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The Psychology of the Supreme Court: Modeling Judicial Semantics from Written Opinions

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ABSTRACT

The construction of knowledge networks from text is a novel way to study the cognitive organization of domain specific content. This dissertation evaluated the application of knowledge networks to legal text. Text analysis methods were used to transform text from 8,014 Supreme Court opinions into matrix data suitable for the construction of knowledge networks known as SCOD networks (Supreme Court Opinion Derived networks). Four specific hypotheses were then tested to better understand the meaningfulness and validity of SCOD networks. The first hypothesis considered differences between SCOD networks and random networks. The remaining hypotheses considered the ability of SCOD networks to reflect known issues of the Court. Monte Carlo simulations, various graph theoretic measures and measures of graph similarity were used to test these hypotheses. Results showed significant structural differences between SCOD networks and random networks. SCOD networks were also shown to have good face validity in representing scholarly characterizations of the Supreme Court, and in particular reflected known issues concerning the influence of ideology on Supreme Court decision making. In general, this work demonstrates the potential in using knowledge networks to help answer a wide variety of questions concerning Supreme Court decision making.

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Chapter 1

Introduction

This thesis explores knowledge representations derived from the text of Supreme Court opinions to investigate and gain insight into legal knowledge. The importance of such an investigation is two-fold.

First, it adds to the progress that scientists have made throughout history in finding valid ways to capture and represent knowledge. Progress in this area is important, namely because the elicitation of knowledge is not simple, and efforts to advance methods of elicitation and representation are valuable in various fields such as psychology (Feltovich, Prietula, & Ericsson, 2006; Hoffman R. , 1987), medicine (McGaghie, McCrimmon, Mitchell, Thompson, & Ravitch, 2000; Pratt, Gooding, Johnson, Taylor, & Tarrier, 2010), education (Goldsmith & Kraiger, 1996; Kraiger, Salas, & Cannon-Bowers, 1995; Wouters, van der Spek, & van Oostendorp, 2011), cognitive science (Chi, Feltovich, & Glaser, 1981; Ericsson & Polson, 1988; Hmelo-Silver & Pfeffer, 2004), expert systems (Hoffman & Lintern, 2006; Shadbolt, 2005) and linguistics (Solé, Valverde, & Steels, 2010)

Second, it provides insight into knowledge used to make decisions that determine every day aspects of our society. The United States Supreme Court plays a very powerful, involved role in the dynamics and evolution of society. The people of the United States vote to have some control over changes implemented into society. However, the Supreme Court has the ability to override the wishes of the people because of its ability to uphold or veto decisions of elected federal and state authorities. A mere five justices have the power to dictate policy for the entire

United States, and when a vote is split, a single justice holds this power. The content and organization of the knowledge used by a justice in deciding a case may reflect whether his or her decision is arbitrary and thwarts democracy for personal agendas, or rather is based within the realm of Constitutional foundations, away from politics and policy-making. A critique of the country's judicial decision making process is essential to the progress of a constitutional democracy. The investigation of the knowledge structures derived from Supreme Court opinions is the primary focus of this thesis.

Before delving deeper into the current approach, however, it is important to first understand the theoretical roots of knowledge representations as modeling aspects of human cognition. The central concept of a knowledge representation in this dissertation is based upon models of semantic memory called semantic networks. Work on semantic networks is discussed first in order to better understand how knowledge networks can yield insight into cognitive aspects involved in Supreme Court decision making.

The remainder of the chapter provides an overview of knowledge research. Included is a short history of knowledge as an academic pursuit, common techniques to extract and study knowledge empirically, and their corresponding findings. The interested reader may refer to Ericsson, Charness, Feltovich, and Hoffman, 2006, part II and III for a wider survey of techniques and findings. The section of this chapter titled "Deriving Knowledge Networks from Text" extends the survey into the domain of text analysis, providing a framework for the methods used for knowledge extraction and analysis introduced in Chapter 2 in this dissertation.

Semantic Networks

Knowledge networks are semantic networks. To better understand why knowledge networks are useful as models of legal knowledge, it is helpful to understand the concept of a semantic network within cognitive psychology. Perhaps the best way to understand the concept of a semantic network within cognitive psychology is to look at its history.

Arguably the most influential, early work in psychology regarding semantic networks was that of Ross Quillian (1968) and the subsequent papers of Collins and Quillian (1969) and Collins and Loftus (1975). The idea of a semantic network- a network of concepts linked by association- has been traced back to the time of Aristotle; however the term "semantic network" was first introduced in Ross Quillian's Ph.D. thesis (1968). Quillian introduced the term to describe how semantic information is organized in human memory (Johnson-Laird, Herrmann, & Chaffin, 1984). The basic assumption of Quillian's thesis is that word meanings can be represented by a set of verbal associations.

The Quillian model of semantic memory consists of a set of nodes (concepts) interconnected by different kinds of associative links, and every concept is defined by its location in this web of relationships between concepts. In particular, two concepts are said to be related if an unguided breadth-first search from each word yields a point of intersection of their respective verbal associations.

Quillian proposed two kinds of nodes: *type* nodes represent concepts and *token* nodes represent particular instances or meanings of words or phrases. Relational links connecting concept nodes to other concept nodes, may be unidirectional, but the majority are bidirectional. The *criticality* of a link is a number that signifies how important, or critical, each link is to the meaning of the concept. A link between concept A and concept B that is bidirectional may have

different criticalities for each direction. That is, the definition of A may be more dependent on concept B, but B may not be equally dependent on A.

For example, it may be very critical for the concept of a dog that it is an animal but it is not critical for the concept of an animal that a dog is a type of animal. The network is such that each node is linked to other nodes, which in turn are linked to other nodes as well. Quillian's theory was that the full meaning of any concept emerges when one begins with the concept node and transverses the entire network. Quillian's theory of semantic memory was proposed as a program for a digital computer and was not meant to be a completely psychologically realistic theory.

The work of Collins and Quillian (1969) was the next major contribution to the development of semantic networks. Unlike Quillian's original nets, Collins and Quillian attempted to create psychologically plausible models of the organization of memory and human inference using semantic networks. They proposed the semantic network as an *isa* hierarchy or taxonomic tree structure (Figure 1). Concepts are represented as nodes, linked by class-inclusion relations such that each concept is connected upwards to its superset and downwards to its subset. Links extending sideways off nodes give characteristic attributes of the node. For instance, the node "bird" is connected upward to the node "animal", downward to the node "robin" and sideways to characteristics of "has wings", "can fly" and "has feathers".

The inheritance structure was designed by Collins and Quillian in order to avoid redundancies. It follows what is known as *the cognitive economy principle* — the principle by which properties of concepts are stored at the highest possible level in a hierarchy and not re-represented at lower levels. Information shared by several concepts is stored in the highest node so that all the subset nodes can access the information about the properties. However, there are

Figure 1. The Collins and Quillian Network (Collins & Quillian, 1969, p. 241).

exceptions- properties of higher nodes are inherited by lower nodes to which they are connected assuming there is no property attached to a lower node that explicitly overrides it. For example, one may infer canaries can fly because birds in general can fly, but is inhibited from making the same inference for ostriches because of the explicit statement at the ostrich node that it “can’t fly”.

Collins and Quillian proposed algorithms for efficiently searching the inheritance hierarchies in order to retrieve or confirm facts such as “fish have fins”. In their proposal, the processes of word retrieval and recognition are simulated in a computer by a breadth first search algorithm. In this process, known as “spreading activation”, input words are given, and the tree is traced out in parallel along the links of the nodes corresponding to the concepts indicated by the input words. The spread of activation constantly expands, beginning with the nodes one link away from the starting nodes, then to all the nodes linked to these nodes and so forth. As

activation spreads among nodes, every node that is along the path of activation is tagged with a label that specifies the initial node and the given node's immediate predecessor. An intersection between two nodes is found if a tag from another starting node is encountered. The path that results in the intersection can be recreated by following tags back to both starting nodes.

The structure of the network was, at the time, a plausible model of semantic memory. In experiments, Collins and Quillian showed that the time of retrieving a concept and the distances in the network correlate. For instance, the time of retrieving the response to the question "Is a turkey a bird?" is a function of the number of links between the "turkey" node and the "bird" node. The longer the path length between concepts, the greater the time required to retrieve a response regarding the relationship of the concepts.

The idea that adjacent concepts are activated more quickly (and thus more quickly accessed by memory) than concepts further apart in the network is called semantic priming and was studied and backed by David Meyer and Roger Schvaneveldt (1971). They used a lexical-decision task in which subjects were presented with pairs of strings of letters, each of which could be a word or non-word. Subjects were faster at determining that pairs of strings were real word pairs if the words were related to each other (or in terms of Collins and Quillian network, if the two words were nearby in semantic network).

While the Collins and Quillian model was able to simulate some properties of semantic memory, the model was not able to explain certain experimental results. For instance, Conrad (1972) challenged the idea that properties are always stored at the most economical super-ordinate node. Landauer and Freedman (1968) challenged the idea that relative path length is the most critical factor in retrieval time, showing that relative size of sets of concepts may be more critical than path length. The most prominent finding against the Collins-Quillian model was that

even where path length was the same for two instances of a concept, one instance may be more prototypical than the other, and assertions about the typical instance (e.g., "A robin is a bird") are verified faster than assertions about the atypical instance (e.g., "A penguin is a bird") (Rips, Shoben, & Smith, 1973; Rosch, 1973; Smith, Shoben, & Rips, 1974) . The culmination of these results implied that cognitive economy is not always in play, and path length by itself is not always the determining factor of reaction time.

Collins and Loftus (1975) tried to account for the above experimental results with a refined version of the Collins-Quillian model. Their model assumes a different data structure than the tree structure of Collins-Quillian (Figure 2). They use a graph structure in which the nodes do not differentiate between concepts and their attributes. That is, nodes in the graph can be either nouns ('apple'), adjective ('red') or compounded expressions ('fire engine'). Their model is organized on the basis of semantic similarity, which depends on the number of properties concepts share, and thus the number of common links between them. They distinguish semantic similarity from semantic distance. Two nodes may be close in terms of number of links away, but may not be highly related in terms of meaning. For instance, *cherries* and *fire engine* are relatively close (small semantic distance) because they are only two links away (adjoined by the node *red*) but they have no other common links (small semantic similarity).

One of the major implications of the Collins and Loftus model is that if, for example, *flowers* is activated, then all the different types of flowers will be activated and will activate each other, whereas if *red* is primed, then *fire engine* and *cherries* will be primed, but there will be much less mutual priming because they have no other links in common.

Figure 2. The Collins and Loftus Semantic Network. (Collins & Loftus, 1975, p. 412)

The authors also proposed a revised version of the decision process put forth by Collins and Quillian. They weighted the connections to explain the typicality effect — the finding that typical instantiations of a category are recognized more rapidly. To decide whether two concepts match, sufficient evidence must accumulate to surpass either a positive or a negative threshold. Information about the concepts arrive from different pathways, with pieces of positive and negative evidence canceling each other out in what could be considered a Bayesian manner. Positive evidence is made of paths that link two concepts if the two concepts are related in at least one of the following ways: If one concept is a superordinate of the other; if the two nodes share a common critical property; or if one concept has a property of an instance of the other concept. Negative evidence is made of paths that link two concepts if the two concepts are related in at least one of the following ways: If one concept is not a superordinate of the other; if

the concepts that they have properties that mismatch on a critical property; if one concept lacks the properties of instances of the other; if the two concepts are mutually inconsistent subordinates of the same superordinate; or if there exists a counterexample to the alleged relation.

The weighting scheme proposed by Collins and Loftus is able to rectify the experimental findings of the typicality effect. This is due to the structure of the model, where atypical instances can elicit negative evidence to a greater extent than does a typical instance, and thus the activation of the typical instance is more likely than the suppressed, atypical instance. The Collins and Loftus model, however, is not able to explain a finding by Glass, Holyoak and Kiger (1979) that subjects can respond to questions that are blatantly untrue such as "Is a chicken a meteor?" (reflecting an underlying set of concepts that in the Collins and Loftus model are far in semantic distance and semantic relation) in a rapid response.

All three models previously discussed are influential models of semantic networks. Perhaps their biggest influence is in establishing the basic elements of models of semantic networks. In particular, each theory is an attempt to model the representation of meaning, is composed of concepts and relationships between these concepts, and uses a diagrammatical representation made of nodes and links to visualize the theory. Thus a semantic network is

1. A way to support inference about the mental representation of meaning through a model that allows for manipulation of internal representations.

2. A representation of knowledge in which there are *concepts* and *relationships* among these concepts.

3. A diagram made of a combination of *nodes*, *links* and *labels*.

Knowledge networks as described in this work are semantic networks and may be thought of as encompassing these three core features. Their purpose is to represent knowledge as a set of concepts that are related to one another. The history of semantic networks in psychology demonstrates their usefulness in understanding human cognition and predicts their utility in modeling legal knowledge.

Hopefully, this background on semantic networks will be of use to the reader in understanding the suitability of knowledge networks as models of legal knowledge. The remainder of this chapter focuses on the methods used to extract knowledge in a non-biased and complete manner so as to study its structure.

Knowledge and Thought

Unbiased communication between minds is impossible, not only physically but perceptually. Every sentence is perceived, however minutely, differently in each mind. Communication is achieved only in a roundabout way. The phrase "expressing one's thoughts" is mere hyperbole in comparison to the actual communication process. Thoughts are never expressed nor received without prejudice. The first barrier to a one-to-one mapping of thought between minds is the uniqueness of the way in which knowledge is represented within the mind of each individual[1].

Thoughts arise as a result of the unique dynamics and evolution of an individual's knowledge representation. To communicate a given thought to another mind, the thought is

[1] This is said within the realm of an exact one-to-one mapping of knowledge. Effective communication requires time and effort so that the knowledge of one individual can be incorporated and understood in terms of the knowledge of the other. However, the presence of knowledge structures is required for communication. If two people have no knowledge of a domain, they cannot communicate about it. Thus communication requires knowledge structures, but the uniqueness of individual knowledge structures implies an initial one-to-one mapping does not immediately (if ever) exist but must evolve through the communication process.

filtered through words and/or expressions that may or may not do justice in representing the thought. The receiver of the filtered thought, in turn, transforms the perceived thought into concepts and relations that resonate with the receiver's understanding of the topic. Finally, this information is integrated into the receiver's domain specific knowledge structure, altering the existing knowledge structure with its addition. Only then is the communication complete. The process of communication is like an unintended mental game of telephone. In the transfer of information, there is much filtering and biasing, and the transfer clearly does not result in a one to one mapping of thought between minds (Piaget, 1970).

Ideally the method used to study the content and organization of knowledge should limit the filtering or biasing that is inherent in trying to capture externalized thought. Psychology maintains a long list of methods developed throughout history, attempting to extract knowledge in a non-biased and complete manner so as to characterize knowledge structures. This task has proven difficult. Indeed, generating good methods for extracting knowledge is often referred to as "the knowledge acquisition bottleneck" (Hoffman R. , 1987). Among the earliest attempts to loosen this bottleneck was introspectionism, followed by think aloud protocols, recall tasks, and categorization tasks. As these methodologies developed, many scientists interested in knowledge representation used experts as subjects. Studies of expert knowledge have contributed to research in a variety of areas such as individual differences, memory limitations, reasoning biases, and the modeling of expert systems (Hoffman R. R., 1996). de Groot's pioneering study on the knowledge structure of chess experts has been followed by a large amount of literature on expertise, especially with respect to differences between experts and novices (deGroot, 1965).

Whether research is concerned with expertise itself or knowledge structures in general, expert/novice studies are useful because knowledge and its implementation are certainly embodied in experts. The use of experts to study knowledge has long aided scientists' efforts to create and refine valid methodologies to elicit knowledge and study its content and structure. The history of studies of knowledge is described next.

Historical Background of Studies of Knowledge

Empirical attempts to study mental phenomena began in the late nineteenth century, with introspective analysis of the experience of stimuli. Ericsson (2003) nicely summarizes the development and decline of introspectionism. The following discussion of introspectionism draws on his historic sketch.

Wilhelm Wundt (1897) argued that the method of introspectionism (the reporting of conscious inner thoughts) could be used in studying the experience of stimuli only with simple physical stimuli- points of light, brief sounds. He argued that attempts to use introspection to study internal experiences of more complex stimuli were not valid because as experience of complex stimuli is relayed, the mental image used to describe the experience changes as it is spoken of, thus tainting the report of thought.

A heated battle between Wundt and investigators at the University of Würzburg began at the turn of the 20th century when the Würzburg investigators reported the existence of "imageless thoughts". The Würzburg team, led by Karl Bühler, asked trained introspective observers to answer questions regarding their understanding of a given proverb. The observers gave their answers quickly and afterward gave reports about the thoughts that led to their answers. Some observers described thoughts that had no corresponding imagery (imageless thoughts). Wundt dismissed the claim of imageless thoughts but was more concerned about the poor experimental

design used by Bühler, believing Bühler's conclusions to be invalid and byproducts of a flawed design. The imageless thoughts debate soured scientists on the use of introspection as a valid method for studying thought.

The influential behaviorist John Watson denounced the introspective method because of its lack of reliability and its dependence on trust in observers' ability to analyze and report their conscious experience. Watson proposed a new methodological approach based on observable behavior and performance (Watson, 1913 ; Duncker, 1945) and was the first to publish a study where a subject was asked to "think aloud" while solving a problem (Watson, 1920).

Watson recognized certain types of complex cognitive processes such as problem solving corresponded to continuous processes, and that these processes were mediated by reportable thoughts. Watson maintained that thinking aloud required no introspective capacity, but rather thinking was accompanied by surreptitious activity of the speech system and thinking aloud made explicit sub vocal verbalizations (Ericsson, 2003). Thus, methods that required judgments by subjects of their own thoughts and perceptions were abandoned for more task-oriented, objective measures with outward looking reports.

The culmination of efforts to study thought through introspection and then through more objective measures led to subsequent, contemporary, empirical methods used to study knowledge organization. These techniques, discussed next, have led to several robust findings regarding the differences between experts and novices and the nature of expert knowledge.

Contemporary Studies of Knowledge: Elicitation Techniques and Findings

Evidence suggests that significant differences exist in the extent and organization of knowledge between experts and novices (Farrington-Darby & Wilson, 2006; Hoffman R. R., 1996) In other words, the *knowledge representations* of experts and novices are distinctively

different.   The techniques of thinking aloud, recall, and concept tasks that have led to present understanding of expert/novice knowledge and the differences between expert and novice knowledge representations are discussed next.

Think Aloud. A widely used and relatively simple method of collecting data on expertise is to interview the experts themselves (Cooke, 1999; Ericsson, 2006; Fox, Ericsson, & Best, 2010; Hoffman R. R., 1989; Shadbolt, 2005). However, one of the main concerns of interviews is the dependence upon experts to be able to describe their thought process and behaviors in a way that is understandable, useful and possible to replicate for non-experts. The reliance on experts to be able to explain processes has long been a point of debate. In an early study on memory and expertise, Binet (1893/1966) studied chess players and their ability to play "blindfolded" without seeing a chess board. Binet prompted the chess players for verbal descriptions of the visual images of the mental chess game and found marked variance in these descriptions. Some chess players gave extremely vivid reports, describing the chessboard as though they were not blindfolded, while other players reported only abstract characteristics of the chess positions. Furthermore, in cases where the expert reported the strategy then performed the task, discrepancies were found between the report and witnessed task procedure (Watson, 1913).

These discrepancies could be explained, in part, by the idea that many tasks performed by experts were not usually performed under circumstances involving self-reports and self-awareness during performance changed the content of thought itself. Clearly, however, verbal reports were not necessarily representative of the actual mental processes used to complete the task. Binet's research showed that experts varied on descriptions of a task and thus questioned

whether it was possible to draw general conclusions about the mental processes of chess expertise and whether experts are capable of explaining the principles of their task completions.

These issues led to Watson's proposal of the "think aloud" method (Ericsson, 2003), subsequently refined into protocol analysis of thoughts, perhaps most prominently by Ericsson and Simon (Ericsson & Simon, 1980; 1984; 1993). During a think aloud protocol a subject's thoughts (which are usually implicit) are verbalized while performing familiar tasks. The think-aloud model is useful in dealing with the problems of introspection (Ericsson, 2006). Think aloud protocols elicit verbal reports which are then recorded and encoded to yield data on the underlying thought. The expert is first trained to verbalize his thoughts using a think aloud technique. Next the expert performs a specified task and verbalizes thoughts while working on the task. The think aloud protocol requires verbalization only of the task to which the subject attends. The process is video-taped and/or audio-taped then transcribed. This taped data is later coded and analyzed (Nguyen, Lemai, Shanks, & Graeme, 2007).

Ericsson and Simon contend think aloud protocols do not change the underlying structure of the thought processes and thus avoid the problem encountered by Binet- namely that of reactivity. Reactivity occurs when the act of generating the reports changes the cognitive processes that mediate the observed performance (Ericsson, 2006). Verbalizing information affects cognitive processes only if the instructions require verbalization of information that would not otherwise be attended to, which is not the case for think aloud protocols (Ericsson & Simon, 1980). There is some disagreement on this point. Lloyd, Lawson, and Scott (1995) question the validity of think aloud protocols, claiming that thinking aloud may affect the problem solving process and result in incomplete data, invalid information regarding the problem

solving process and false insight into expertise. Regardless of this difference, think-aloud protocols have provided a rich source of information on expert performance and the ways in which experts and novices differ in their representations of knowledge.

In one of the earliest formal studies on expertise, de Groot (1965) looked at the way chess experts choose their moves. He instructed the players to think aloud as they analyzed the chess board for the best move. Using these verbal reports de Groot found chess experts first familiarized themselves with the current position and assessed its strengths and weaknesses. Next they systematically considered the results of potential moves and their opponents' countermoves by looking several moves ahead.

From the chess players verbalizations, de Groot, and later Charness (1981), mapped the sequence of explored chess moves as trees. These trees were then compared to the trees constructed from verbal reports given by non-expert chess players and the amount and depth of planning for chess players at different levels was measured. The results showed that as chess ability increased, the amount and depth of search increased to a given point, after which no further systematic differences were found (Ericsson & Charness, 1994). That is, once a player became an expert, there was no systematic difference in amount and depth of search. However, expert chess players still differed in their ability to locate and selectively explore the best moves. This study implied experts and novices differ in the structure of their internal representation of chess positions.

