obedience of another person?

How we conceive of knowledge affects how we view the nature and importance of the people and institutions that produce it. Scholars certainly do not have a monopoly on the utilization of production of knowledge in society, but their occupational roles are conditioned by the stuff of knowledge at the same time that knowledge is itself conditioned by the technology and social arrangements that constitute scholarly occupations.

4.14.1 Scholarly Communication vs Knowledge Terrain

If the production of culture perspective were to argue against Marx's German Ideology, it might say, "Not all mental laborers have soft hands." Marx drew a course distinction between mental and material labor to demonstrate that the former is not possible without the latter, even when at the time mental labor had already been commodified with the advent of print media. The production of culture perspective simply effaces the distinction altogether; mental labor, or cultural products, are like any other industrialized commodity.

The production of culture perspective is at odds with public sector economics that argues that non market mechanisms create value where markets fail to do so. (Hayes, 2000)

Remuneration

Are culturally interior products referenced by socially superior producers?

4.14.2 Mapping Knowledge Terrain

4.14.2.1 knowledge stuff

There are two reasons to map knowledge spaces. First, we may want to know how knowledge develops as a resource unto itself. Second, we may want to exploit such a map for a productive purpose. Here we will attempt the second as prologue to the first. We will tackle the technical problems of constructing a map. We will show how a map can be put to use. Finally, we will investigate how the particular map we make may tend to predictably get us lost.

All knowledge mapping requires first an ontological and then an analytical action. Ontological actions delineate the things that matter. They arbitrarily construct from perception the items that we then think about. While ontological decisions tend to define the scope of everything that may be learned from an investigation, they are often assumed rather than demonstrated. Actor Network Theory (ANT) provides a unique example of a method of research that, because it is ethnographic and thus marinating in an abundance of perception, allows the cast of ontic characters to grow. Literally anything can be deigned significant for inclusion in a web of knowledge. In an ANT study of science, if the feel of a reading chair modifies a reader's orientation to a text they are reading, the chair counts.

The lion's share of knowledge mapping studies are not so ontologically radical as ANT. Take the field of bibliometrics. The ontological decision here is to take documents as the primary ontic. Documents are nothing but collections of glyphs, so the first task of bibliometricians tends to be to map glyphs to terms and analyze them. Here we have already used the ontic triad underlying bibliometrics. In the sentence

"Go, dog, go!"

there are twelve discrete glyphs and two terms. A grammatical cutting rule renders the glyph sequences as

"Go," "dog," "go!"

and a tokenization rule maps the cuts to two terms

"go" "dog" "go"

which may in turn be analyzed, for instance by counting the tokens. The documents form the bins within and across which the terms will be analyzed. The token, as a mere operational step, is used and then dispensed with unless questions

of measurement surface. Clearly the *glyph-term-document* (GTD) ontic does not care about the armchair of a reader of a document, and indeed does not even care about the reader herself.

So the reader is invisible because she is not inscribed in the document. What about the writer? Bibliometricians may back fill GTD by entity recognition or grounding. Once terms are recognized, we may further recognize that we know more about them. A simple example of this is pulling out "metadata", for instance, the author of a document. The author's name is not just any term, but a conceptually very important one. Grounding is how bibliometrics may be linked to theories and programs of greater importance.

Bibliometrics has indeed been based more on the reference of a text as a particular grounded entity rather than on the use of the full text of a document. If a text is a building, the reference is its address. More precise than a name, an address is a codification of different hierarchically ordered elements that describe the location of an entity. The consistent tokenization of a reference is not an easy task, as it depends on entity recognition of several different kinds of things, including year of publication, author, title, and source.

The citation became the basis of the concept of a web of knowledge as coined in the work of Eugene Garfield and institutionalized in the Institute for Scientific Information (ISI).

Citations solved the problem that ideas do not have signatures or addresses that we can trace reliably. Jargon is an attempt to give an idea a unique address as an idiosyncratic term, and etymology seeks to hierarchically order words according to their origins, but an idea per se will always elude precise identification. Unlike a document, an idea is not mechanically reproducible; it always requires interpretation and understanding in a mind, and a mental event as subtle as an idea cannot be observed.