The importance of experts' internal representations of problems and solutions has been shown in other domains using think aloud protocols. Chi, Feltovich, and Glaser (1981) examined differences in the ways expert and novice problem solvers represent physics problems. They

found novices categorized problems by specific entities contained in the problem statement- for instance blocks or incline planes. Experts categorized problems by major physics principles that governed the solution of each problem- for instance using Newton's Second Law $(F = MA)$. The authors viewed the categorization of problems as linking the given problem to a library of internal diagrams where category names allowed access to the appropriate diagram. They concluded that knowledge useful for a given problem is tagged when a given physics problem is classified as corresponding most closely to an internal representation (diagram). One implication is that expert-novice differences may be related to superficial, poorly formed, qualitatively different, or nonexistent categories in the novice representation.

Other think aloud studies have demonstrated the idea of superficial versus deep representation of novices and experts. One study looked at the participants mental models of aquaria using a range of expertise from middle school children to teachers to aquarium experts. Novices' representations focused on perceptually available, immediate, static components of the system (i.e. gravel/rock), whereas experts combined structural, functional, and behavioral elements (i.e. gravel/rock in terms of its importance in reproduction in some fish) (Hmelo-Silver & Pfeffer, 2004).

A think aloud study by Larkin et al. (1980) provided evidence for two major differences in the way experts and novices represent and solve physics problems. They found novices solved problems by recalling formulas associated with the problem statement. For example, a novice recalled formulas associated with velocity if the problem asked for velocity as a solution. Novices then created a sequence of formulas, moving backward from the goal (finding the velocity) to the information in the problem statement, a process called "backward thinking" or

“backward reasoning”. The experts found solutions using “forward thinking” or “forward reasoning”. Experts read the problem statement, generated a representation of the situation and then continually updated the representation as new information was revealed about the problem. When experts finished reading the problem statement they simply retrieved the solution strategy from memory (Larkin, McDermott, Simon, & Simon, 1980). This work suggests that experts possess pre-existing knowledge structures of problem domains. These structures are quickly accessed and altered to adjust to the particulars of a given problem. Novices, lacking pre-existing, familiarized structures, build structures from pieces of the problem. In other words, novices possess no domain structure when beginning a problem or their structures are poorly organized, not coherent, and/or sparse in terms of core concepts and their relations.

Recall. Recall is a method of measuring memory. A great deal of understanding of expert/novice knowledge structures has come from free recall tasks. In free recall, the subject is shown a list or configuration of items which must then be recalled in any order. Recall tasks are useful in that they can reveal information about how memory for a given domain is organized.

A robust finding is that experts display superior memory on chess specific recall tasks. This is a classic, highly established phenomenon in expertise, first discovered in the game of chess (Feltovich, Prietula, & Ericsson, 2006). de Groot (1965) pioneered the study of pattern recognition and memory differences between experts and novices. A basic experimental task captured the immediate perception of chess positions by experts and novices. de Groot presented subjects with a legitimate chess configuration for approximately five seconds and then removed the configuration from view. When asked to recall the configuration of the chess board, experts were able to reproduce the positions of the 25 chess pieces almost perfectly. Weaker or amateur

chess players were only able to recall around five pieces- about the number of items that can be maintained in short-term memory (STM) exclusively by rehearsal (Cowan, 2001; Miller, 1956).

The nature of the underlying cognitive aspects of superior recall for chess pieces was subsequently investigated. The classic study by Simon and Chase (1973a) established that structure of knowledge is the critical distinguishing factor between expert and novice chess players. In the Chase and Simon study (1973a; 1973b) the expert, as in de Groot's study, displayed superior short-term memory, recalling four to five times the number of pieces recalled by the novice. Chase and Simon then presented these same subjects with chess configurations with randomly rearranged chess pieces. Memory for these scrambled positions was uniformly poor across skill level, leading Chase and Simon to reject the idea that an innate difference exists between the general memory capacity of novices and experts.

Rather, Chase and Simon proposed that experts' superior short term memory for chess positions was due to their skill in recognizing structure in meaningful positions of chess positions and encoding them into "chunks". Experts had long-term memory structures that allowed them to recognize meaningful perceptual chunks. When Chase and Simon reanalyzed memory performance in terms of experts and non-expert chunks, they found the superior performance of stronger players derives from their ability to encode the chess configurations into larger perceptual chunks. While the size of the chunks was larger, the number of chunks recalled for both types of chess players was still constrained to the limits of normal short-term memory (STM), which are approximately four to seven chunks[2] (Cowan, 2001; Miller, 1956).

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[2] At that time, Chase and Simon believed that storage of new information in long term memory was extremely time consuming and that memory for briefly presented stimuli could be held only in STM for both experts and non-experts. However, later research by Chase and Ericsson **Invalid source specified.** has shown that with extended practice (more than 200 hours), subjects can improve performance by more than 1,000%. In contrast to their original hypothesis, the improvements in chess recall are not mediated by increasingly larger chunks in STM but instead

Chunking explains how experts recall four to five times more pieces of meaningful chess configurations than novices. Specifically, if a chess expert can recall the location of 20 or more pieces of a configuration but is constrained to about five chunks in STM, then each chunk consists of four or five pieces, placed in a single relational structure. Novices, however, do not see structure within meaningful configurations and thus each of the five chunks may consist of only one piece. Chunking theory explains the poor performance of experts with random configuration of chess pieces. Since no meaningful patterns exist, experts do not recognize significant enough structure on the board to construct chunks of more than one or two pieces. Chase and Simon (1973a) reported that chunks of experts tended to consist of common patterns that are seen in regular routine playing of chess. A single chunk contains pieces bound by relations of mutual defense, proximity, attack over small distances and common color and type.

Subsequent studies confirm the importance of structured domain-relevant knowledge in expertise. In the domain of architecture, Gobert (1999) showed experts' representations of building plans were much richer than novices' representations. In addition, he found experts' understanding of the building's architectural genre to be superior to that of novices. Other domains, such as circuit fault diagnosis, have shown that expert circuit technicians chunk circuit elements by function. For instance, a technician would chunk resistors and capacitors because they pair up to perform the function of an amplifier (Egan & Schwartz, 1979). Other evidence of chunking in experts has been shown in waiters (Ericsson & Polson, 1988), and computer programmers (McKeithen, Reitman, Rueter, & Hirtle, 1981).

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reflect the acquisition of memory skills that enable subjects to store information in LTM and thus circumvent the capacity constraint of STM.

Conceptual methods. Verbal reports and recall tasks previously discussed indicate an organizational property to knowledge. Conceptual methods are special in that they allow researchers not only to elicit knowledge but also construct a representation of this knowledge in the form of domain related concepts and their interrelations. One of the goals of conceptual methods is to construct a visual representation of knowledge properties. Visual representations of knowledge are extremely useful for work in many domains such as education (Trumpower & Goldsmith, 2004) diagnostics (Pratt, Gooding, Johnson, Taylor, & Tarrier, 2010) and hypermedia navigation (Barab, Fajen, Kulikowich, & Young, 1996).

Several steps are required for conceptual methods and each step is associated with a variety of methods. The steps are as follows: (a) determine the core concepts in the domain, (b) elicit term relations, (c) formally represent the term relations, and (d) evaluate the quality of the representation. The last step is used to draw conclusions about the particular nature of the knowledge structure and the relation between behavior or skill and knowledge organization.

Determining concepts to best represent the domain is a critical step. There are various methods used (i.e. concept listing, step listing, chapter listing and interview transcription) to select core concepts (see Cooke, 1989) and each method differs in terms of the quantity and type of concepts obtained. To assess the adequacy of the concept set, domain experts are often consulted to evaluate whether the chosen concepts are key concepts within the domain and sufficiently span the domain. Another assessment technique is to construct hypothetical expert and novice knowledge structures from the concepts. If meaningful distinctions between expert and novice structures cannot be theorized with the concept set, then it is most likely inadequate (Cooke, 1999).

Conceptual methods elicit knowledge from domain experts in a number of ways such as pairwise relatedness ratings, sorting techniques, and frequency of co-occurrence (Cooke, 1999). The output of these methods is generally a proximity matrix where each value of the matrix gives the relatedness between a pair of concepts. This matrix itself is a representation of domain knowledge. However, scaling procedures are often used to clean the data and reveal the data's underlying organization.

One of the most common scaling procedures is Pathfinder network scaling which yields a graph with nodes and links, where concepts are represented by nodes and relations between the nodes represented by links (Schvaneveldt R. W., 1990; Schvaneveldt, Durso, & Dearholt, 1989). The Pathfinder technique will be discussed in more detail in the methods section. Two other common scaling procedures are multidimensional scaling (MDS) (Kruskal, 1964) and hierarchical cluster analysis (Johnson S. C., 1967).

MDS displays the structure of distance data in a spatial layout. Each concept is represented by a point in multidimensional space, arranged so that similar concepts are grouped closer together and dissimilar concepts are grouped further apart. The display may reveal well defined groupings along different dimensions that enable the researcher to characterize what features best differentiate the concepts.

Hierarchical clustering of data (Johnson, 1967) uses iterative clustering and the output display is a hierarchical tree with the most related concepts grouped highest together on the tree. This method starts by taking the set of concepts and assigning each concept to a cluster. For instance, if the concept set contains N concepts, there are initially N clusters, each containing one item. The distances between the clusters are defined to be the distances between the concepts in the relatedness matrix. Next, the most similar pair is merged into one cluster, yielding $N-1$

clusters. Then the distances between the new cluster and the other *N-2* clusters are computed using one of a variety of distance computing algorithms. Using this new *N-1* cluster set with the corresponding distances, the most similar clusters are found and merged into one cluster, resulting in a set with *N-2* clusters and *N* terms. This process is repeated until there is one cluster containing *N* terms. Once the hierarchical tree is complete, if *k* clusters are desired, the *k-1* longest links are cut.

All three methods- MDS, hierarchical clustering and Pathfinder reduce the set of relatedness judgments to a graphical form that provides a way to visualize organizational principles of the data. The method chosen to represent relatedness data depends upon many factors, for instance- the type of data (MDS may be better for visual concepts- i.e. pieces of art), the amount of information one is willing to lose (Johnson S. C., 1967), and the type of relations (local versus global) that is to be conveyed (Schvaneveldt, Durso, & Dearholt, 1989; Tversky & Hutchinson, 1986). Regardless of the technique used, the resulting representation is expected to yield information about the subject's conceptual structure for a set of domain stimuli.

To assess the conceptual organization of derived knowledge structures, it is usually necessary to have a referent structure against which other structures can be compared. Sometimes there is a logical, theoretical structure ideal for comparison purposes but it is often the case that an empirical referent is used. The empirical referent may be derived, for instance, from the relatedness data of a high performer or a pre-defined expert (Cooke, 1999). The use of a referent structure implies that there is a superior organization of knowledge that best reflects the native organization of the domain.

Acton, Johnson and Goldsmith (1994) compared different types of referents to determine if there is a most valid referent to use for assessing domain knowledge. The validity of a referent

structure was measured in terms of its ability to predict exam performance in computer programming courses and to distinguish the levels of expertise as a function of programming experience. The similarity between structures was quantified using a set theoretical measure called *closeness* C. Similarity as measured by C reflects the degree to which a concept has the same neighbors in two different Pathfinder networks (PFNETs) (Goldsmith & Davenport, 1990). Students who performed well on exams or who had more programming experience were likely to have knowledge structures most similar to the referent structure as quantified by C. The possible referent structures were derived from relatedness ratings of the instructor, other experts, averaged experts, and an average based on the best students in the class. Their results showed that even when ratings varied considerably from one expert to another (correlations were as low as .31 between experts' ratings), the averaged ratings provided the most valid and consistent referent structure.

There are important findings regarding knowledge organization that emerge from studies comparing individual knowledge structures to a referent. A robust finding is that as domain experience increases the corresponding knowledge structure becomes more similar to the referent structure. Wouters, van der Spek, and van Oostendorp (2011) showed that novice players of the video game *Code Red: Triage* developed similar knowledge structures to those of the referent structure, where similarity was the same as measured in the study by Acton, Johnson and Goldsmith (1994) and the referent structure was an average of the three *Code Red: Triage* instructors.

Gonzalvo, Cañas, and Baja (1994) used both MDS and Pathfinder to create representations of students' knowledge of psychology terms before and after reading a history of psychology textbook. They found as students' knowledge of terms increased (as evidenced by

test performance on term definitions) their knowledge representations became more similar to the averaged experts' referent structure. Similarity was measured in terms of angular multidimensional distances for MDS and the *C* metric for the PFNETs.

Other domains including naval decision making (Kraiger, Salas, & Cannon-Bowers, 1995) and physics (Shavelson, 1972) have shown that student and expert representations become more similar as instruction increases. Along the same lines, it appears that learning is enhanced when novices are presented with tools that steer the development of their knowledge structure to be more similar to that of an expert's (Trumpower & Goldsmith, 2004).

The idea that novices organize their knowledge in a more random, less coherent manner than experts is supported by comparisons of novice and expert knowledge structures (Kraiger, Salas, & Cannon-Bowers, 1995; McGaghie, McCrimmon, Mitchell, Thompson, & Ravitch, 2000; Stout, Salas, & Kraiger, 1997). A study by Schvanevelt et al. (1985) presented expert and trainee fighter pilots with a list of fighting pilot related concepts. The subjects were asked to make pairwise comparisons of the concepts and rate the items' similarity. The resulting knowledge representations revealed that experts produced similar networks, in which the important concepts and their relations were made salient, while the novices' networks varied, were less organized and more random. This difference of internal consistency of the representation has been measured quantitatively in terms of coherence, where coherence measures the consistency of an individual's conceptual relations. Coherence is a measure of expertise in that it reflects that subjects with more domain expertise generally produce higher coherence scores compared with less experienced subjects (Goldsmith & Kraiger, 1996).

Measures of coherence have reflected differential levels of expertise in empirical studies. For instance, Stout (1997) studied the knowledge structures of two groups of aviators of the same

level of expertise. One group was given a one day training course on helicopter related material. Both groups were asked to give relatedness ratings on concepts covered in the training course. The coherence was computed for the knowledge networks of the experts in the study (a course instructor and someone who developed the course curriculum), aviators who participated in the training course, and aviators who did not participate in the training course. The mean coherence scores were 0.81, 0.63 and 0.26, respectively, exemplifying how coherence reflects the degree of expertise.

As evidenced above, conceptual methods are advantageous in that they create meaningful structural representations that allow for data visualization and unique insight into knowledge organization. In addition, with respect to PFNETs, insight is gained from the use of metrics such as coherence and closeness. Recently, graph theoretic metrics (e.g. clustering coefficient, betweenness centrality, eigenvector centrality, average path length) have been applied to cognitive representations (Solé, Valverde, & Steels, 2010; Steyvers & Tenenbaum, The large scale structure of semantic networks: statistical analyses and a model of semantic growth., 2005) yielding insight into the topology and evolution of human semantic networks.

There are other methods besides conceptual tasks that are used for deriving knowledge networks, one of which is text analysis. The use of first person writings to derive knowledge networks is a valid method of accessing and studying knowledge and knowledge structure (Villalon & Calvo, 2011). It has several advantages, namely that it is (a) closest to the source of human thought, (b) less constrained than other methods, (c) applied to a source of latent, highly consolidated knowledge, and (d) novel. The theoretical advantages to constructing knowledge networks from text and the work conducted in this area are discussed next.

Deriving Knowledge Structures from Text

The methods of think aloud, verbal recall and conceptual tasks are only a few examples of methods used to elicit knowledge from an individual. The summary of the different methods used in the study of knowledge shows that experts and novices differ in terms of knowledge structure, processing and content. These methods depend upon the subject performing a task within an experimental or laboratory setting that is designed to elicit knowledge. The resulting knowledge structure is drawn from data of a particular task, and is one specific instance of the knowledge structure of the domain. The implication is that the knowledge structure exists outside of this particular task and that the task serves to capture the essence of the knowledge structure. Knowledge structures clearly exist independent of techniques used to intentionally elicit them and may be reflected in any number of activities that an individual performs. One such activity is writing.

To derive a knowledge structure from text is to essentially reconstruct a knowledge structure from existing artifacts. To date, there has been little research on deriving knowledge structures from text, let alone research on whether or not knowledge structures derived from text are meaningful. In theory, knowledge structures extracted from text offer a unique and advantageous perspective of knowledge content and organization when compared to the traditional, non-text based methods.

The methods discussed- think aloud protocols, recall tasks and conceptual tasks all study knowledge in ways that restrict access to the knowledge structure. All three methods use only knowledge elicited within an experimental setting. Categorization tasks assume the components of the knowledge network by choosing a basis for the term set. Recall tasks consider how

knowledge is organized with respect to a particular task and do not necessarily take into account the content or organization of the knowledge structure over a broader range of the domain. Think aloud protocols bound the subject into thoughts that can be verbalized, and thus miss some potentially important data.

The ideal method would be to open the head of an individual, peer inside and view the knowledge network directly. Of course, this is not possible. A more realistic, but still perhaps unobtainable method is one that makes no assumptions about the knowledge structure and does not constrain the elicited information to such an extent that the result is an incomplete knowledge structure. Introspectionism, putting aside its validity issues, makes no assumptions about the underlying representation, is non-restrictive and can give access to unrestrained stream of consciousness which may provide more information about the knowledge structure than other methods. Of course, there are problems in building a knowledge network from introspective data. The looseness of introspective protocol results in a wide range of methods for gathering and formatting data. The variability reduces both the reliability and validity of the data, rendering data from introspection a poor candidate for effectively representing knowledge.

It appears that verbal expression of thought is not optimal for the construction and analysis of knowledge representations. Written speech, especially with the use of drafts, allows time for the alteration and consolidation of knowledge and for the selection of words that best reflect an understanding of the topic. The evolution from planning to write to first draft to final draft reflects mental processes embodied in the formation and consolidation of the writer’s knowledge network.

Bereiter and Scardamalia (1987) think of writing as knowledge transformation. Reflection on what has been written restructures existing representations of the topic. Transformations in knowledge that result from the writing process are incorporated into written exchanges of knowledge and ideas are relayed in a very cohesive, rich manner. Verbal exchanges of knowledge, however, consist of chains of ideas that are simply connected by "and".

Others have expressed the effect of writing on the formation and consolidation of representations, arguing that the nature of writing forces the integration of ideas, the establishment of relations between pieces of information and the conscious exploration and conceptualization of the writing topic (Emig, 1977; van Nostrand, 1979; Odell, 1980). Schumacher and Nash (1991) argue that writing brings about knowledge restructuring because it involves the active manipulation of representations of ideas through the writing process. As the writer prepares to translate these ideas to text, the representation of ideas becomes progressively more lingual in character, forcing a greater specification of the writer's ideas. This forced specification results in a more refined representation of ideas, clarifying amorphous and contradictory concepts within the representation, and allowing for the realization of new relations which may have been unclear or not specified in a more abstract instance of the representation. Thus, the power of writing appears to be that it forces consolidation and clarification of a knowledge structure that otherwise would not be organized to this extent.

In this way, knowledge representations constructed from text can yield more organized, coherent knowledge structures than those extracted from traditional elicitation methods. Knowledge networks are active in both written and oral speech but in some situations a clearer, more consolidated representation of domain knowledge may be gained by constructing

meaningful knowledge representations from first person writings[3]. Nearly all research conducted on expert knowledge representations comes from methods that require verbal elicitation. As described above these representations have proved to be valid, useful, meaningful representations of expert knowledge.

Limited work has been conducted toward developing methods to construct meaningful knowledge networks from text. The knowledge structures that have been produced from text are not knowledge networks as represented by PFNETs but rather are *concept maps* as developed by Novak (1984). Concept maps reflect a person's understanding of a topic in a hierarchical way, with more general terms placed at the top of the map and terms become more specific as they branch away from the more general terms (see Novak & Cañas, 2008 for more details). Unlike PFNETs, concept links are labeled, so that concepts relations are made evident by propositions such as "is founded on", "requires", and "focuses on". An example provided by Novak and Cañas (2008) shows a concept map of "Exploring Mars" where the concept of "Exploring Mars" is linked to "Human Missions" by the proposition "will eventually lead to" and to "Robotic Missions" by "is presently carried out by".

Though concept maps and PFNETs are both considered to represent knowledge (Novak & Cañas, 2008) , concept maps are used primarily as a classroom aid to assess student knowledge (Ruiz-Primo, Shavelson, Li, & Schultz, 2001) or facilitate learning (Chang, Sung, &

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[3] Creating knowledge structures from text also has practical implications for expertise applications. Government and private sector organizations often need to capture expert knowledge prior to or subsequent to the retirement of experts. Elicitation of knowledge from experts using traditional elicitation methods is often time consuming and burdening if the method requires performing a task outside the experts usual routine of work. It would be of great benefit to incorporate a process of ongoing knowledge capture into the ordinary activities of the experts without burdening them with an additional task (Hoffman, 2006). A method that extracts knowledge structures from text written by experts in carrying out their job duties would be a very good, efficient way to capture knowledge of experts, even after the experts retire, for government and non-sector organizations.

Chen, 2002) ; whereas PFNETs, while they can be used for educational purposes, address theoretical questions about the nature of human knowledge- its content and organization from a cognitive psychology perspective.

There are many differences between PFNETs and concept maps that reflect this divergence. Unlike PFNETs, the links and concepts within concept maps are not a product of a predetermined list or rigorous computational algorithms; rather, concept maps have no fixed terms or links, and are composed of concepts and relations chosen to be made explicit by the constructor (Leake, Maguitman, & Cañas, 2002). For instance a concept map may be created by a subject linking concepts together himself or by an interviewer taking responses of a subject and creating concept maps from an interpretation of these responses. Also unlike PFNETs, there is no uniform measure of similarity or dissimilarity between concept maps or measurements such as the Pathfinder's *C* metric, but instead a wide range of methods are used to score and assess concept maps (Rice, Ryan, & Samson, 1998). Another difference is that links in PFNETs are rarely if ever labeled but concept maps have labeled links. In fact, the labeling itself is a big part of testing student's knowledge (Novak & Cañas, 2008)

Concept maps produced from text are a pioneering effort to begin to represent knowledge from text, though the primary focus of these attempts are for purposes of automated essay grading rather than philosophical in nature. Clariana (2004) created a software tool for automated essay analysis called *ALA-Reader* that takes written essays as input data. To construct concept maps derived from text by way of the *ALA-Reader*, the researcher first chooses a core set of terms to represent the text, either by selecting pairs of terms that possess high word co-occurrence frequency and/or by having an expert choose the term set. *ALA-Reader* then uses this

set of terms to search for co-occurrences of these terms within the provided written text. The term co-occurrences are translated into propositions which are then totaled across all sentences into a proximity array. Clariana's method recognizes the usefulness of Pathfinder algorithms and measures, using Pathfinder to read in the proximity data and output the corresponding concept maps and relevant metrics.

Clariana and Koul (2004) used this software to assess student essays about the circulatory system. The essays were scored both by human raters and from the PFNETs. Scores from PFNETs were derived by comparing the students PFNETs to the PFNET constructed from the essay written by an expert biologist. The validity of the PFNETs as representations of written text was assessed by obtaining student assessment of structures and by comparing the correlation of human rater scores to the scores generated by the *ALA-Reader* ($r = 0.69$).

ALA-Reader has also been used to create average knowledge representations from both low performing and high performing business school students from written essays for comparison to a knowledge representation extracted from the essay written by the expert referent (Clariana & Wallace, 2007). They found that the average structure of high performing students was more similar to the expert referent than the average structure of low performing students, and that average structures of high and low performing students were more similar to each other than to the expert referent.

Recently, Villalon and Calvo (2011) put forth software called *Concept Map Miner* (CMM) which is not dependent on Pathfinder, and that takes essays and automatically generates corresponding concept maps with labeled links which can be viewed by the writer for learning enhancement. In general, work on concept maps extracted from text demonstrates that

constructing knowledge representations from written documents provides useful information about the knowledge structure of the writer.

Goal of the Dissertation

This thesis builds upon efforts to derive knowledge representations from text by constructing knowledge representations from the opinions of the Supreme Court justices. The major goal of this work is to decide whether or not these knowledge representations can be can provide intuitive and useful representations for modeling legal knowledge and inference. Within the paradigm of semantic network models, we can ask at least two distinct kinds of questions concerning the value of these representations.

The first type of question concerns the structure of the representation- Does the structure of knowledge representations derived from Supreme Court opinions contain information about semantic organization within the documents? This question may be answered by assessing knowledge representations derived from Supreme Court opinions both in terms of their structural make up and their face validity. In this vein, the structure of knowledge networks derived from Supreme Court opinions will be compared to the structure of random networks. Many important natural networks, including semantic networks in natural language, have been shown to have different structural properties than random networks (Steyvers & Tenenbaum, 2005). If the method used to derive knowledge representations from text is valid, we would expect knowledge representations derived from Supreme Court opinions to be structurally different than random networks.

The second type of question concerns the semantic information reflected in the networks- Do knowledge representations derived from Supreme Court opinions reflect known information ,

about the Supreme Court? That is, does the information they provide mesh with generally accepted theories or understanding about the Court? Thus, to test the validity of knowledge representations with respect to their information content, the information provided by knowledge representations of Supreme Court opinions are assessed in terms of what is already known about the Court. In particular, this work tests the ability of knowledge representations to reflect known characterizations of conservative and liberal rulings on the Court, and it is expected that knowledge representations will be able to reflect these characterizations.

Chapter 2

Motivation and Hypotheses

There are several important legal issues that can be explored using knowledge representations. The value of knowledge representations applied to these issues is, however, unknown and is explored by testing five specific hypotheses, described next.

Motivation

The question of how justices make decisions is of great interest in legal and political realms (Lax & Radar, 2010; Segal, Westerland, & Lindquist, 2011). There is debate about how much of a role judicial ideology plays in Supreme Court rulings. Legal scholars have spent time trying to resolve this debate and predict the role of political ideology in decision making (George & Epstein, 1992; Lax & Radar, 2010; Segal, Epstein, Cameron, & Spaeth, 1995). Much effort is spent trying to place Supreme Court justices into classes such as “liberal”, “moderate”, and “conservative” to explain judicial behavior. The assumption that these labels reflect fixed belief systems of justices underlies many theories of judicial behavior. For instance, legal scholars advance a positive theory of "partisan entrenchment," whereby the President can change constitutional doctrine by appointing justices who share the political preferences of the presidential party (Balkin & Levinson, 2006).

However, the assumption that justices are “entrenched” in their initial ideologies throughout their career is incorrect. Rather, long-range behavior of justices is relatively unpredictable (Epstein, Martin, Quinn, & Segal, 2007). Republican appointee Justice Blackmun drifted to the left on issues such as abortion and death penalty (Martin & Quinn, Dynamic Ideal Point Estimation via Markov Chain Monte Carlo for the U.S. Supreme Court, 1953-1999, 2002),

away from the conservative views that had once dubbed him Chief Justice Warren Burger's "Minnesota Twin". Justice David Souter, appointed by the first President Bush to be a conservative voice in the Court, drifted leftward as well (Martin & Quinn, Dynamic Ideal Point Estimation via Markov Chain Monte Carlo for the U.S. Supreme Court, 1953-1999, 2002). Interestingly, Bush appointed Souter to replace another conservative disappointment- Eisenhower's Justice William Brennan- whose drift was even more pronounced than Souter's (Martin & Quinn, Dynamic Ideal Point Estimation via Markov Chain Monte Carlo for the U.S. Supreme Court, 1953-1999, 2002). The unpredictability of the long term behavior of such justices is costly for presidents and their legacies.

The finding that judges' preferences and voting behavior might vary significantly in their careers is called ideological drift (Epstein, Martin, Quinn, & Segal, 2007). The study of ideological drift has major implications in areas such as judicial nominations (Owens & Wedeking, 2012), changes in legal doctrine (Epstein, 2007), and the Court's legitimacy within the American public (Bartels & Johnston, 2013).

Work by Epstein and colleagues (2007) shows that most justices demonstrate ideological drift during their career. Epstein et. als' work analyzed the voting behavior of 26 justices who served 10 or more terms on the Court since 1937. Changes in voting behavior patterns revealed that of these 26 justices, 22 drifted ideologically and only four remained ideologically consistent.

Some question the validity in using voting behavior to measure ideological drift (Farnsworth, 2007). Most empirical studies of judicial ideology use voting behavior to categorize a justice's ideology (Fischman & Law, 2009). Using only voting data to assess drift is limiting because it does not help us understand the nature of ideological drift, or how justices structure legal knowledge. A better approach would be to answer the question of why a justice's

knowledge structure changes over time. There is reason to predict that using knowledge networks will be useful in characterizing Supreme Court justice's knowledge organization. As previously discussed, knowledge representations have proved to be valid, useful, meaningful representations of expert knowledge. Certainly a Supreme Court justice can be viewed as a domain expert in the same way a physicist, chess player, or computer programmer is viewed as a domain expert. It follows that knowledge representations from Supreme Court justices are representations of expert legal knowledge, and as such, these representations should prove useful in understanding the organization of legal knowledge.

Using the Supreme Court written opinions, the current research extracts knowledge networks from the written opinions of the Supreme Court, providing the first direct look into the cognitive framework used by justices to make decisions. The networks provide a unique perspective into understanding how much ideology influences the decision making process. The ultimate test of the value of these networks is whether scholars can collect useful information that would not be uncovered with other research methods. The following section lays out the hypotheses that were tested in an effort to better understand the value of Supreme Court Opinion Derived networks (SCOD networks) in understanding legal knowledge.

Hypotheses

Because deriving knowledge representations from text is a novel pursuit, a main goal of the dissertation is to assess the usefulness of this method. Thus, the validity of the method will be tested by whether or not the information derived from the representations is meaningful. The meaningfulness of the representations will be tested through five different hypotheses. The first hypothesis assesses the method of deriving meaningful proximity information from written

opinions. The second hypothesis assesses the meaningfulness of SCOD networks by its comparison to random networks. The third hypothesis assesses SCOD networks' meaningfulness by its face validity. The fourth and fifth hypotheses assess meaningfulness by whether or not a network yields valid information in terms of known findings on the role of ideology in Supreme Court.

Deriving Proximity Information from Written Opinions. Before considering the validity of the network structures themselves, it is important to consider whether the proximity information derived from Supreme Court opinions is meaningful. If proximity data obtained from Supreme Court opinions is meaningful, we should expect multi-dimensional scaling of the data to separate the data into appropriate categories. Using a statistical analysis of the ideological classifications of justices' votes on cases, Landes and Posner (2009) ranked the ten most and least conservative justices on the Supreme Court during the time period of 1937-2006. The following hypothesis uses this ranking to test the validity of proximity data derived from Supreme Court opinions:

> Multi-dimensional scaling of the opinions written by the "least" and "most" conservative justices' as proposed by Landes and Posner (2009) should reflect a separation of the most and least conservative justices. This hypothesis will be referred to as **Justice Separation Hypothesis.**

Landes and Posner (2009) list the following, in order, "most conservative" justices in the Supreme Court (where Thomas is the most conservative): Thomas, Rehnquist, Scalia, Roberts, Alito, Burger, O'Connor, Powell, Whittaker, Kennedy. They list the following, in order, "least

conservative" (i.e., most liberal) justices in the Supreme Court (where Marshall is the least conservative): Marshall, Douglas, Murphy, Rutledge, Goldberg, Brennan, Black, Warren, and Ginsburg. If the Justice Separation Hypothesis is supported, MDS should capture a separation of these justices into similar groups.

Comparing SCOD networks to random networks. A first step in determining the usefulness of SCOD networks is to compare them to random networks. There are different methods to construct a random graph (Newman, 2010) . Two of the most widely used random graphs are known mathematically as $G(n, m)$ and $G(n, p)$. $G(n, m)$ is a graph in which the number of nodes, *n*, and the number of links, *m*, is fixed and the way in which the links are placed among the nodes is random. $G(n, p)$ is a graph in which the probability of links rather than the number of links between nodes is fixed.

The random networks constructed in this dissertation represent networks were of the $G(n, m)$ variety. A SCOD network would be constructed with a specific set of nodes that corresponded to the top *n* terms as rank ordered in the term by category matrix corresponding to the SCOD network. To compute the similarity between a SCOD network to another network, both networks need to have the same nodes. Thus, to make a comparison with a "random" network, the links of the SCOD network were shuffled, yielding a network with the same number of nodes and links as the SCOD network, but whose links were arranged differently between nodes.

Random networks are useful in understanding the structure of non-random networks (Steyvers & Tenenbaum, 2005). A comparison between networks derived from Supreme Court opinions to random networks is important in verifying the inherent structure in the knowledge of Supreme Court justices. If networks constructed from Supreme Court are meaningful, then we

should expect their network structure to be distinct from random, non-semantically meaningful networks of the same number of nodes and links. If SCOD networks contain significant, structured information, we expect their organization to be more meaningful than random networks. One way to assess this characteristic is to compare graph indices of random networks to SCOD networks. Still another way is to compare the similarity between random networks and SCOD networks. With respect to these two comparisons, the following hypothesis is proposed:

> SCOD networks will be more meaningful than random networks. In particular, SCOD networks will show greater values of node coherence and clustering coefficients. In addition, SCOD networks will have zero similarity to random graphs and a higher similarity to each other. This hypothesis is known as the **SCOD vs. Random Network Hypothesis**.

Face validity of SCOD networks. Another way to determine whether or not SCOD networks are useful for legal research is to judge their face validity. That is, do the terms and link between terms appear to be reasonable, given what is superficially known about the Court? With this question in mind, the following hypothesis will be tested:

> If SCOD networks are to be useful for legal research, we expect them to have meaningful concepts and link concepts in a way that is meaningful as well. That is, we expect that SCOD networks will reflect at least superficial information about the Court. This hypothesis will be referred to as **The Face Validity Hypothesis.**

To test the face validity of SCOD networks, networks were derived from two different SCDB categories, Criminal Procedure and Civil Rights, and for both liberal and conservative decisions. One way to determine the goodness of the networks is whether or not themes found within the networks are consistent with what is known about the Court. To this extent the

existence of focuses within a network were investigated to determine whether or they made sense in light of facts about the Court.

Using SCOD networks to investigate the ideology of the Supreme Court. The fourth and fifth hypotheses involve the issue of ideology in the Supreme Court, discussed above in the "motivation" section. The fourth hypothesis considers the ideology of a well-documented "ideological drifter" on the Court and the fifth concerns the ideology of different eras of the Court.

Justice Blackmun's network evolution will reflect ideological drift. This hypothesis will be referred to as **The Blackmun Drift Hypothesis**

To test this hypothesis, three separate networks were constructed from a collection of 827 opinions written by Blackmun during his tenure on the Court. The first network was constructed from the 276 opinions written by Blackmun from late June, 1970 through mid-April, 1979. The second network was constructed from the 276 opinions written by Blackmun from late April, 1979 to early June, 1986. The third network was constructed from the remaining 275 opinions written from mid June 1986 through the end of June, 1994.

In her book on Justice Blackmun, Linda Greenhouse (2005) details Blackmun's transformation as he drifted from a moderate conservative to become a champion of women's rights. A reflection of Blackmun's transformation via network evolution should be indicated by changes in key words associated with women's rights.

SCOD networks will reflect particular Courts ideology. This hypothesis will be referred to as **The Court Ideology Hypothesis.**

To test this hypothesis and determine whether knowledge networks reflect the historical assessment of the different courts, the similarity between the average liberal, average conservative and various court networks (Vinson, Warren, Burger, Rehnquist, and Roberts) were calculated and compared.

There is a consensus among Supreme Court scholars and journalists that the Supreme Court has experienced a conservative drift over the last fifty plus years. This rightward drift purportedly began with the shift from a liberal Warren Court, to a Burger Court with no built in ideological majority (Spaeth H. , 2005), intensified in the Rehnquist Court and became most pronounced in the Roberts Court (Liptak, 2010).

In particular, what is perhaps one of the most noted drifts in the Courts ideological leanings occurred during the Warren Court (1953-1969). The Warren Court is almost universally recognized for its liberal rulings, using judicial power to expand civil liberties. In fact, the Warren Court is often considered by liberals to be the golden age of the Supreme Court and considered by conservatives to be the peak of inappropriate judicial meddling (Liptak, 2010). Using measures of network similarity, SCOD networks will reflect known characteristics of the Court's ideologies. In particular, it is hypothesized that the similarity between the civil liberties liberal network and the Courts networks will be highest for the Warren Court. The similarity between the conservative networks and the Courts' networks will increase from the Warren Court through the Roberts Court.

Chapter 3

Methods

In general, network representation of text derived knowledge involves a three step procedure: Obtaining and formatting the corpus, transforming the corpus into a format that can be read by network building software such as *Pathfinder*, and building the network. After discussing these general methods, the methods used for each specific hypothesis are reviewed.

Obtaining the Corpus

The first step in constructing knowledge representations from Supreme Court opinions is to select a corpus of opinions. The complete list of opinions may be obtained from the author. Websites such as http://www.findlaw.com/, http://supreme.justia.com/ and http://www.law.cornell.edu/ provide links to full opinion text. The set of 8,014 opinions obtained for this work were downloaded from http://www.findlaw.com/.

Description of the corpus. An opinion is the name for the entire written decision. The majority opinion, concurring opinion(s) and dissenting opinion(s) are the main parts of the opinion, though not all opinions contain concurring and/or dissenting opinions. The opinions vary in content. That is, there is no particular format requirement for an opinion, but there are some common patterns of what is often contained in an opinion, usually based upon decision type (Lupu & Fowler, 2011). An opinion may contain (a) only a majority opinion (if the decision is unanimous) (b) concurring and dissenting opinions, (c) a majority opinion with dissent noted on part of the opinion, (d) majority and dissenting opinion but with dissenting opinion still concurring with majority on part of the opinion.

Opinions also vary in length. Black and Spriggs (2008) studied Supreme Court opinion lengths across eras and found extensive variation in length. For instance, under the Roberts Court, the median word count of a decision (which includes the majority opinion and all separate opinions) is 8,265 words. However, in the 1950's the median word count was around 2,000. The word count in *Citizens United v. Federal Election Commission*, a decision that lifted restrictions on corporate and union candidate funding, was 183 pages and more than 48,000 words and contained the ninth longest majority opinion. The U.S. Department of Commerce Technology Administration estimates the total word count to be around 14.5 million for the 7,407 decisions made between 1937-1975[4]. The analyses discussed next are based upon the set of individual opinions extracted from 8,014 cases which spanned the years 1946-2013 and were downloaded from http://findlaw.com/.

Form of the Data. To create knowledge networks from Supreme Court opinions the documents must be properly formatted. The text was downloaded, case by case, from the internet in html format. A commercial software package (MATLAB 2012b, The MathWorks, Inc., Natick, MA) was used to remove the markups and transform each case into a .txt file. Thus, the data was initially divided into documents in which one document represented one case. A total of 8,014 cases from the years 1946-2013 were downloaded from www.findlaw.com and stored in ascii text format.

[4] http://supcourt.ntis.gov/

Transforming the Corpus into Pathfinder Readable Data

Pathfinder accepts square matrices containing proximity data as input and outputs a Pathfinder Network (PFNET) based on the proximity data. To derive a proximity matrix from text, a term by document matrix (tdx) and a term by category matrix (tcx) are constructed. The formation of the tdx is dependent upon the selection of a set of key terms. The following section gives an overview of the methods involved in selecting the key term set, creating the tdx, the term by category matrix, and the term by term proximity matrix for the set of 8,014 Supreme Court opinions. This overview should give the reader sufficient background to follow the methods described in testing each specific hypothesis, discussed toward the end of this chapter.

Defining a subset of key terms and constructing the tdx. The tdx is a mathematical matrix that describes the frequency with which terms occur in a document or set of documents (Figure 3). The tdx is often used in areas of natural language processing to mathematically represent the semantic content of a document set (Sebastiani, 2005). It is the basic unit of analysis for deriving networks from text. Because the number of terms contained within a corpus is often very large, it is often desirable to represent the corpus by the frequency of only semantically significant terms. The first step in constructing a tdx that captures semantic information of a corpus is to identify a relatively small subset of terms that captures much of the content of the document set. This small set of terms is called the *key term set*. The goal in defining key terms is to identify a relatively small subset of terms that captures much of the content of the document set. The set of key terms may be the set of unique terms across documents. However, depending upon the database, the number of unique terms may be too large or redundant to be used for building knowledge networks.

$$
\begin{array}{ll}
 & \text{Document 1} \quad \ldots\ldots \quad \text{Document 8014} \\
\begin{array}{l}\text{Term 1} \\ . \\ . \\ \text{Term 848}\end{array} & \begin{pmatrix} 0.9 & \cdots & 0.4 \\ \vdots & \ddots & \vdots \\ 0.01 & \cdots & 0.3 \end{pmatrix}
\end{array}
$$

Figure 3. Term by document matrix. Rows represent key terms and columns represent documents. The matrix entries give the normalized frequency of a term within a document. The "full" tdx constructed from the Supreme Court corpus was represented by 848 terms across 8014 documents.

Various methods or combinations of these methods are applied to subset of unique terms while maintaining its' covering properties. These methods include (a) eliminating any term that does not occur in at least a certain percentage of the documents (e.g.0.1%), (b) eliminating words (including stop words) that are used with the same relative frequency as used in standard English, and (c) combining word forms through stemming. In addition, standard key term selection methods are available for automatic key term selection. To define a unique term set for the corpus of Supreme Court opinions, (a) through (c) were performed on the data set. In addition, the *Wikipedia Category Based Key Term Selection* algorithm (Lippert & Goldsmith, 2014) detailed in Appendix A, was used to further reduce the key term set.

The tdx matrix is then constructed from this reduced key term set. Each row in the tdx represents a key term and each column represents a document. The cell values give the frequency each term occurs in each document. In this case, the individual documents are defined by author. Thus, a particular document of the set may be a concurring opinion written by Justice Thomas, another document may be a dissenting opinion written by Justice Warren. In this way a Supreme Court decision that corresponds to a single case could contain multiple documents as defined by

units of data. For example, *Bell versus Ohio* 438 U.S. 637 (1978) contains four documents: the majority opinion by Justice Burger, a concurring opinion by Justice Blackmun, a concurring opinion by Justice Marshall, and a dissenting opinion by Justice Rehnquist. Alternatively, each case could map onto a single document of a set. In this case, individual documents are defined by case.

All analyses in this work were based upon tdxs whose rows represented the 848 key terms derived from the full set of 8,014 opinions. However, the tdxs may have varied in the documents that were represented in the columns. Regardless, the construction of each tdx was the same: select the subset of text from the 8,014 opinions, use the set of 848 key terms to represent the rows of the tdx and then count the frequency of these terms for each document representing the column.

The set of 848 key terms was selected by first identifying all unique, one-gram, two-gram, and three-gram terms within each document in the set of 8,014, along with their frequency counts. Once identified, this list of terms was intersected with the list of legal terms derived using the Wikipedia Category Key Term Algorithm (WCKTA). The WCKTA and the derivation of the key term set used in this work are described in Appendix A. There were initially 2,647 terms represented in the matrix after key term extraction using *WCKTA*. This term set was reduced to 848 after rank ordering the sum of the term frequency inverse document frequency (tf-idf) (Salton & Buckley, 1988) scores for each term, and retaining terms that had the most significant top scores.

Reducing the key term set using tf-idf scores. The tf-idf score for each term is the product of two statistics, term frequency and inverse document frequency. It is intended to reflect the importance of a term within a document or set of documents. It increases proportionally to

the number of times it occurs within a document or document set but is offset by the frequency of the word in the corpus (inverse document frequency), which helps to control for the fact that some words are more common than others. Various ways for determining the exact values of both the term frequency and inverse frequency exist (Manning, Raghavan, & Schutze, 2008). For this work, a term's tf-idf score for the entire corpus was computed by computing its' tf-idf score within each document and then taking the sum of these scores over all the documents. Specifically, the tf-idf score of term i for the corpus of N documents was given by (1)

$$tfidf_i = \sum_{j=1}^{N} f_{i,j} * \log\left(1 + \frac{N}{df}\right) \qquad (1)$$

Where $f_{i,j}$ is the number of times term i occurs in document j, N is the number of documents in the corpus, and df is the number of documents in which term i occurs. The tf-idf scores were computed for each of the remaining 2,647 terms and the terms were rank ordered by the tf-idf score. The largest tf-idf score was normalized to one. The term corresponding to this score was "*Court*". The smallest tf-idf score was 3.1 x 10^{-5} and corresponded to over 200 terms.

To determine which of the terms were kept based on tf-idf scores, the normalized, ordered tf-idf scores were plotted (Figure 4). The tf-idf scores asymptotically approached zero as the number of terms increased. In particular, the scores started to rapidly approach zero as the number of terms surpassed around 200. The top 850 terms were selected, assuming this set more than encompassed the set of terms with significantly high tf-idf scores. From that set of 850 terms there were two terms that seemed to be not semantically meaningful as stand-alone terms and were removed. These were the terms "*in re*" and "*f*". Combining the like terms resulted in the final 848 terms, represented in the 848 by 8014 tdx. See Appendix B for the original list of 2,647 terms and their tf-idf scores. The reduced set of 848 is simply the 850 terms with the highest tf-idf scores, and then removing the terms "*in re*" and "*f*".