(Lederberg, 2000) Garfield conflates citations with several roles in the network around ideas. Compares value of citations to value of subject coders, coding meaning of paragraphs intractable. ISI became a commercial pursuit because Garfield failed to get scientific institutions, especially the NSF, to fund it. The goal was primarily practical, to give researches access to current or historical references relevant to articles, perhaps especially their own, they knew they were already interested in.

Unlike ideas, documents are physical artifacts and can be traced empirically. They are fungible, reproducible, and locatable with addresses.

The reproduction and location of ideas cannot be reliably observed, and documents only contain ideas in a metaphorical

sense, as a Leyden jar was once thought to contain electricity.

Documents are the tangible and fungible currency with which scholars communicate about ideas, yet how knowledge is actually communicated via documents is not amenable to direct observation at scale. In bibliometrics they have served as a proxy for ideas.

There have been two main orientations to mapping the web of knowledge, description and conscription. Description has either scientific aims, to understand and explain the facts of knowledge development, or practical aims, to locate and retrieve knowledge required for a particular purpose. Conscription on the other hand aims to mobilize bibliometric patterns of knowledge as measures of value in competitive markets, namely hiring, promotion, and awards within scholarly professions.

There are several ways to digitally represent texts as knowledge.

From an empirical perspective, texts are nothing but collections or bins of glyphs. The current paradigm is to render glyphs and recognize them as terms. Such terms may then be analyzed, for instance, by counting diction. Alternative paradigms are cropping up

Second is entity recognition or grounding, where recognized terms are mapped to an existing database of structured knowledge.

(Pilkington and Meredith, 2009)

4.14.3 Disciplines as a Large World Co-reference Network

A large world network is not amenable to traditional visual representations due to its extreme density. Scholars often use edge filtering to reduce this density down to a manageable size for visualization. Unfortunately this convenience function renders a large world as a small world and grossly misrepresents the true structure of the network. In the KCC representation, the network is partitioned into subnetworks of differential density. Nodes are included in a subnetwork if they are involved in ties at a given floor of density, for instance, they need to be tied to at least five other nodes. At a level of five, then, nodes involved in only four ties would be excluded. As this standard is raised, more nodes are excluded. This results in a nested set of subnetworks, where nodes included in a community at a lower threshold are excluded at a higher threshold. Subnetworks of lower density thresholds are always as big or larger than those at higher thresholds. Moreover, higher density subnetworks are always subsets of lower density communities, as their density meets and exceeds the standard for inclusion at the lower level. As one can imagine, inclusive levels are larger. As the threshold is raised subgroupings

are sloughed off until reaching points of maximal density. In a world where almost everything is connected, there are no structural holes to reveal differences between subnetworks. Instead, we can view the structure as gradations in density within a very densely connected world.

Nodes meeting the highest standards can be thought of as omnivorous; their ties draw them to the masses, but the masses are not sufficiently tied to the higher standard community. Where the gentry may be as comfortable at the movies as at the symphony, the laity lacks access to the more erudite circles.

What is the credential that would allow a node to climb the hierarchy? One's list of acquaintances must overlap by a certain amount (defined by the threshold) with the membership of the higher tier. Indeed their inclusion would change the credentials of everyone they are tied with, as anyone who was just under the standard would be tipped in based on their friend's promotion.

In the KCC model the references are the members of the hierarchy. Their association with each other is determined by how they are used by published authors. Authors who include two references on their bibliography tie those references together in the network. Indeed each citing article lays down a dense clique of references, and the impact of an article grows quadratically with the length of its reference list.

4.15 Methods

4.16 Data

4.17 Results

The structure of a large world as revealed by KCC can be explored in a bottom-up and top-down fashion. Bottom-up observes 3-clique communities first. In the social science co-reference network.

Figure **??** shows a KCC model of the social sciences in the first half of the twentieth century.

Disciplinarity and interdisciplinarity are revealed in a novel fashion in the KCC model. Disciplinarity is shown as a level of exclusion.