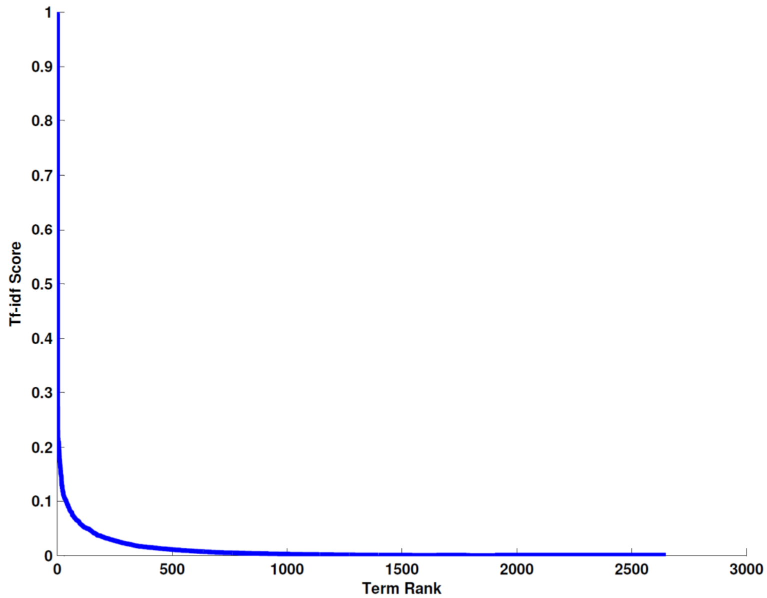

Figure 4. tf-idf scores for the set of 2,647 candidate key terms. Scores are normalized. Of the 2,647 terms, only 848 were retained.

Creating the term by category matrix. Although the key term set may be significantly smaller after term reduction methods are applied, the set may still be too large to be useful for network visualization purposes. In this case, term relevance should be defined. The use of document categories provides a means to define term relevance, either overall for the complete document set or for document subsets.

Each document may be assigned to one or more categories that represent the nature of the document. The categories are those defined by the Supreme Court Database (SCDB)[5]. The SCDB houses an immense amount of data regarding justices' votes from 1953-2013. It is regarded as the core dataset for systematic analyses of the Supreme Court for scientific research (Li, Ding, & Hendler, 2010) and contains over two hundred pieces of information about each

[5] http://scdb.wustl.edu/

case (e.g. the votes of the justices, parties to the suit, etc.) decided by the Court between the 1953 and 2013. A link to the written opinion is provided for each case.

Complete descriptions of SCDB categories are provided by the SCDB in the form of a codebook[6]. The SCDB classifies documents into one of 14 categories: Criminal Procedure, Civil Rights, First Amendment, Due Process, Privacy, Attorneys, Unions, Economic Activity, Judicial Power, Federalism, Interstate Relations, Federal Taxation, Miscellaneous, and Private Action. These same categories were used in constructing the term by category matrix.

The categorization of documents allows term relevance to be defined. For each key term two values are computed: (a) the number of documents in which it occurs, and (b) the term's variance across the documents within a category. These two values are then rank ordered separately across terms for each category. The average of these two sets of ranks gives the final measure of term relevance, presented as a category matrix (tcx) of relevance values for each term in each category. For instance, the "full" tcx was an 848 by 14 dimensional matrix, where each row represented a key term and each column represented a category (Figure 5). The matrix entries represented the relevance value of key terms for each category. The tcxs used in this work differed in the number of columns represented. Because the tcxs were derived from tdxs representing different document sets, these document sets may or may not have included all 14 SCDB categories.

[6] The codebook contains descriptive explanations of the data that make up the SCDB, organized by substantive category, and is updated with each data release. It is available in online and downloadable format at http://scdb.wustl.edu/documentation.php.

$$\begin{array}{lc} & \text{Category 1} \quad \ldots \ldots \quad \text{Category 14} \\ \begin{array}{l}\text{Term 1}\\ . \\ . \\ \text{Term 848}\end{array} & \begin{pmatrix} 0.5 & \cdots & 0.7 \\ \vdots & \ddots & \vdots \\ 0.04 & \cdots & 0.6 \end{pmatrix} \end{array}$$

Figure 5. Example term by category matrix. Rows represent key terms and columns represent one of 14 SCDB assigned categories. The matrix entries give the normalized relevance value of key terms for each category. Relevance values were calculated by counting the number of documents in which a term occurs, and the term's variance across the documents within a category. These two numbers were then ranked ordered and the average of these two rank orders gave the non-normalized relevance value.

Constructing the term by term proximity matrix. A knowledge network of terms derived from Supreme Court opinions shows relationships between relevant terms. The network derivation requires a measure of how related each term is to every other term. These measurements are called term proximities and are assumed to reflect the semantic similarities of the terms as used by the opining justice. A knowledge network forms direct links between terms having high semantic similarity but forms only indirect links between terms having less semantic similarity. Term relationships are symmetrical, meaning the degree to which Term A is related to Term B is the same as the degree to which Term B is related to Term A. Because term relationships are symmetrical, term proximity matrices are symmetrical. Term proximity matrices may be continuous real valued but must ultimately be converted into Boolean values in order to construct a knowledge network. This matrix of Boolean values is called the adjacency matrix and is the matrix that represents the actual network links.

For instance, the “full” term by term proximity matrix is derived from the “full” 848 by 14 term by category matrix by computing the pairwise cosine similarities between values of the term by category matrix. The cosine similarity of term A and term B is given by (2),

$$similarity_{AB} = \frac{\sum_{i=1}^{14} A_i B_i}{\sqrt{\sum_{i=1}^{14} {A_i}^2}\sqrt{\sum_{i=1}^{14} {B_i}^2}} \tag{2}$$

where each A_i gives term A’s relevance value for the i^{th} category.

The resulting 848 by 848 matrix of term by term similarities reflects category level information inherent in the term by category matrix (Figure 6). Thus the term by term proximity matrix contains semantically meaningful similarity values between term pairs. The term by term proximities used for different analyses in this work differed in that they were derived from tdxs distinct in the documents represented in their columns. Once the term by term proximity matrix is formed it is fed into Pathfinder to yield the corresponding PFNET, a process described next.

Constructing Knowledge Representations Using Pathfinder

Once the term by term proximity matrices have been constructed, the next step is to input them into Pathfinder. Pathfinder algorithms take proximity data and translate the data into PFNETs. There are many algorithms available to convert proximity data into network structures. For instance, two nodes may be linked if their proximity value is above a given threshold (McRae, Cree, Seidenberg, & McNorgan, 2005), or if they are connected because of their location along the shortest minimum both between two given nodes (Xu & Chen, 2004).

PFNETs were selected to represent the data among numerous methods of network creation because they demonstrate psychological validity. The Pathfinder algorithm was developed to model human semantic memory and to provide a standard for scaling psychological similarity data (Schvaneveldt, Dearholt, & Durso, 1989). Psychological and design studies have

$$\begin{array}{cc} & \begin{array}{ccc} \text{Term 1} & & \text{Term 848} \end{array} \\ \begin{array}{l} \text{Term 1} \\ \cdot \\ \cdot \\ \text{Term 848} \end{array} & \begin{pmatrix} 1 & \cdots & 0.3 \\ \vdots & \ddots & \vdots \\ 0.8 & \cdots & 1 \end{pmatrix} \end{array}$$

Figure 6. Example term by term proximity matrix. Rows and columns both represent key terms. Matrix entries give the cosine similarity value between terms, calculated as in (2).

compared PFNETs with other scaling techniques and found that they provide a useful tool for uncovering conceptual structure in human subjects. For instance, Cooke and colleagues (1986) used both MDS and PFNETs to study recall performance and memory representation in 180 undergraduates. They derived ordered lists based on the distances between concepts derived by both Pathfinder and MDS. On tests of recall, subjects learned the network-organized list faster than the MDS-organized list. In a free-recall paradigm, proximity of concept pairs in PFNETs was a better predictor of free recall organization than MDS proximities.

The proximity data fed into Pathfinder can be in terms of correlations, similarities, distances, etc. and the type and patterns of proximity data determine the links between concepts in the network. Many PFNETs are based upon the pairwise similarity of the proximity data where nodes represent the concepts of the proximity data and links connect concepts of high similarity (Schvaneveldt, Durso, & Dearholt, 1989). In this case, the term by term proximity matrix will consist of similarity values between key terms.

There are variations of the PFNET that is yielded from a given set of proximity data depending on the parameters chosen for Pathfinder. The topology of a particular PFNET from a

given set of proximity data depends upon two Pathfinder parameters, r and q. The q parameter limits the number of links in the network by restricting the number of indirect proximity relations considered in building the network. q can take on values from 2 to $n-1$ where n is the number of concepts in the proximity matrix. The r parameter gives the Minkowski metric, used to measure the distance of a path, and takes on the values between one and infinity. As r and/or q are increased, the number of links in the network is decreased. In the case of the networks derived from Supreme Court opinions, r and q will initially be set such that $r = \infty$ and $q = n - 1$, yielding the network with the minimum number of links. However, depending upon the apparent goodness of the resulting network, r and q may be modified to uncover more meaningful results.

Analyses of PFNETS. The goodness of the resulting PFNETs may be assessed through visual inspection alone, however, more objective measures of the goodness of the resulting network will be made. Two objective measures previously discussed- similarity (closeness) and coherence will be used. In addition, PFNETs may be objectively studied using measures from network theory. Network theory is rooted in graph theory, an area of pure mathematics. Graph theory's rigorous proofs, measures, and metrics are used to study networks in various fields including sociology (Newman, 2001a; Newman & Park, 2003) , computer science (Albert, Jeong, & Barabási, 1999; Page, Brin, Motwani, & Winograd, 1998), cognitive science (Griffiths, Steyvers, & Firl, 2007; Steyvers & Tenenbaum, The large scale structure of semantic networks: statistical analyses and a model of semantic growth., 2005), linguistics (Motter, de Moura, Lai, & Dasgupta, 2002; Solé, Valverde, & Steels, 2010) and law (Fowler & Jeon, 2008; Lupu & Fowler, 2011).

The Network Theory indices used in testing the hypotheses of this work are average path length, and clustering coefficient. The average path length of a network refers to the average number of links between every node in the network and every other node in the network (Watts & Strogatz, 1998). In knowledge networks, it may be thought of a measure of efficiency. The shorter the average path length, the more efficiently information moves between nodes. Clustering is a property of networks, where two nodes connected to a common node are likely to be connected themselves. The clustering coefficient (Watts & Strogatz, 1998) is often used to quantify the level of clustering in a network on both the global and local level. At the local level, the clustering coefficient for a single node indicates how likely its neighbors are neighbors of each other. The global clustering coefficient is the mean probability that two nodes with a common neighbor are themselves neighbors.

Methods for Testing Specific Hypotheses

Methods for testing the Justice Separation Hypothesis. To make the term by document matrix for MDS, information provided by the SCDB was used to collect only text corresponding to certain majority opinions. Of the set of 8,014 opinions, the SCDB identifies the majority author for 6,798 opinions. From this set of 6,798 majority opinions, the opinions of Justices Scalia, Black, Burger, Douglas, Ginsburg, Kennedy, Marshall, O'Connor, Powell, Rehnquist, Thomas, Warren, Douglas and Alito were extracted. The only justices that were not included in the MDS analysis but were included in Landes and Posner's (2009) list were Goldberg, Rutledge, Brennan, and Whittaker. These justices were excluded because the set of 6,798 opinions contained less than 40 documents written by each of them. A 848 by 14 dimensional matrix was constructed for the MDS analysis. The 848 rows represented the same

key term set derived from the full Supreme Court corpus of 8,014 opinions. The 14 columns represented the opinions of the subset of 14 justices from Landes and Posner's (2009) study. The column representing a particular justice was constructed by counting the frequency of each key term within each majority opinion written by that justice. These frequency counts were summed over all of the particular justice's majority opinions, giving a total frequency count for each key term across all the justice's opinions. The justices varied in the number of majority opinions they authored, as well as the lengths of the opinions. Descriptive statistics corresponding to the opinions from which each column of the tdx was derived are listed in Table 1.

Table 1

Summary of number of majority opinions, average word count, and standard deviation of word count for the opinions of each justice represented in the tdx used in the MDS analysis.

Justice	Num Opns	Avg	Std dev
Douglas	365	4766.5	4104.8
Black	310	5274.0	5568.5
Warren	169	7443.5	6940.1
Kennedy	237	11885.0	7413.8
O'Connor	301	10268.0	6039.8
Scalia	259	9616.0	6759.2
Rehnquist	457	9832.8	7313.0
Thomas	168	7935.0	4899.6
Marshall	322	7446.7	3792.1
Powell	254	10310.0	6239.0
Roberts	54	13276.0	11410.0
Ginsburg	161	9202.8	5568.6
Alito	49	11674.0	10309.0
Burger	257	8483.4	6140.9

Methods for testing the SCOD vs. Random Network Hypothesis. Recall, this hypothesis stated that SCOD networks will be more meaningful than random networks. In particular, SCOD networks will show greater values of node coherence and clustering coefficients. In addition, this hypothesis predicted that SCOD networks will have zero similarity to random graphs and a higher similarity to each other.

Two Monte Carlo simulations were run in order to compare Supreme Court Opinion networks to random networks. Both simulations were conducted for a range of network sizes. In addition, for a given network made of *n* nodes, multiple runs of the experiment were performed. Each run differed in the number of *r* randomly chosen documents from the set of 8014 that were used to derive the SCOD network. In particular, the number of randomly chosen opinions varied from 200 to 1000 in increments of 100.

The first simulation compared graph indices of SCOD networks to random networks. For a given trial of a given run on Simulation 1, *r* randomly chosen documents were used to generate a SCOD network. The links of the SCOD network were then randomly shuffled to create a corresponding random network. Network indices for both networks were then calculated. Each run consisted of 100 trials. The average value of the graph indices over all 100 trials was recorded for each run. This simulation was performed six times, for network sizes of 100, 75, 50, 30, 20 and 10 nodes.

The second simulation compared the similarity between two SCOD networks and the similarity of SCOD networks and corresponding random networks. As in Simulation 1, a given trial of a given run for Simulation 2 consisted also of choosing *r* random opinions from the set of 8014, deriving a SCOD net, shuffling its links and deriving a corresponding random network.

In addition, while the first SCOD network was derived, a second SCOD network with the same number of nodes and links was derived. This was done by taking two samples of *r* documents, finding the union of documents across both, applying the term selection algorithm to this union to find the top *n* terms. This ensured the specific set of *n* terms was uniquely derived for each trial for each set of documents.

It was important to consider the number of nodes and number of documents in that would give rise to meaningful similarity values. Computations of similarity between two networks assume both networks have the same terms as nodes. The fewer nodes there are in a network (for this study $m \sim n - 1;\ \ m = num\ links, n = num\ nodes$), the fewer ways there are of arranging the network links among the nodes. Therefore, if the number of nodes is small enough, network similarity will always be high simply because the chance of the networks receiving the same link arrangement is high. Thus, the similarity of networks with 50 nodes was considered to ensure high network similarity was not an artifact of the limited number of possible link arrangements.

In the same way, because the networks being compared were derived from choosing *r* random documents from a set of *D* documents, it was important that *D* be large enough to ensure the same *r* documents were not chosen from the larger set. Otherwise, the similarity between networks would increase because the networks were being derived from the same set of documents. In this way, similarity values between two networks would not capture semantic similarity of two different SCOD networks, but would instead be reflective of the similarity inherent in deriving two networks from non-unique data. Thus, *N* was chosen to be the maximum number of opinions available (8,014) and *r* was always less than *N*. In addition, *r* varied to ensure a range of similarity values. That way it would be possible to estimate values reflective of

true semantic similarity between distinct networks rather than similarity that arose as r approached N.

Methods for testing the Face Validity Hypothesis. This hypothesis posited that if SCOD networks are to be useful for legal research, we expect them to have meaningful concepts and meaningful links between concepts. Criminal Procedure networks for liberal and conservatively decided cases were derived from using opinions classified by the SCDB as dealing with issues of "Criminal Procedure". According to the SCDB, issues of Criminal Procedure are concerned with the rights of persons accused of crime, except for the due process rights of prisoners. The liberal criminal procedure network was derived by using only criminal procedure opinions that were decided in a liberal manner, and the conservative criminal procedure network was derived by using only criminal procedure opinions that were decided in a conservative manner according to the SCDB. The liberal and conservative criminal procedures networks were made from 787 and 1035 opinions, respectively. The average number of words in the liberal criminal procedures opinions was 7,021, with a standard deviation of 6,761.5. The average number of words in the conservative criminal procedures opinions was 7,836.4, with a standard deviation of 6,155.2 words.

Civil rights networks for liberal and conservatively decided cases were derived from using opinions classified by the SCDB as dealing with issues of "Civil Rights". According to the SCDB, issues of civil rights are concerned with non-First Amendment freedom cases which pertain to classifications based on race, age, indigency, voting, residency, military or handicapped status, gender, and alienage. The liberal and conservative civil rights networks were made from 711 and 590 opinions, respectively. The average number of words in the liberal civil rights opinions was 7,550, with a standard deviation of 6,892.8 words. The average number

of words in the conservative civil rights opinions was 8,603.6, with a standard deviation of 7,168.4. The tcxs all were formed using the 14 categories designated by the SCDB as described in the general methods section. Thus, all tcxs were 848 rows by 14 columns and were used to contruct the 848 by 848 proximity matrices. All networks were comprised of nodes representing the top 38 terms selected from the rank ordered term by category matrices.

Methods for testing the Blackmun Drift Hypothesis. To test this hypothesis I created three separate networks from a collection of 827 opinions written by Blackmun during his tenure on the Court. The 827 opinions served to form the base tdx from which subset tdxs were taken in order to perform different types of analyses. The base tdx formed from these 827 opinions consisted of 3,722 unique terms. After intersecting

The first network was derived using a tdx (early tdx) constructed from the 276 opinions written by Blackmun from late June, 1970 through mid-April, 1979. This tdx initially contained 66,660 unique terms. The average document length of this document set was10,273 terms with standard deviation of 9,074 terms. The second network (middle network) was derived from a tdx constructed from the 276 opinions written by Blackmun from late April, 1979 to early June, 1986. This tdx initially contained 56,961 unique terms. The average document length of documents represented in this tdx was10,420 terms with a standard deviation of 5,971.4 terms. The third network (late network) was derived from a tdx constructed from the remaining 275 opinions written from mid June 1986 through the end of June, 1994. This tdx initially contained 66,660 unique terms. The average document length of documents represented by this tdx was11,349 terms with a standard deviation of 6,799.7 terms. The list of documents used to construct each of these three tdxs is available on request from the dissertation author. Each set of unique terms for each term set was intersected with the 848 key terms derived from the original

set of 8,014 opinions. After this intersection was performed, the dimensions of the early, middle, and late tdxs were reduced to 839 by 276, 840 by 276 and 838 by 275 tdxs, respectively. The networks were constructed by deriving tcxs using the 14 categories used by the SCDB to categorize documents, and then deriving ttxs. The ttxs were 20 row by 20 column matrices made of the top 20 terms as rank ordered across categories.

Methods to Test the Court Ideology Hypothesis. Recall, this hypothesis posited that SCOD networks will reflect particular Courts ideology. Because a Court may be characterized as liberal in social issues but conservative in economic issues (or vice-versa), four referent average networks were constructed. where each network was derived from opinions falling into one of four categories: those concerning issues of civil liberties and whose ruling was conservative, those concerning issues of civil liberties and whose ruling was liberal, those concerning issues of economic activity and whose ruling was conservative, and those concerning issues of economic activity and whose ruling was liberal.

Definitions provided by Segal and Spaeth (1989) were used to categorize opinions into issues of civil liberties or economic activity. Civil liberties issues involve criminal procedure, civil rights, the First Amendment, due process and privacy. Economic activity issues include any case involving unions or general economic activity. The SCDB designation of decisions as liberal, conservative, or unspecifiable were used to label the decision direction of the opinions. The SCDB characterizes liberal decisions in the area of civil liberties as pro-accused or person convicted of crime, pro-civil liberties or civil rights claimant, pro-indigent, pro-Indian and antigovernment in due process and privacy (Segal & Spaeth, 1989). Liberal decisions in the area of economic activity are pro-union, anti-business, anti-employer, pro-competition, pro-liability, pro-injured person, pro-indigent, pro-small business vis-a-vis large business, pro-debtor, pro-

bankrupt, pro-environmental protection, pro-economic underdog, pro-consumer and pro-accountability in governmental corruption (Segal & Spaeth, 1989).

To create the four referent networks, tdxs were derived for each case category, using majority opinions (dissenting opinions were not used since they would not reflect the Court's final decision). To compare the similarity of two networks, each network must have the same terms. To select term sets that would be representative of both the liberal and conservative terms for the two issue types, a network was constructed for each issue type using the union of the liberal and conservative documents. The top *n* terms for these two unique sets of documents was then derived. In this way the specific set of *n* terms was uniquely derived for each set of documents. The similarity between each of the two network types for each Court, then, was compared to each of the referent networks, for different network sizes.

Chapter 4

Results

The Justice Separation Hypothesis

This hypothesis tested whether MDS of a set of opinions by the “most” and “least” conservative justices would reflect a separation of the data into these respective categories. If so, it suggests that the proximity data from Supreme Court opinions is a valid source of data from which to construct knowledge representations. Figure 4 shows the results of a two-dimensional MDS performed on the set of 14 Supreme Court justices. The stress value for the MDS configuration was 0.07. A Shepard’s plot for data configurations given by MDS (Figure 7) show a narrow scatter of the data around the line $= x$. This indicates that the MDS configuration of data does a good job in approximating the observed distances between justices. The results indicate that MDS did indeed separate the proximity data into two meaningful categories. A three-dimensional MDS was also performed on the same dataset but the stress value was no lower than the two-dimensional fit.

The justices on Landes’ and Posner’s (2009) “most conservative” and “least conservative” list are shown in blue and red, respectively, in Figure 8. It is evident that MDS separated the justices by degree of conservatism, along the *y* dimension. This nice separation of proximity data indicates that Supreme Court opinions may be viewed as legitimate sources of data for legal knowledge.