4.17.1 Continents

The global map is made of many separate regions ranging in scale from large continents to small isles. These regions are either shallowly connected or entirely separated from each other. The vast majority of these regions are “flat isles” with little to no internal structure of their own. Most flat isles are supported by only a single article, some by a couple of articles penned by the same author, and only a few represent real activity among a small group of different authors.

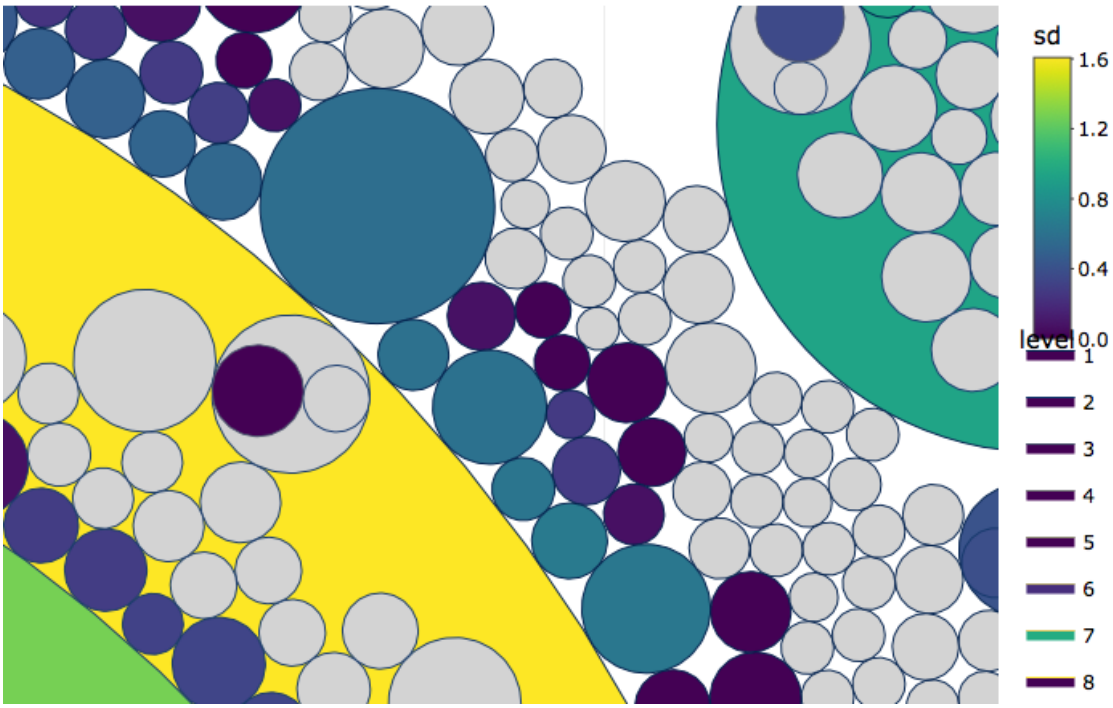


Figure 4.6: Flat Isles, where Reviewers tend their Flock

The most substantial flat isle , the largest unenclosed and unenclosing circle in Figure 4.6, comes from four authors publishing in the same 1930 issue of *Zeitschrift Fur Nationalokonomie*. It includes 50 references the most prominent of which are Angell's 1926 *The Theory of International Prices* and Tugwell's 1924 *The Trends of Economics*. The structure of the group is provided entirely by an article by Robert Reisch ; the other three shared no references in common and Reisch's article, titled "The 'Deposit'-Myth In Banking Theory" and containing 108 references, is likely to have been written as an introduction to the journal on the basis of what had already been accepted for publication.

Another flat isle of four articles has the exact same pattern, also from *Zeitschrift Fur Nationalokonomie* but from an issue in 1937, the article on the first page of the issue, titled "Theory Of Capital, Introduction" by von Hayek and containing 25 references, includes subsections of the bibliographies of three other articles that do not themselves overlap. Normally the longer a bibliography the more likely it is that an article functions as a review linking other disparate bibliographies. That von Hayek's article has such a short bibliography and yet still links three otherwise separate articles confirms its derivative character.

The following features then suggest when a flat isle represents an issue introduction. All articles are published in the

same issue. The removal of the longest bibliography in the community yields a network of disconnected components each uniquely representing the remaining bibs. This longest bib is also either the first article in the issue or precedes the others in pagination. These characteristics suggest authorship internal to the editorial process itself. Later we will explore how the removal of such articles helps to reveal "bottom-up" structure by removing the editorial advantage of certain authors to bestow an ad hoc intellectual coherence on scholarship.

Table **??** enumerates issue introductions and shows how many are the structuring article in their community.

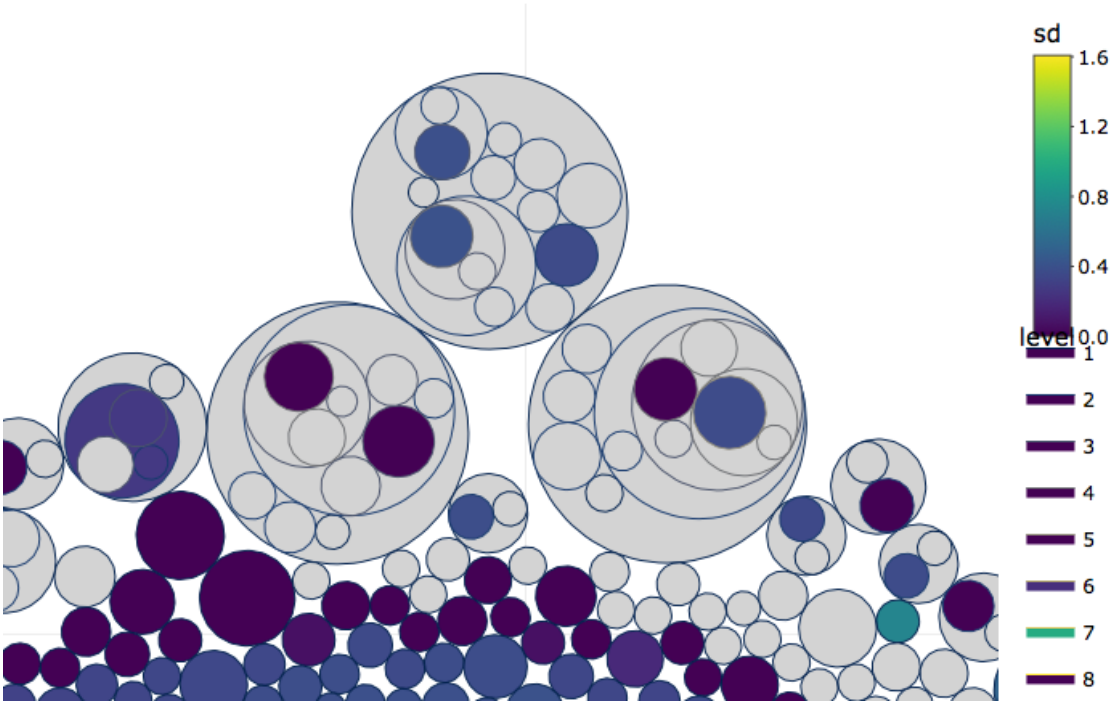


Figure 4.7: Hill Isles, where the Wild Things Are

Reviews, whether they are self described as such, borrow directly from the bibliographies of one or more seed articles, and in this way they contribute a disproportionate amount of the global structure of the co-reference network. This kind of review, rather than looking again at an existing intellectual trend, creates the cohesion it purports to describe. Flat isles, especially if they are large, are flat due to the retrospection of a usually solitary reviewer. Compare this to "hill isles" with more internal structure growing out of the related but uncoordinated reference activity of authors.