The locations of justices among the *x* axis was compared to estimations put forth by Lauderdale and Clark (2012) of justice position among 24 different dimensions of judicial

preference. For each of the 24 dimensions, Lauderdale and Clark's (2012) estimations for justices' positions were mapped onto a sequence of ordinal numbers, thus providing a rank ordered set of values for justices for each of these 24 dimensions. Next, a rank ordered list was derived from the locations of justices from left to right (and right to left) along the *x* axis in Figure 8. The norm between each of the 24 rank ordered lists and the rank ordered list from Figure 8 was performed. The minimum of these norms indicated the most likely candidate to uncover a dimension of the *x* dimension from the MDS analysis, and was determined to correspond to the dimension Lauderdale and Clark named "offense, criminal, jeopardy." This dimension represented the combined average locations of each justice's ideology within the issues most distinctly represented by the terms "offense", "criminal", and "jeopardy". According to the SCDB, these issues fall under the category of "Criminal Procedure". Two justices were listed in Figure 8 but not included in Lauderdale and Clark's analysis-Justice Alito and Justice Roberts. As Figure 9 shows, there is somewhat of a separation along the *x* axis when grouping justices by Lauderdale and Clark's rankings. Justices Alito and Roberts are in black to designate they were not included in the analysis. Only Justice Marshall, Justice Thomas and Justice Douglas do not seem to separate into their Lauderdale and Clark groupings. Thus, one could interpret the *x* dimension derived with MDS as somewhat separating justices into justices that are more conservative (Douglas, Rehnquist, Thomas, O'Connor, Scalia, Kennedy) on issues of criminal procedure, and those that are more liberal (Burger, Ginsburg, Powell, Marshall, Warren, Black).

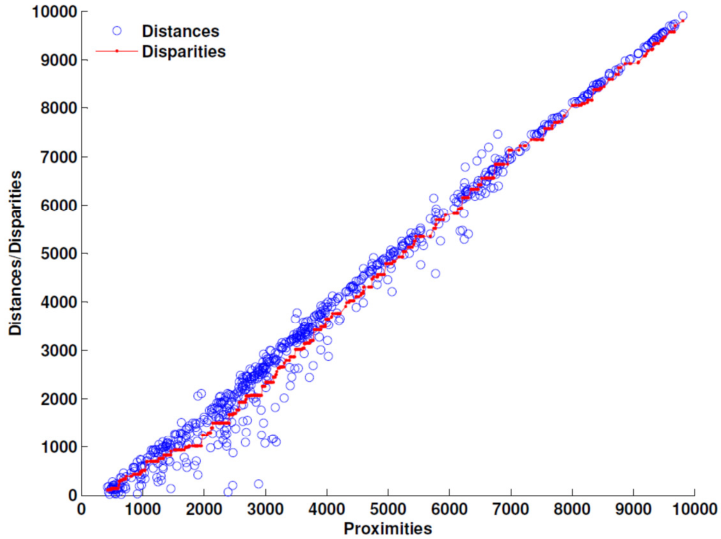

Figure 7. Shepard's plot from a two dimensional MDS applied to Supreme Court data. The data used was a term by document matrix derived from the written opinions of the "most" and "least" conservative justices between 1952-2006 (Landes & Posner, 2009).The stress value for the fit was 0.07.

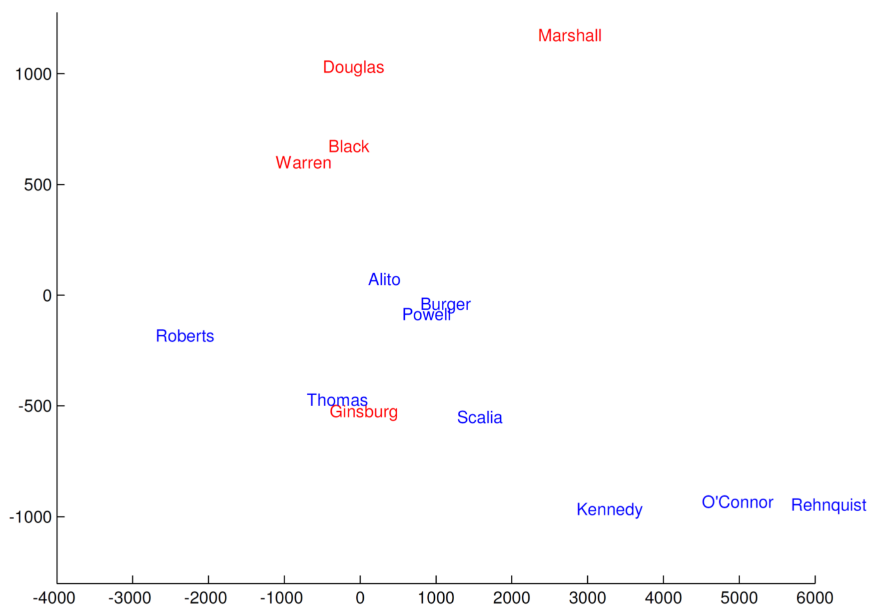

Figure 8. MDS of proximity data derived from the Supreme Court opinions of the "most conservative" and "least conservative" justices as defined by Landes and Posner (2009). This figure shows the separation of justices into the groups set forth by Landes and Poser (2009) along the *y* axis, with the most conservative justices appearing in blue and most liberal in red.

Figure 9. MDS of proximity data derived from the Supreme Court opinions of the "most conservative" and "least conservative" justices as defined by Landes and Posner (2009). This figure shows the somewhat decent separation of justices into groups set forth by Lauderdale and Clark (2012) along the *x* axis, with the most conservative justices on issues of criminal procedure appearing in orange and most liberal on these same issues in green.

The SCOD vs. Random Networks Hypothesis

This hypothesis tested whether or not SCOD networks would have meaningful structural differences as compared to random networks. The results of simulation by network size are shown in Table 2. Both the average clustering coefficient and average node coherence across all network sizes for both SCOD and random networks was close to zero. Average edge coherence decreased with network size and ranged from 0.01 to 0.11 for SCOD networks and from 0 to 0.08 for random networks. Correlational coherence was negative for both networks, and decreased in magnitude with an increase in network size. Values ranged from zero to -0.01 for SCOD networks and -0.01 to -0.07 for random networks. Average path length increased with increasing network size and ranged from values of 3.06 to 12.26 for SCOD networks and 2.73 to 6.57 for random networks.

Table 2

Summary of mean network indices for random and SCOD networks.

	Net	Nodes	nlinks	Ncoh	ecoh*	corcoh*	avgpl*	Cc
	Rand	100	99	0.00	0.00	-0.01	6.57	0.00
	SCOD			0.00	0.01	0.00	12.26	0.00
	Rand	50	49	0.00	0.01	-0.01	5.26	0.00
	SCOD			0.00	0.02	0.00	8.52	0.00
	Rand	20	19	0.00	0.04	-0.04	3.75	0.00
	SCOD			0.00	0.05	-0.01	4.72	0.00
	Rand	10	9	0.00	0.08	-0.07	2.73	0.00
	SCOD			0.00	0.11	-0.01	3.06	0.00
Mean**	Rand	45	44	0.0000	0.0359	-0.0315	4.5770	0.0000
	SCOD			0.0002	0.0468	-0.0070	7.1387	0.0004

A t-test was conducted on the average values of graph indices for each run, for each node size. The findings from testing this hypothesis indicate that the population of SCOD networks is significantly different than random graphs. In particular, SCOD networks differed from random networks in that they had greater average edge coherence, more positive correlational coherence, and a greater average path length. These results suggest there is some inherent structure in the way in which SCOD networks are constructed, which is representative of features within the SCDB opinion set. However, that they are inherently more structured, and contain more coherence than random networks was not demonstrated at a statistically significant level. This was due namely to the fact that the two indices of node coherence and clustering coefficient measure the likeliness that two neighboring nodes have a common neighbor (measure the amount of clustering that occurs). The tree like structure (*n* nodes and *n-1* links) lends itself to minimal clustering, and so these values are low.

Figure 10 plots the average similarity between SCOD networks and between SCOD networks and random networks as a function of document set size and network size. The similarity between SCOD networks and random networks was close to zero for each network size and across all sizes of document sets. The similarity between SCOD networks, however, never reached as low as the similarity between random networks and SCOD networks. The higher similarity values between SCOD networks reflect that the structure of SCOD networks is not random, and is dependent on the information within the document sets.

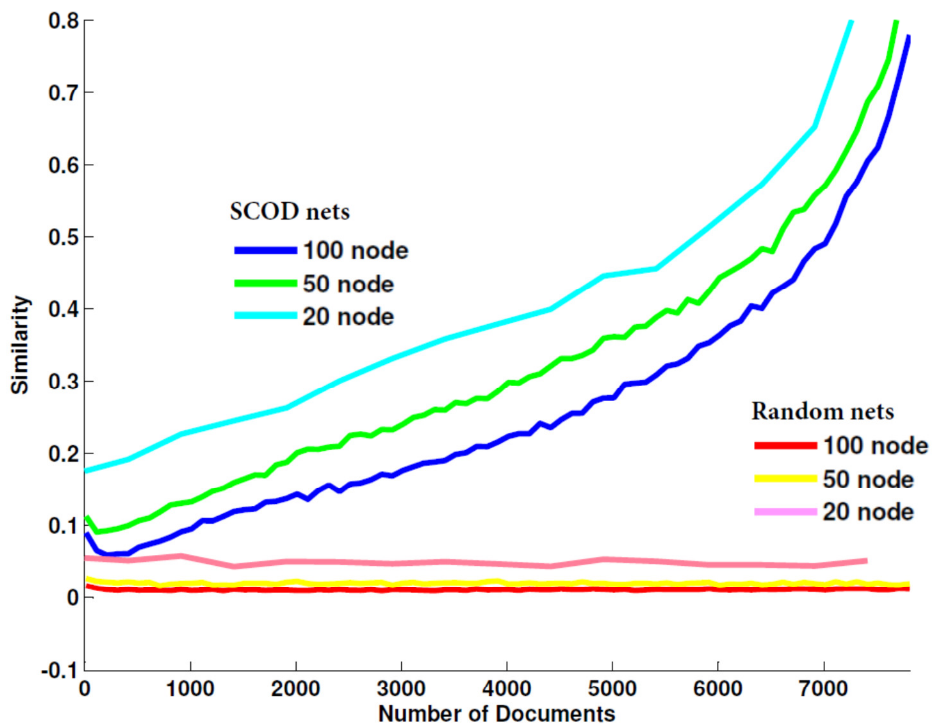

Figure 10. The similarity of SCOD networks with other SCOD networks and random networks as a function of document set size. Data labeled SCOD nets shows average similarity values between two SCOD networks each derived from a different set of a fixed number (x-axis values) of random Supreme Court documents. Data labeled Random nets shows average similarity values between a SCOD network derived from a set of a fixed number (x-axis values) of random Supreme Court documents and a network derived from a random shuffling of that SCOD's links.

The Face Validity Hypothesis

The Face Validity Hypothesis tested whether or not knowledge networks derived from Supreme Court opinions would match at least superficial characterizations of the Court. If so, this indicates a good face validity of SCOD networks.

Criminal procedure networks. With respect to issues of criminal procedure, the network should reflect issues of pro-defendant (Segal & Spaeth, 1989). Indeed, Figure 11 shows two strong focuses on the liberal criminal procedure network. On the left side of the network is a "death penalty" focus with the *Furman v. Georgia* and *Eddings v. Oklahoma* cases. *Furman v. Georgia* put a moratorium on the death penalty in 1972 (Furman v. Georgia, 1972) and in *Eddings v. Oklahoma* the Court reversed the death penalty sentence because of failure to consider mitigating circumstances (Eddings v. Oklahoma, 1982). The second focus, on the right of the network, is that of "right to an attorney" and consists of the nodes *Powell v. Alabama*, *Betts v. Brady* and "benefit of counsel". *Powell v. Alabama* (1932) granted the right to an attorney as part of due process to defendants in a capital trial. *Betts v. Brady* (1942) involved the right to an attorney for indigents when prosecuted by the states.

Another interesting consistency of the liberal network with known Court information regards the fourth amendment concepts regarding search and seizure, including "arrest warrant", "*Ker v California*" and "*Stoner v California*". These terms are randomly dispersed throughout the network. This reflects scholars' criticism of the courts Fourth Amendment jurisprudence as being a somewhat non-coherent body of law that has failed to provide clarity to lower courts (Allen & Rosenberg, 2012; Amsterdam, 1973; Rickless, 2003).

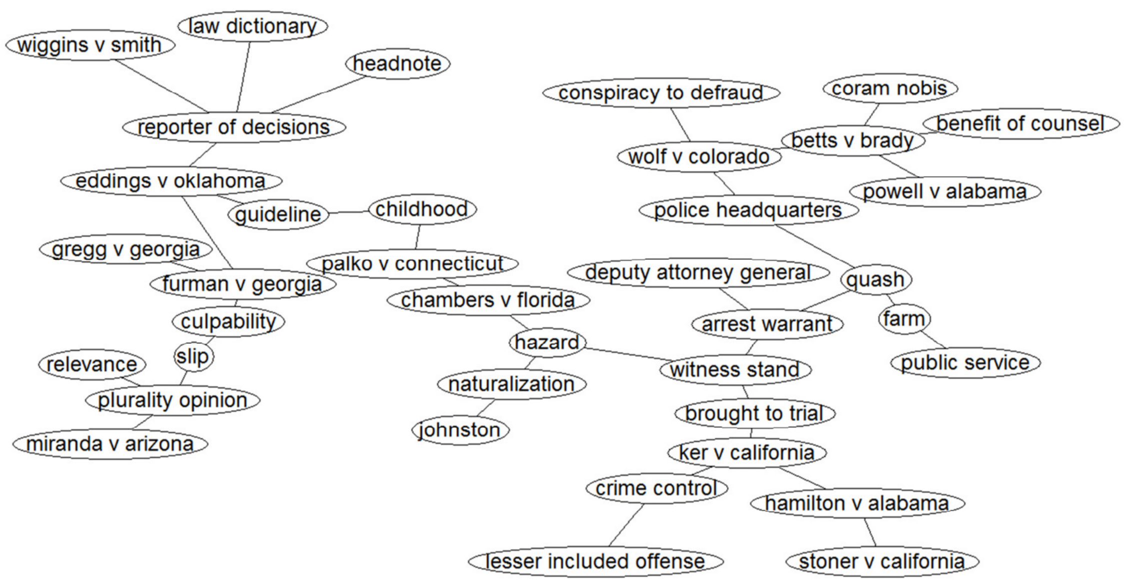

Figure 11. Face Validity of SCOD Networks. Networks derived from cases decided liberally in the issue of criminal procedure

On the conservative network (Fig 12) there is a small death penalty focus as well with *Gregg v. Georgia*, *Eddings v. Oklahoma* and *Locket v. Ohio*. In addition, the *Strickland v. Washington* case involved a death penalty sentence though the case was primarily about ineffective counsel (Sixth Amendment). It is also interesting that the conservative graph had “violent crime” as part of its network while the liberal side did not, which is consistent with psychological research suggesting that conservatives are motivated cognitively by fear (Jost, Glaser, Kruglanski, & Sulloway, 2003). Finally, a weaker focus on the conservative side is one of the Fifth Amendment right against self-incrimination, with the *Adamson v. California* and *Malloy v. Hogan* cases.

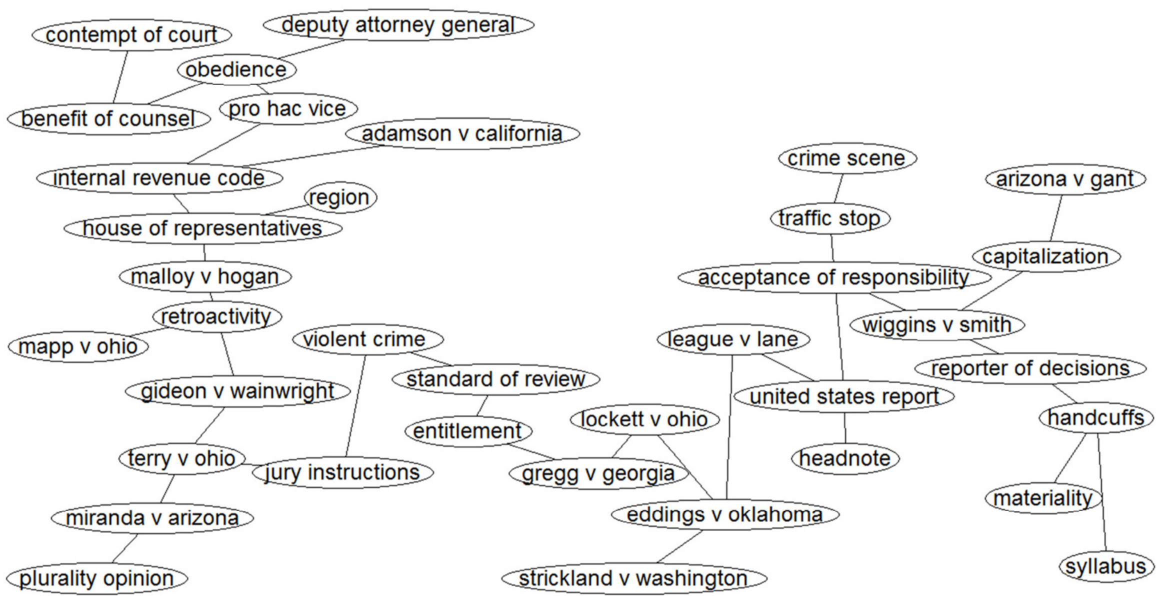

Figure 12. Face Validity of SCOD Networks. Networks derived from cases decided conservatively in the issue of criminal procedure.

Civil rights networks. Civil rights networks for liberal and conservatively decided cases were derived from using opinions classified by the SCDB as dealing with issues of "Civil Rights". According to the SCDB, issues of civil rights include non-First Amendment freedom cases which pertain to classifications based on race (including American Indians), age, indigency, voting, residency, military or handicapped status, gender, and alienage. The liberal civil rights network was derived by using only civil rights classified opinions that were decided in a liberal manner, and the conservative civil rights network was derived by using only civil rights classified opinions that were decided in a conservative manner according to the SCDB.

The liberal network in Figure 13 displays terms consistent with liberal ideology related to civil rights. A strong focus on race and desegregation is shown with the cases of "*Smith v Allwright*", "*Shelley v Kraemer*", *"Sweat v Painter"* and "*Boynton v. Virginia*". Race also is a common factor in *Bell v Maryland*, as well as *Chambers v. Florida*. There is a small focus on

voting rights on the left side with "*Reynolds v. Sims*" and the "apportionment" node, both suggestive of the issue of underrepresentation of urban counties. In the bottom there is a strong immigration focus with the term "immigration reform" and "*Clark v Martinez*" (case dealing with the legality of detaining immigrants) and "*Clark v Ashcroft*" (case dealing on deporting aliens).

There are two focuses of the conservative civil rights network (Fig 14). The first focus or concentration is on the lower right on racial gerrymandering involving minority-majority districts with the cases "*Miller v Johnson*" and "*Shaw v Reno*".

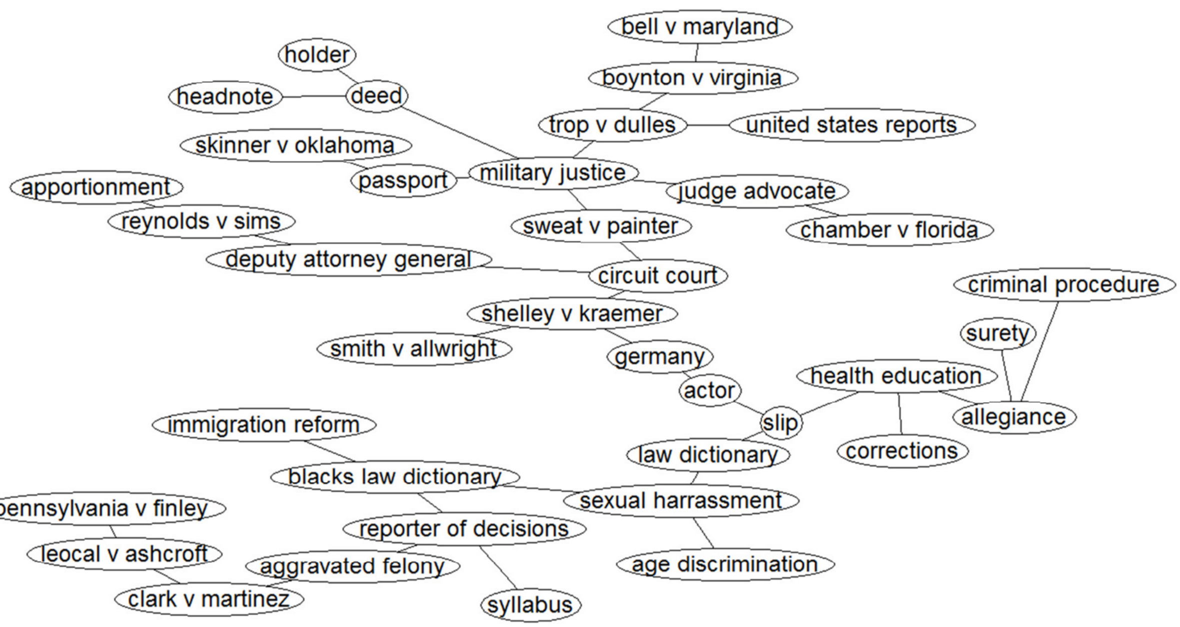

Figure 13. Face Validity of SCOD Networks. Networks derived from cases decided liberally in the issue of civil rights

The second concentration is in the same lower right area dealing with ineffective counsel/sixth amendment ("*Strickland v Washington*", "penalty phase", "mitigating evidence" and "*Wiggins v Smith*"). In addition, with its lack of highly notable civil rights cases, the conservative civil liberties network is in some ways consistent with most tellings of the history of the Court, since most landmark civil rights cases were in the liberal direction.

Less meaningful terms. All four networks appear to have some procedural words that are not meaningful without more context (e.g., Latin phrases- pro hac vice, coram nobis, house of representatives, internal revenue code). In addition, there are some terms that are part of opinions that may not be useful: e.g., reporter of decisions, headnote, slip, law dictionary, united states report, syllabus. These terms were removed for the remainder of the analyses.