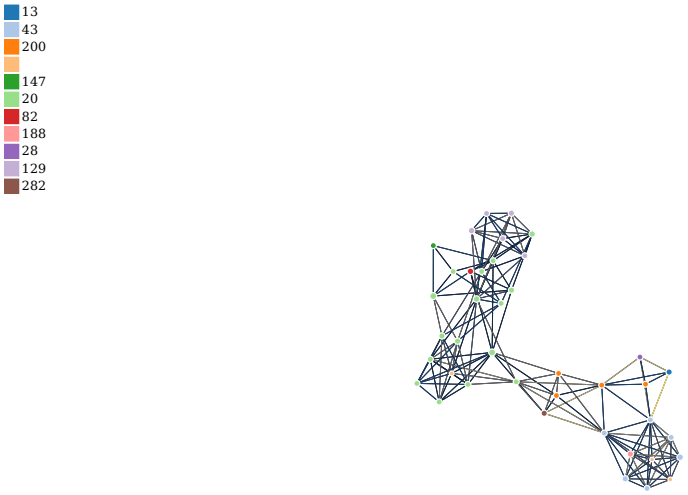


Figure 4.8: Hill Isle in Graph Layout

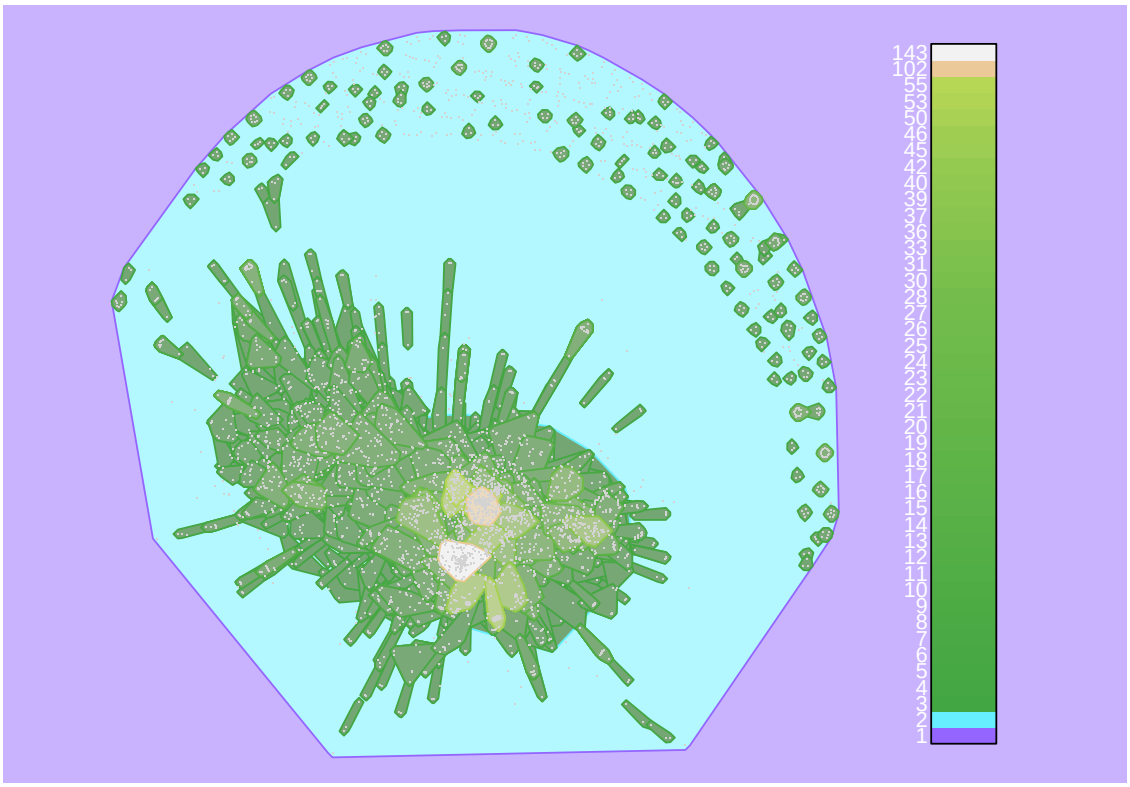
4.17.2 Peaks

The KCC model reveals

4.17.3 Valleys

4.17.4 Do reference lists describe author knowledge?

The peer review process can now be thought of as a process of auditing credentials. An author makes an opening bid with the submission of a particular reference list. What this reference list implies about what the author knows is unclear. One may omit a knowledge signal because it is truthfully irrelevant or in a deceptive sin of omission oriented to what they expect to be the expectations of editors and reviewers. One may also include what they do not know out of error, braggadocio, carelessness, or fraud. Part of the work of reviewers will be to validate those claims to knowledge.



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