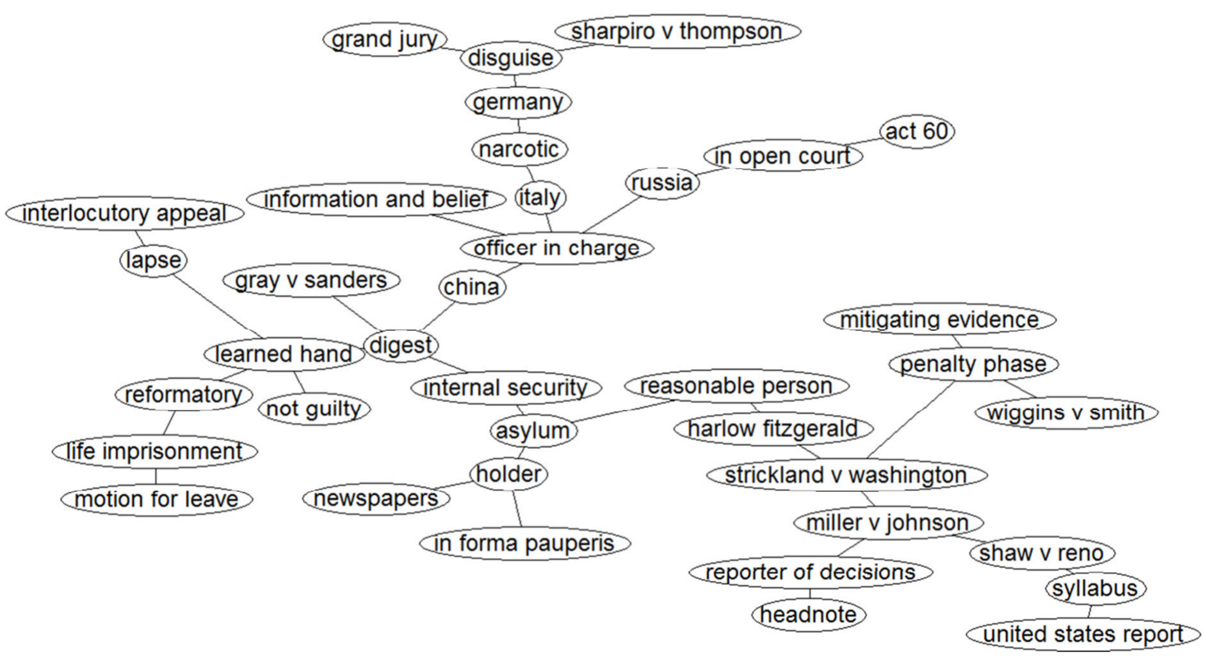

Figure 14. Face Validity of SCOD Networks. Networks derived from cases decided conservatively in the issue of civil rights

It is evident that the networks discussed above are reflective of known information regarding the Court. They contained known, important focuses of the Court that made sense given the nature of the network (i.e. a civil liberties network for liberally decided cases). A next step would be to improve the key term set so as to weed out the less meaningful terms.

The Blackmun Drift Hypothesis

Networks derived from Blackmun's opinions are shown in Figure 15. The number of terms displayed in Blackmun's networks was based purely on the ease with which twenty node networks could be visualized. More terms could be included but were not in this case. Blackmun's network evolution in shows how key words associated with women's rights have changed. The network in Figure 15A, constructed from Blackmun's early opinions does not display terminology and structure necessarily indicative of a preference for women's rights. Rather, the network suggests abortion is more of an issue of health care than a women's right issue, since "*Roe v. Wade*" and "pregnancy" are closely linked to the terms "patient" and "health care". However, in the later networks, abortion becomes an issue of privacy. This is seen in Figure 15B, where "abortion" is linked to "freedom of information", which in turn is linked to "privacy". The concept of "freedom of information", in this case, may be referring to the issue of freedom of expression (489, 1979) which may be viewed as a right to privacy (Samuels, 1999).

In Figure 15C, the terms connected to abortion do not seem to provide much in the way of Blackmun's ideology, however, the issue of abortion is interestingly connected to the term "nuisance". The classic black-letter legal definition of a nuisance is "an act or omission which obstructs or causes inconvenience or damage in the exercise of rights common to all" (Prosser, 1941, p. 566). It may be a stretch, but if by nuisance, Blackmun was referring to the act of

making abortion illegal, this would mean he deems the right to have an abortion a right common to all. This would support the notion of ideological drift in Blackmun.

The Court Ideology Hypothesis

Referent average liberal and conservative networks for issues of civil liberties and economic activity are shown in Figures 16-19. Results comparing these two networks with networks derived from different Courts for issues of civil rights and economic activity are shown in Figures 20-29. Figures 30-38 plot the similarity values for each network to the referent liberal and conservative structure. The data was fit with exponential or power functions and the goodness of fit was calculated for each set and listed in Appendix C. Table 3 shows the average similarity for each Court's conservative or liberal network constructed from civil liberties or economic activity opinions with the referent liberal/conservative networks for each issue type.

The Burger Court had the highest similarity with the conservative civil liberties referent structure, as well as the highest similarity with the liberal referent economic activity network. The Warren Court had the highest similarity with the conservative economic activity network, and, as predicted, the highest similarity with the liberal civil liberties referent network. That the Burger Court has the highest similarity to the referent liberal economic activity network and the referent conservative civil liberties network may be explained by the large percentage of Burger's opinions that make up the document set from which the referent networks were constructed. Only Warren contributed more opinions than Burger for the issue of economic activity, and only by around 30 opinions. The fact that Warren's civil liberties network yielded the highest similarity to the referent liberal civil liberties structure, despite contributing fewer opinions than both Burger and Rehnquist to the document set bodes well for the idea that SCOD networks are reflective of Court ideology.

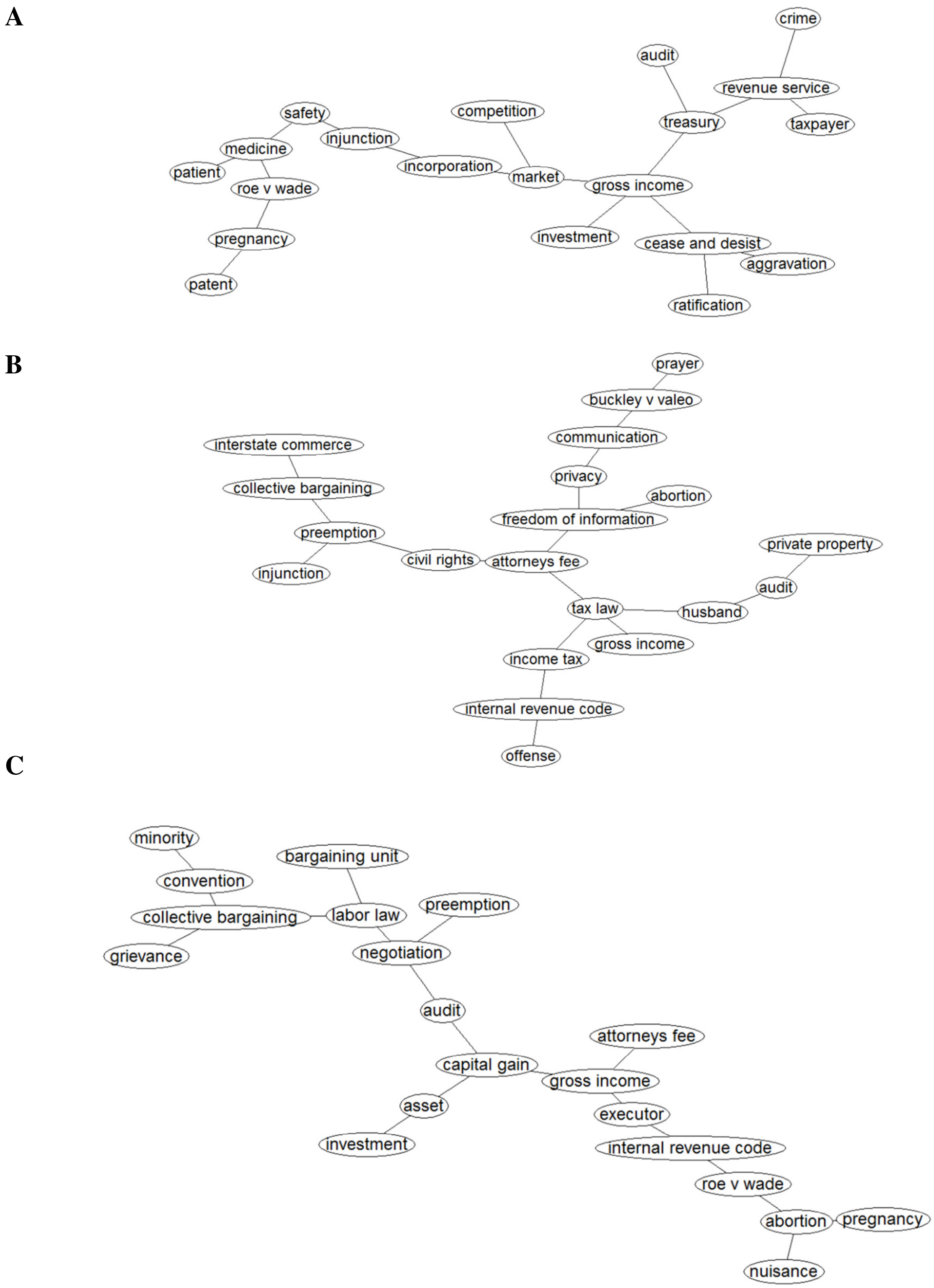

Figure 15. Ideological Drift of Blackmun. (*A*). SCOD Network of Blackmun for late June, 1970-mid April 1979. (*B*). SCOD Network of Blackmun for late April 1979-early June1986 (*C*) SCOD Network of Blackmun for middle June 1986-end of June 1994

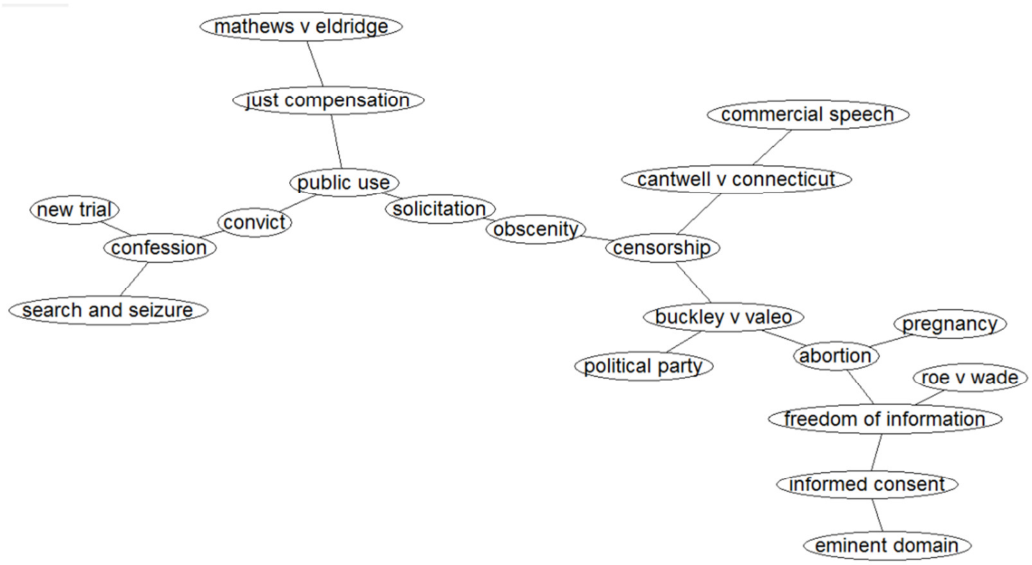

Figure 16. Conservative SCOD civil liberties network. SCOD network derived from cases during 1946-2013 concerning civil liberties where a conservative decision was rendered.

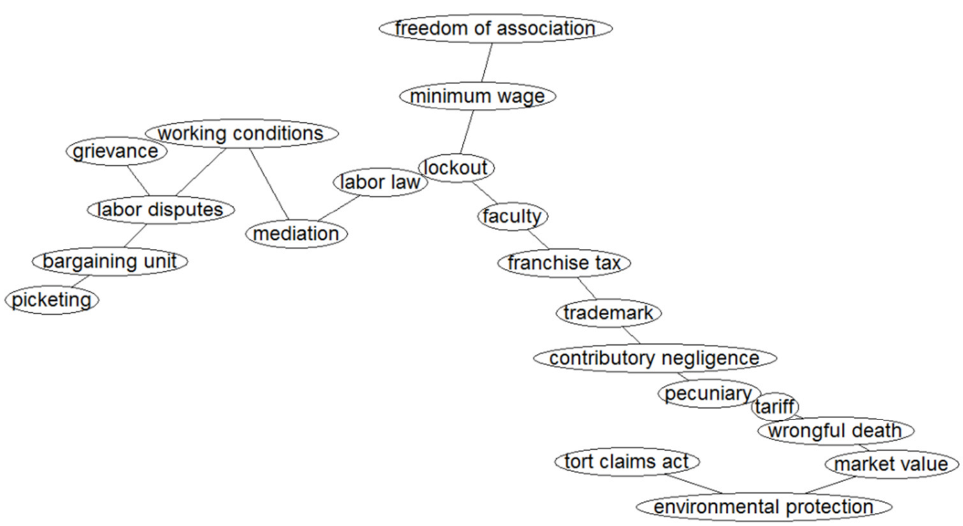

Figure 17. Conservative SCOD economic activity network. SCOD network derived from cases during 1946-2013 concerning economic activity where a conservative decision was rendered

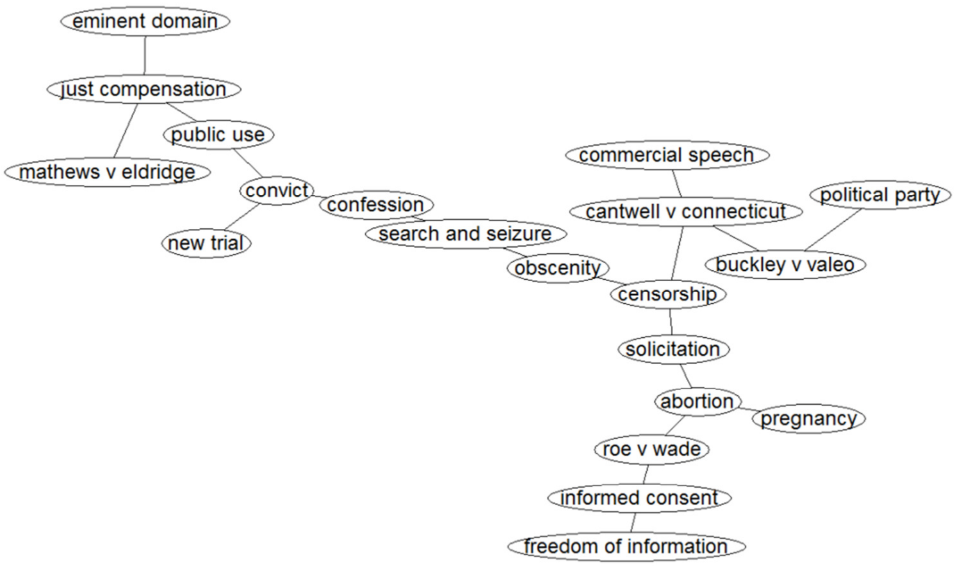

Figure 18. Liberal SCOD civil liberties network. SCOD network derived from cases during 1946-2013 concerning civil liberties where a liberal decision was rendered.

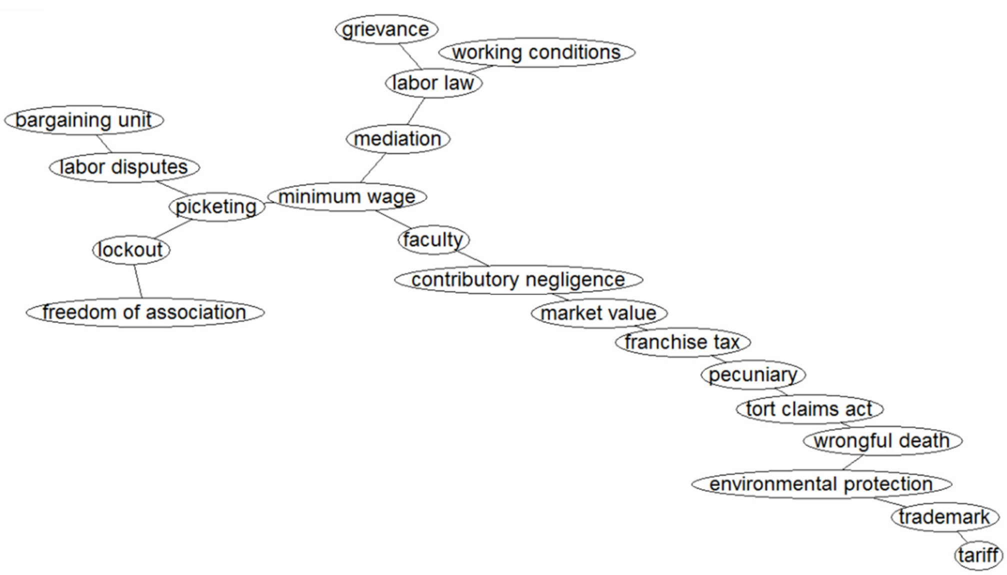

Figure 19. Liberal SCOD economic activity network. SCOD network derived from cases during 1946-2013 concerning economic activity where a liberal decision was rendered.

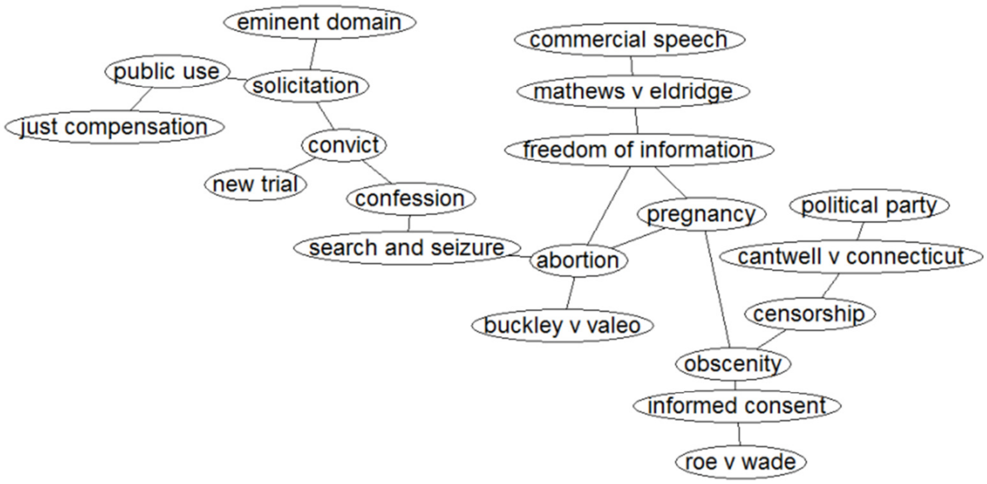

Figure 20. Vinson SCOD civil liberties network. SCOD network derived from cases decided during the Vinson Court, concerning civil liberties issues.

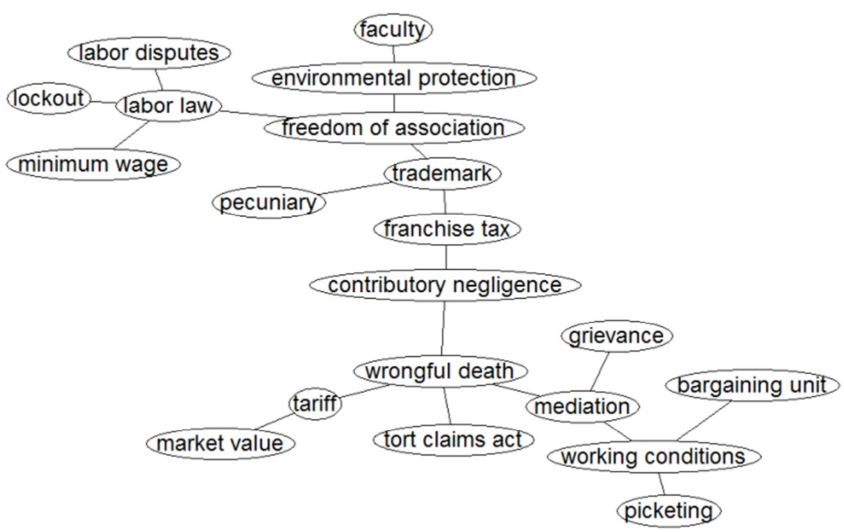

Figure 21. Vinson SCOD economic activity network. SCOD network derived from cases decided during the Vinson Court, concerning economic activity issues.

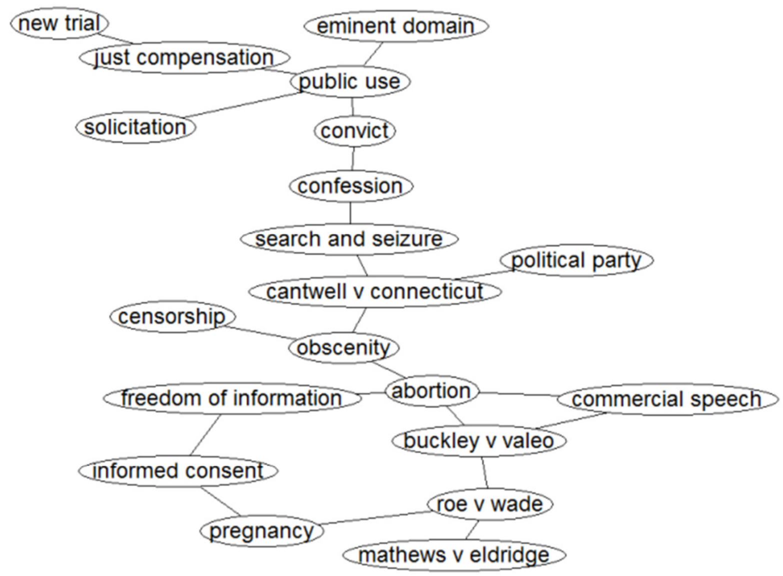

Figure 22. Warren SCOD civil liberties network. SCOD network derived from cases decided during the Warren Court, concerning civil liberties issues.

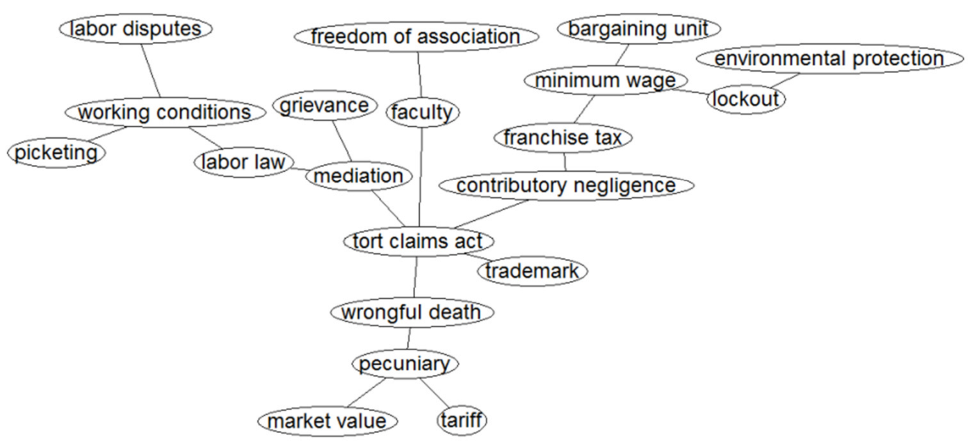

Figure 23. Warren SCOD economic activity network. SCOD network derived from cases decided during the Warren Court, concerning economic activity issues.

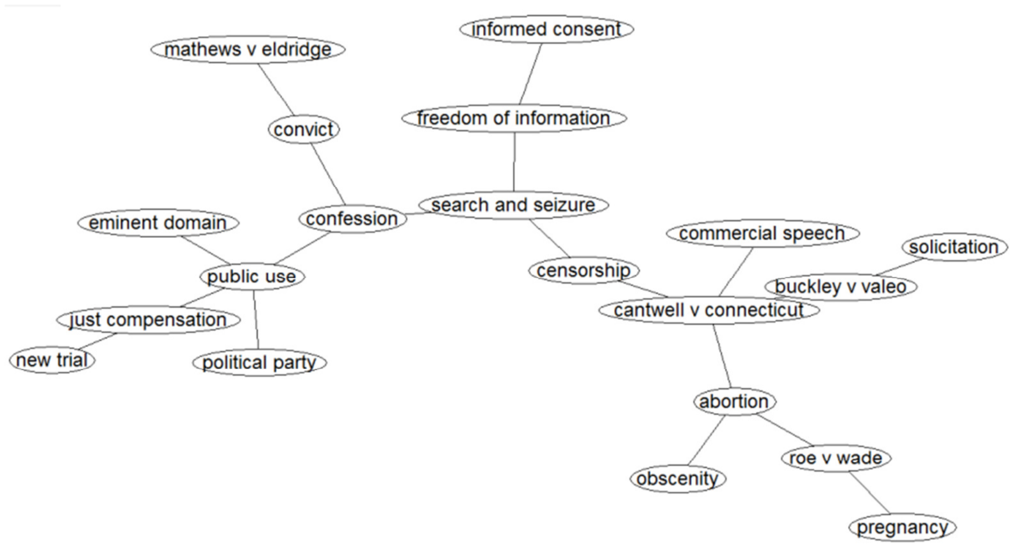

Figure 24. Burger SCOD civil liberties network. SCOD network derived from cases decided during the Burger Court, concerning civil liberties issues.

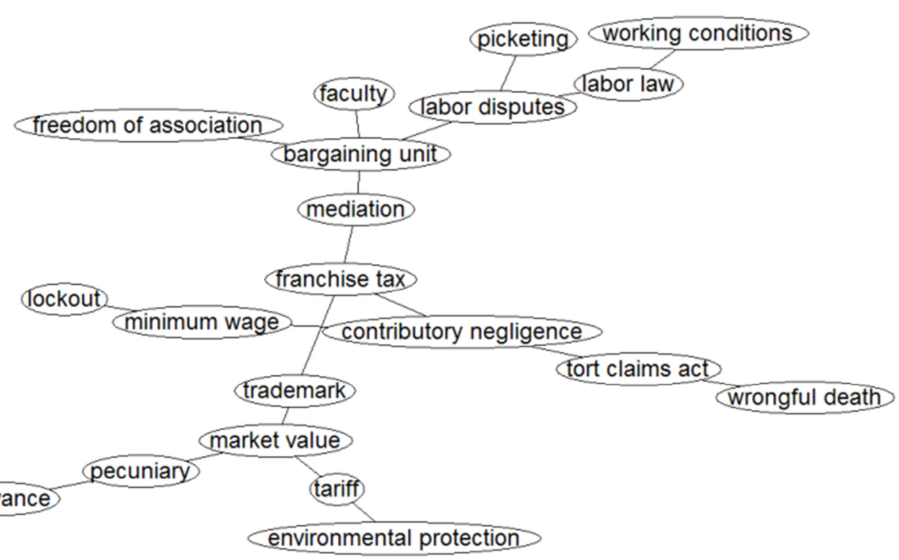

Figure 25. Burger SCOD economic activity network. SCOD network derived from cases decided during the Burger Court, concerning economic activity issues

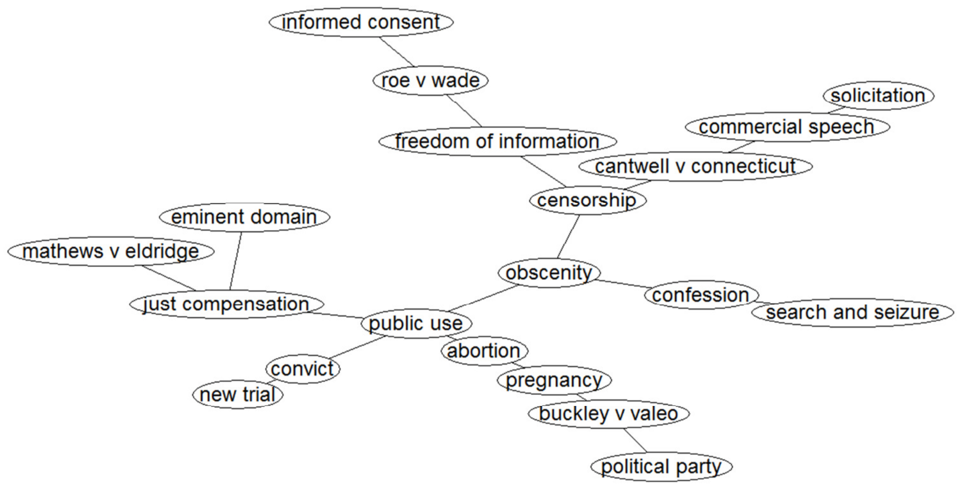

Figure 26. Rehnquist SCOD civil liberties network. SCOD network derived from cases decided during the Rehnquist Court, concerning civil liberties issues.

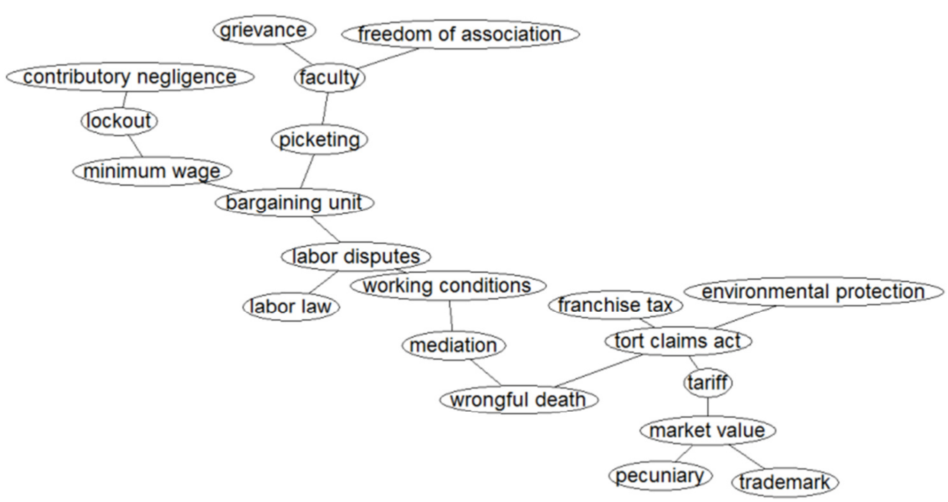

Figure 27. Rehnquist SCOD economic activity network. SCOD network derived from cases decided during the Rehnquist Court, concerning economic activity issues.

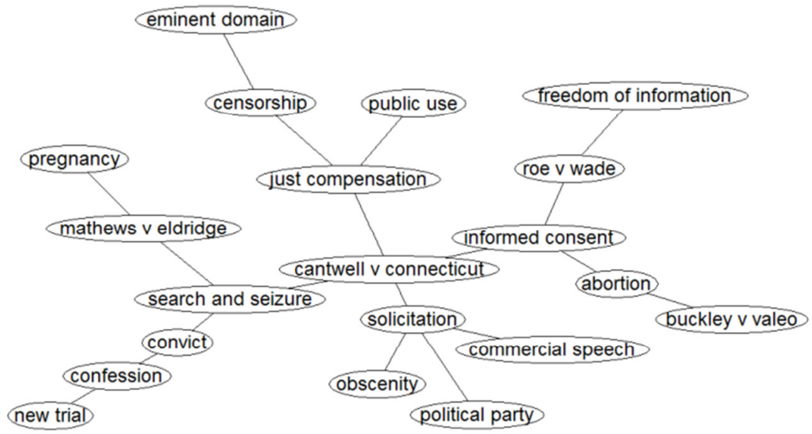

Figure 28. Roberts SCOD civil liberties network. SCOD network derived from cases decided during the Roberts Court, concerning civil liberties issues.

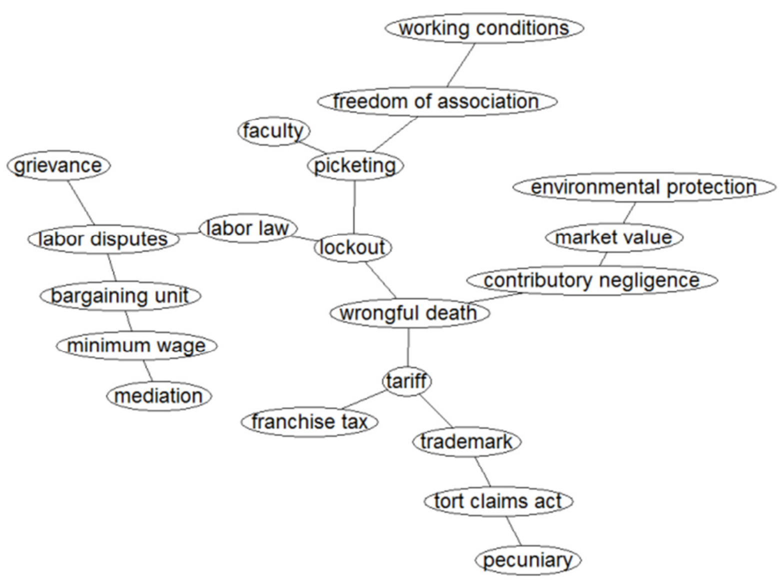

Figure 29. Roberts SCOD economic activity network. SCOD network derived from cases decided during the Roberts Court, concerning economic activity issues.

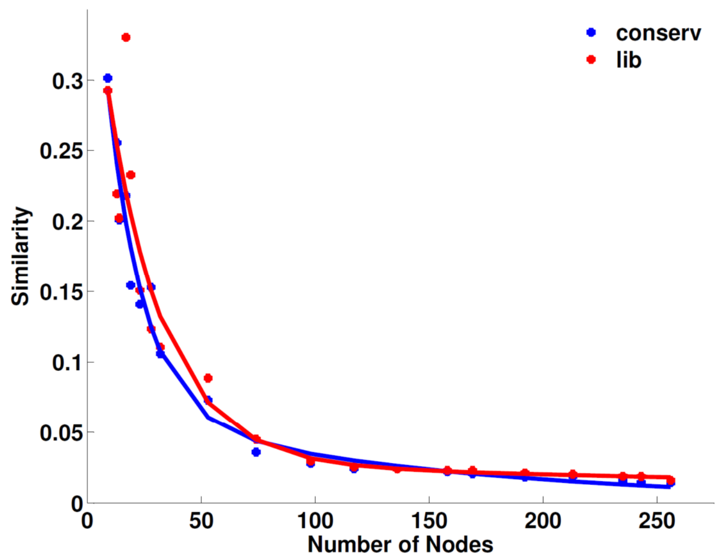

Figure 30. Similarity of Vinson's civil liberties network to liberal and conservative SCOD civil liberties networks. Dots give the actual similarity values between Vinson's networks and the other networks. Lines are non-linear least square fits of the data (see Appendix C)

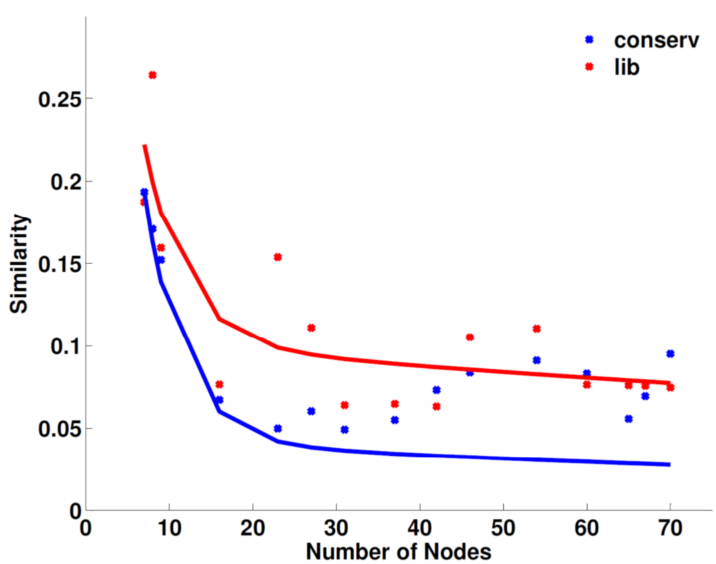

Figure 31. Similarity of Vinson's economic activity network to liberal and conservative SCOD economic activity networks. Dots give the actual similarity values between Vinson's networks and the other networks. Lines are non-linear least square fits of the data (see Appendix C)

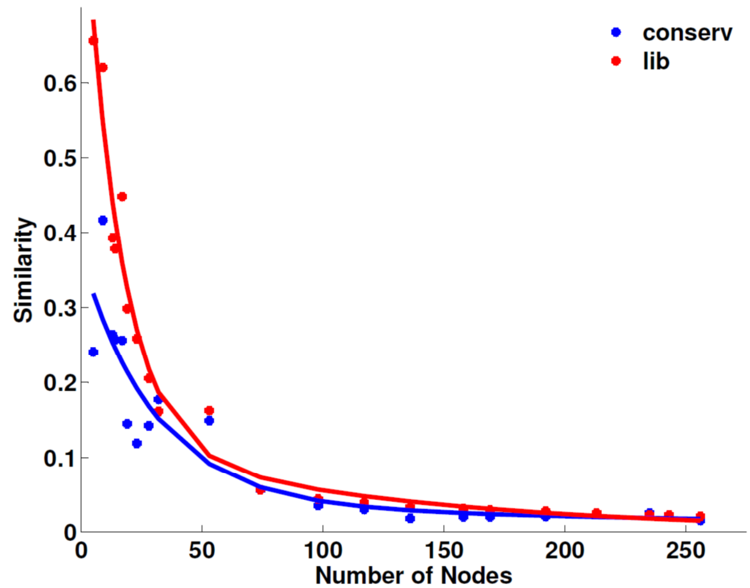

Figure 32. Similarity of Warren's civil liberties network to liberal and conservative SCOD civil liberties networks. Dots give the actual similarity values between Warren's networks and the other networks. Lines are non-linear least square fits of the data (see Appendix C)

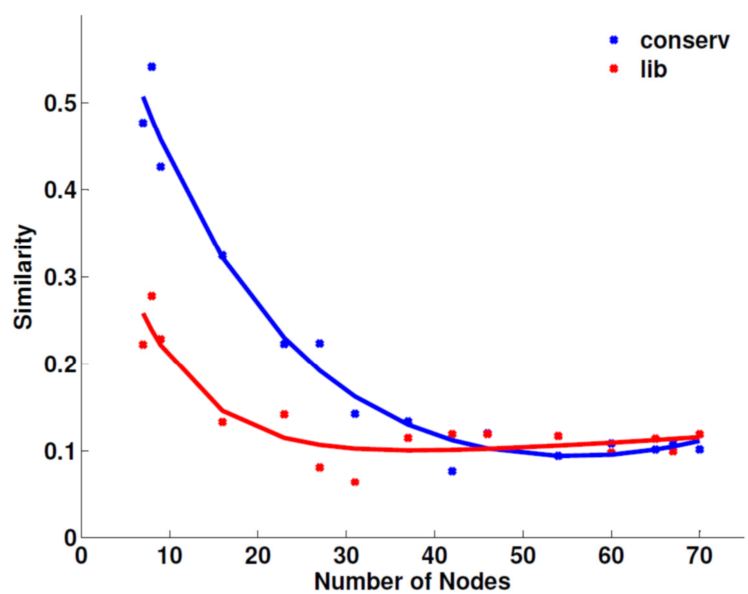

Figure 33. Similarity of Warren's economic activity network to liberal and conservative SCOD economic activity networks. Dots give the actual similarity values between Warren's networks and the other networks. Lines are non-linear least square fits of the data (see Appendix C)

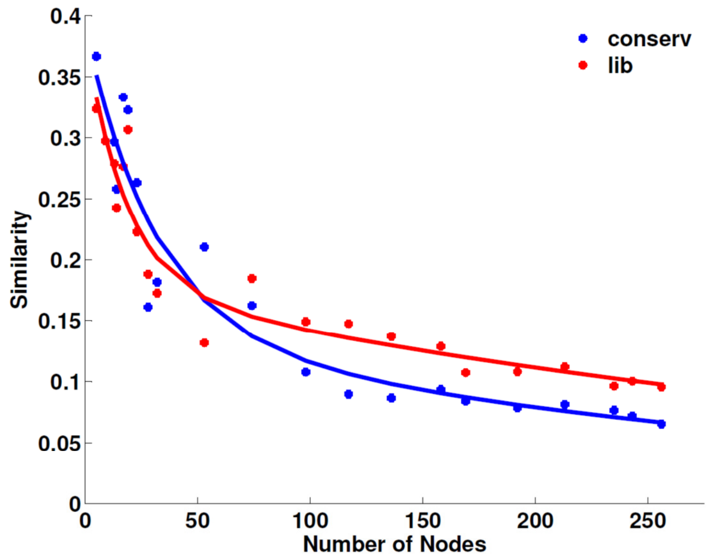

Figure 34. Similarity of Burger's civil liberties network to liberal and conservative SCOD civil liberties networks. Dots give the actual similarity values between Burger's networks and the other networks. Lines are non-linear least square fits of the data (see Appendix C)

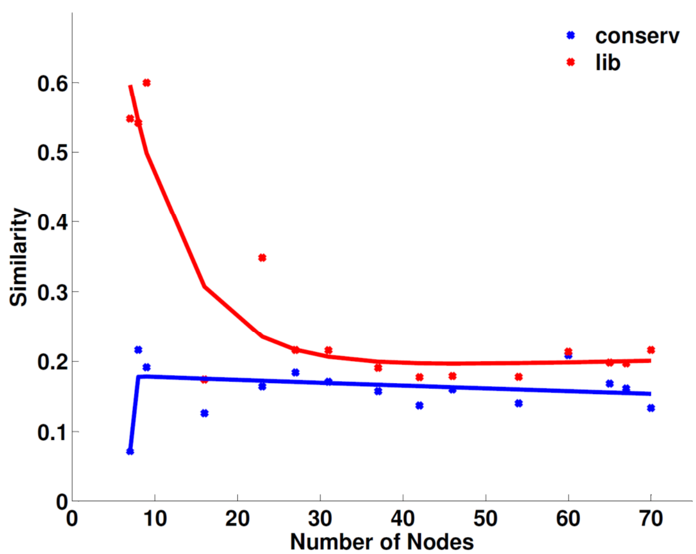

Figure 35. Similarity of Burger's Economic activity network to liberal and conservative SCOD economic activity networks. Dots give the actual similarity values between Burger's networks and the other networks. Lines are non-linear least square fits of the data (see Appendix C)

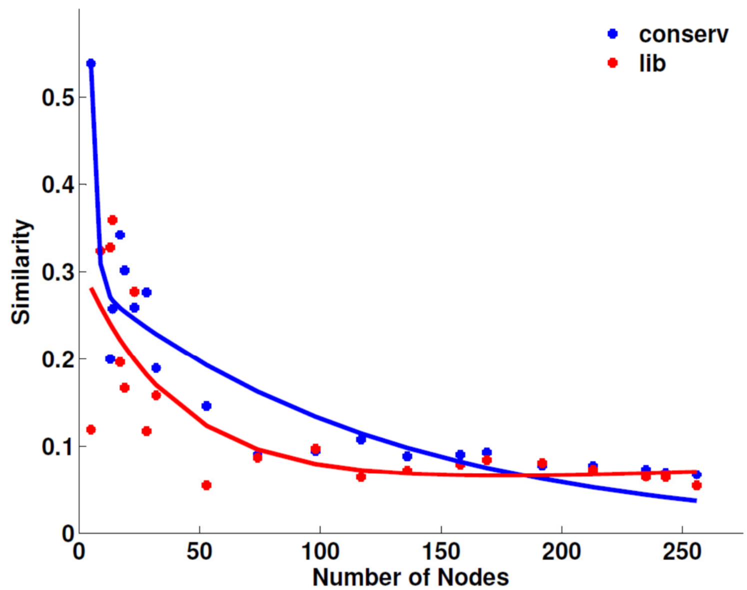

Figure 36. Similarity of Rehnquist's Civil liberties network to liberal and conservative SCOD civil liberties networks. Dots give the actual similarity values between Rehnquist's networks and the other networks. Lines are non-linear least square fits of the data (see Appendix C)

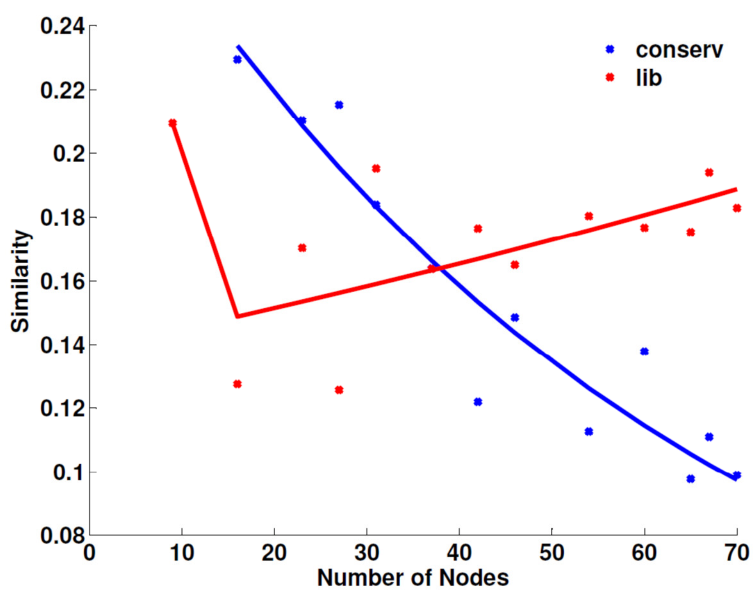

Figure 37. Similarity of Rehnquist's economic activity network to liberal and conservative SCOD economic activity networks Dots give the actual similarity values between Rehnquist's networks and the other networks. Lines are non-linear least square fits of the data (see Appendix C)

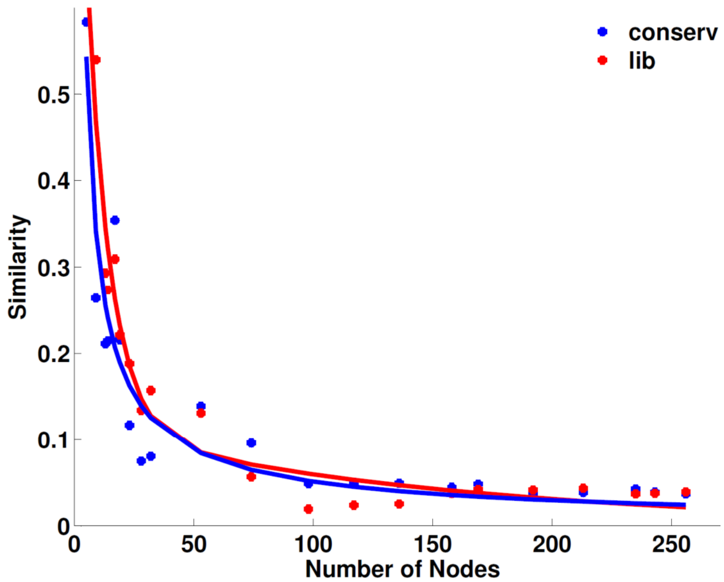

Figure 38. Similarity of Roberts's Civil liberties network to liberal and conservative SCOD civil liberties networks. Dots give the actual similarity values between Roberts's networks and the other networks. Lines are non-linear least square fits of the data (see Appendix C)

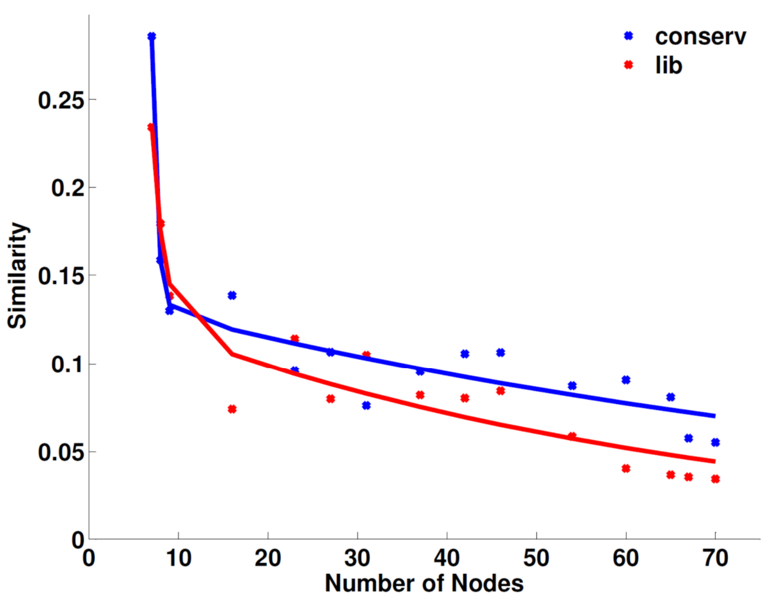

Figure 39. Similarity of Roberts's Economic activity network to liberal and conservative SCOD economic activity networks. Dots give the actual similarity values between Roberts's networks and the other networks. Lines are non-linear least square fits of the data (see Appendix C)

Table 3

Summary statistics for average similarity of Courts with referent networks

	Civ Lib			Econ Act		
Court	num docs	sim w Con	sim w Lib	num docs	sim w Con	sim w Lib
Vinson	291	0.16	0.18	265	0.08	0.10
Warren	881	0.20	0.30	586	0.20	0.12
Burger	1574	0.25	0.23	555	0.16	0.25
Rehnquist	1097	0.24	0.21	396	0.17	0.17
Roberts	327	0.18	0.23	123	0.10	0.09

Note: Con=conservative referent network, Lib=liberal referent network. Avg. network size of Civil Liberties was 28.2 nodes, for Economic Activity, 31.7 nodes. 115 of 8014 decisions were unspecifiable as to being a liberal or conservative ruling.

Chapter 5

Discussion

Since the seminal work of Collins and Quillian (1969), there has been a longstanding effort in cognitive psychology to understand the organization of human semantic knowledge. In particular, there have been numerous attempts to characterize expert knowledge (Chase & Simon, 1973a; Chase & Simon, 1973b; Chi, Feltovich, & Glaser, 1981; Ericsson & Charness, 1994; Ericsson & Polson, 1988; Gobert, 1999; Goldsmith & Kraiger, 1996; McKeithen, Reitman, Rueter, & Hirtle, 1981; Shavelson, 1972). This dissertation extends previous work in the representation of expert knowledge. However, this work is different from other expertise research for two reasons.

Firstly, the expert knowledge under investigation was that of Supreme Court justices. To my knowledge, there have been no attempts to study the semantic knowledge of legal experts, let alone Supreme Court justices, using empirically derived knowledge representations. Secondly, samples of written text were used as sources of expert knowledge. Again, to my knowledge, there have been no attempts to derive knowledge representations of experts from their writings. It is clear the work in this dissertation is original and important in that it provides a first step into explorations of legal knowledge and methods to study expertise from sources of text.

The goal was to empirically derive semantic knowledge from samples of Supreme Court writings in hopes of capturing meaningful knowledge about judicial opinions. To this end, data was extracted from Supreme Court opinions in the form of term by document matrices. The application of MDS and Pathfinder scaling techniques resulted in knowledge representations corresponding to the written opinions. The value of these representations was subsequently tested by exploring five specific hypotheses and analyzing results.

Summary of Hypotheses and Results

To understand the value of deriving knowledge networks from Supreme Court opinions, five specific research questions were put forth: (a). Is the method for extracting proximity data from text a valid one? (b) Are there meaningful differences between SCOD networks compared to random networks? (c) How good is the face validity of SCOD networks? (d) Do SCOD networks reflect the ideological drift of Justice Blackmun? (e) Do SCOD networks reflect the well-known liberal ideology of the Warren Court with respect to issues of civil liberties? Though the research is highly exploratory in nature, results of the simulations and network analysis gave rise to some significant findings.

To investigate (a), I performed multi-dimensional scaling of data corresponding the set of written opinions of the "least" and "most" conservative justices according to Landes and Posner (2009). The visual representation of the pattern of proximities provided by MDS reflected a good separation of these two groups. Figure 7 showed that all justices were grouped into their "correct" category along the y-axis, with the exception of Justice Ginsberg. However, it should be noted that Justice Ginsberg was ranked last on the list for "least" conservative and so it may be more likely that her categorization would be incorrect, than, say, Justice Marshall. The good separation provided by MDS suggests that the proximity data provides semantically meaningful information that can be recognized by scaling techniques. Thus, using proximity data derived from text appears to be a valid method for investigating expert knowledge.

With respect to (b), meaningful differences were found between SCOD networks and random networks. In particular, the similarity between SCOD networks and random networks was close to zero across different sizes of document sets and different sizes of networks. Thus, the similarity between a SCOD network and a network derived from a random shuffling of the

SCOD networks links is close to zero, with a maximum value never reaching 0.05. However, the similarity between two SCOD networks was always greater than 0.1 and averaged a value of 0.3 for networks of 50 nodes when deriving networks from 85 percent of the document population and below.

We can think of these differences in terms of standard group difference tests in psychology: Say there are two populations of entities, P_1 (SCOD networks) and P_2 (random networks), and we want to know if these populations are different from each other. We randomly select members of P_1 to compare to other members of P_1 and randomly select members of P_1 to compare to randomly selected members ofP_2. If we find that the average similarity between compared members of P_1 is greater than the average similarity between members of P_1 and P_2, it would suggest that members of P_1 have unique traits that separate them from members of P_2. In the sense of classic t-test of group differences, if there is a large similarity between members of P_1 relative to the amount of similarity between members of P_1 and P_2 , we can conclude the groups are different. These group differences mean information contained in the members of P_1 that reflect qualities special to that population. Thus, uncovering these specific structural and later semantic differences specific to the population of SCOD networks should help in understanding the nature of legal knowledge.

Further, there were significant differences between SCOD networks and random networks in the indices of coherence, average path length, and clustering coefficient, but not with the measures of node coherence and clustering coefficient. The lack of difference in these last two measures may have resulted from the nature of the network construction imposed by Pathfinder. Because Pathfinder attempts to create minimal tree structures (i.e., n nodes linked

by $n-1$ links), and the random networks that were compared were also “trees” that contained $n-1$ links for n nodes, the structure of the two networks on a local level was very similar.

With respect to (c), the face validity of the SCOD networks was demonstrated in that network terms and links among terms reflected known Court characterizations. Themes consistent with the research and rulings specific to a Court topic could be seen in each network that was constructed from the opinions dealing with those topics. For instance, terms relevant to conservative tendencies on issues of criminal procedure were found in networks derived from conservative rulings on issues of criminal procedure. In addition, there were neighborhoods of the networks that indicated terms were linked in a meaningful way (e.g., “death penalty”, “civil rights” focuses). Because both the terms in the network are relevant and the links among the terms are meaningful, SCOD networks can be said to have good face validity. That the networks had good face validity was also evidenced in (d). Networks constructed from Justice Blackmun’s opinions did seem to reflect his well-known ideological drift. The terms concerning abortion appeared to reflect a shift from abortion as a medical issue and more toward an issue of women’s rights.

With respect to (d), SCOD networks did appear to reflect the ideology of the Warren Court, at least in terms of civil liberties issues. Using referent networks constructed from all rulings, liberal and conservative, in the areas of civil liberties and economic activities, the most similar network to the liberal civil liberties network was the civil liberties network for the Warren Court. However, the expectation that the similarity between Courts post Warren and the conservative networks would increase, was not borne out.

Limitations

Network stability. One question that arises when deriving networks from text is whether there is a minimum number of documents needed to make a "stable" network. A stable network is one that is a good representative of the population of networks that can be derived from that same set of documents. More specifically, given a set of m documents, if we derive networks from randomly chosen *n* documents (n much less than m), we would expect that on average, the networks would be similar. The question of stability, then, is a question of how similar networks that are representative of a document set should be. This issue is addressed in detail in Appendix E. There it was shown that the number of documents necessary to make a stable 50 node network is the number for which two networks derived from some universe of documents have an average similarity of 0.2.

The role of law clerks in Supreme Court opinions. Since 1922, Congress has appropriated money for each Supreme Court Justice to have one law clerk. The role of the law clerk is to do legal research on pending cases, and then draft most opinions for their justice (Wrightsman, 2006). A concern in using SCOD networks to draw conclusions about individual justices is whether the opinions reflect the knowledge of the justice or of the clerk. It could be argued SCOD networks reflect the legal knowledge of the law clerks, and not of the justices.

Indeed, the impact of the clerks on opinions became an issue in spring 2005 when the Library of Congress made the files of Justice Blackmun available to the public. *Legal Affairs* journalist David Garrow accused Blackmun of "a scandalous abdication of judicial responsibility" (Garrow, 2005, p. 34), in which Blackmun relinquished too much control over his official work to his law clerks. However, it seems difficult to make a statement about the clerks' role that applies equally to every justice, given that some justices, such as Justices Scalia and

Stevens, write much or all of their own first drafts (Wrightsman, 2006). Indeed, there are reports that Justice Stevens delegated nearly no role for his clerks and was rumored to give his clerks opinion drafts with the instructions, “You put the footnotes in” (Taylor, 1988, p. 22).

It seems unlikely, however, that knowledge networks of Supreme Court opinions reflect the clerks rather than the justice’s cognitive framework. As Justice Rehnquist explains “the law clerk is not simply turned loose on an important legal question to draft an opinion embodying the reasoning and result favored by the clerk” (Rehnquist, 2001, p. 262). Instead, Rehnquist asserts, clerks are engaged in “a highly structured task that has been largely mapped out for him” by his or her justice (Rehnquist, 2001, p. 262). Whatever the input of the clerk, it is the ultimate responsibility of the justice for his or her vote and opinion, and it is the justice who receives the applause or criticism for the final opinion. Though it seems unlikely that a justice would allow another’s views to go in place of his or her own in matters of national importance, it is not entirely impossible. But even if this is the case, there is evidence that the ideology plays a major role in the selection of law clerks, and that justices choose clerks who are ideologically compatible with their own leanings (Lazarus, 1998). Thus, it would appear SCOD networks are reflecting at least a similar, shared cognitive framework, if not the unique framework of individual justices.

Future Work

One of the greatest strengths of knowledge networks is their visualization of information. Future investigations of the Supreme Court should capitalize on the face validity of these networks as demonstrated by the support the use of knowledge representations for issues of ideology. For instance, using scores of justice ideology (e.g., Segal-Cover; (1989) Martin-

Quinn; (2002) knowledge networks could be constructed for the most and least ideological justices. Networks of these justices could then be analyzed both in terms of content and topology to see if there exists a difference in the legal and ideological foundations making up the networks. The networks could also be assessed to see if particular key concepts associated with the most ideological justice “fade” or disappear from less ideological justices’ networks.

Future work could also look at the specific structure of networks rather than at just what terms are included. For example, networks containing the same set of terms can be derived for both liberal and conservative opinions. These networks could be used to determine how semantic relationships among the terms vary between the two ideologies.

In addition, the metric of network similarity could be used to investigate other issues in the Court. For instance, some observers of the Court maintain that a “freshman effect” operates on new justices (Maltzman & Wahlbeck, 1996). That is, new justices initially rely on the opinions of others on the court and even emulate them. Measurements of network similarity could be used to investigate which new justices display the freshman effect and which expert justices serve as their models.

Knowledge networks could be applied to other sources of legal text other than written opinions to help understand the psychology of the Supreme Court. For instance, Black, Johnson and Wedeking (2012) found that oral arguments play a key role in the Supreme Court's decision-making process. Knowledge networks derived from transcripts of oral arguments could be compared to knowledge networks derived from the corresponding decisions. Measures of term and structure similarity between the two network classes (oral and decision) could build upon Black, Johnson and Wedeking’s (2012) work.

Future work should also investigate different methods for deriving and constructing networks from Supreme Court opinions. For instance, better key terms may be selected by using a legal expert to choose the top most meaningful terms from a Wikipedia Category Key Term Algorithm (WCKTA) derived list (see Appendix A). Given a user specified domain, WCKTA will automatically return a list of terms important to that domain based upon human derived categories and category relationship contained in Wikipedia. This key term algorithm has been shown to surpass standard methods in selecting meaningful terms to represent domain specific content (Lippert & Goldsmith, 2014). Using an expert to further rank term importance from this already meaningful term set could even improve upon the already good face validity of the networks.

Because the network theory indices were overall low for measures of coherence for both SCOD and random networks, extensive work on structural differences using graph theoretical metrics to compare the two network types was not performed. Future work should to consider different ways of creating networks from proximity matrices. For instance, rather than using the Pathfinder linking algorithm, a simple cut off score on the proximities could be used to link the most highly related concepts (McRae, Cree, Seidenberg, & McNorgan, 2005). It may also lead to non-tree like networks that could, by their nature demonstrate higher clustering and modular properties.

In addition, exploring different values of Pathfinder parameter, q and r, should be explored to adjust network density. Appendix F presents networks from the analysis of Blackmun's ideological drift, when the q parameter is decreased to be proportionate to one-third the number of nodes in the network. Though there appears to be greater structure in the resulting

networks, the measures of node coherence and clustering coefficient are zero, indicating further tweaking of these parameters should be explored.

Summary

The construction of knowledge networks from text is a novel way to study the cognitive organization of domain specific content. Because Supreme Court opinions are written, the process of writing may consolidate the structure of knowledge networks and reveal network characteristics that may not be apparent with standard elicitation techniques.

There are other advantages to deriving knowledge networks from text compared to standard methods. For instance, elicitation of knowledge from experts using traditional elicitation methods is often time consuming and burdening but eliciting knowledge from existing writings requires none of the expert's time. In addition, knowledge representations derived from text allow for investigations of historical issues, using written records of the time period. Text based knowledge representations also make it possible to analyze proximity data over large periods of time, examining changes in semantic structures that may be dependent upon changes that happen over lifetimes (e.g. how societal influences affect semantic knowledge). This type of analysis would allow for truly longitudinal studies involving semantic networks, for instance, studies that derive knowledge representations from series of textbooks from different time periods to investigate paradigm shifts in academic disciplines. Knowledge networks derived from text also present an advantage over traditional methods in that the structure of semantic knowledge can be assessed in perhaps a more objective way, using the metrics of network theory. Finally, since the development of the internet, greater amounts of textual data are

becoming accessible. Automated text analysis algorithms and network construction techniques such as Pathfinder make it possible to capitalize on this explosion of information.

Characterizing Supreme Court justice knowledge is important because of the role the judicial system plays in society and progression of a democracy. The structure of the knowledge underlying decisions may yield information about the extent to which justices are influenced by various factors, some of which may not be acceptable to society at large. The current work provides an objective methodology for deriving and analyzing knowledge networks of legal text. In general, this work demonstrated the potential in using knowledge networks to help answer a wide variety of questions concerning Supreme Court decision making.

APPENDICES

Appendix A

Wikipedia Category Key Term Algorithm

Appendix A describes the Wikipedia Category Key Term Algorithm (WCKTA), the algorithm used for key term extraction in this dissertation. WCKTA was written in and carried out using a commercial software package (MATLAB 2012b, The MathWorks, Inc., Natick, MA). WCKTA automatically returns a list of key terms from a user simply giving it an initial domain of a set of documents. To do this, WCKTA first fetches the category page for the human provided domain name corresponding to a set of documents. If a category page for a given domain exists, it is located at *http://en.wikipedia.org/wiki/Category:domain*, where "domain" is replaced with the specific domain name, for instance, "law" or "sports" or "animals", etc. A category page of a domain lists all the subcategories of the domain as well as the pages belonging directly to that category. The algorithm records all the category page names and the names of the subcategories as part of the term list. Next, the algorithm proceeds to the category page of each subcategory, recording all the subcategory names and page names for that subcategory of the domain category. Because subcategories are categories themselves, their respective category pages are located in the same manner- i.e. by accessing http://en.wikipedia.org/wiki/Category:*subcategory*, where "subcategory" is replaced with the name of the specific subcategory.

In addition, all names of topics listed on the page "Index of   Articles" are recorded as candidate terms. An index page in Wikipedia is an index of all titles of Wikipedia pages related to a particular topic. The blank should be filled in with the corresponding category name. For

instance, the “Index of Law Articles” is an alphabetical list containing names of 3,705 Wikipedia pages related to law. A majority of these terms from the “Index” page will have been recorded as terms extracted from the subcategory and page name retrieval step, and so this step is not essential, but may help to ensure a covering of all essential category relevant terms.

To obtain the final category key term set, we take the intersection of the unique terms from the candidate term list and the list all possible words or word phrases from the set of domain specific documents. The intersection will be the list of key terms for the set of documents in question. This is called the Wikipedia key term list, and has been derived using the WCKTA.

Thus, the WCKTA extracts a term list for a domain category, as follows:

Extract all page titles,$p(C)$, and subcategory titles, $s(C)$, listed under Wikipedia category C. Record $p(C)$ and $s(C)$ as part of the domain term list.

For each subcategory title, $s(C)$, go to its’ corresponding category page, C_s. Extract all page titles, $p(C_s)$, and subcategory titles, $s(C_s)$, listed under Wikipedia category C_s. It should be noted, however, that not every category page contains subcategory titles.

Retain as terms all names of topics listed on the page “Index of   Articles”.

Take the unique terms within this compiled term list and find the intersection of this term list with all possible words or word phrases from the set of domain specific documents. The intersection will be the list of key terms for the set of documents in question and is called the Wikipedia key term list.

Redirect and Disambiguation Functions. Included in the algorithm are a "redirect" function and a "disambiguation" function to help address the issues of polysemy and synonymy of words. Automated key term selection in natural language must deal with the problems of polysemy and synonymy. A word is polysemous if it is characterized by more than one meaning. For example, the word *mug* can mean a coffee mug, as well as a face, as well as the act of being mugged. Polysemy is problematic in that it depresses recall (an algorithm's ability to return the most relevant results) by causing false matches (Voorhees, 1993). Synonymy refers to multiple words having the same meaning, such as *end* and *finish*. Synonymy is problematic in that it lowers precision (the ability of algorithm to return substantially more relevant results than irrelevant results) by causing true conceptual matches to be missed (Voorhees, 1993).

In theory, it is possible to resolve the issues of polysemy and synonymy by assigning different senses of a word different concept identifiers and assigning the same concept identifier to synonyms (Voorhees, 1993). In practice, this requires methods that can recognize synonyms, distinguish different senses of an ambiguous word and determine which meaning of the word is intended in each case (Voorhees, 1993).

Wikipedia "redirect" pages act as a synonym identifier for WCKTA. A redirect page has no content itself but sends the reader to another article from an alternative title. Redirect pages are used for titles that have alternative names (e.g. Abusive language goes to profanity), are plurals (e.g. taxes goes to tax), are closely related words (worker's compensation is redirected to workmen's' compensation), and other uses (Redirect, 2013). Thus a redirect page assigns the same concept identifier to synonymous terms.

Wikipedia “disambiguation” pages present various possible meanings of a term from which users can select articles corresponding to their intended concepts. For instance, the Wikipedia page for the term “steal” is a disambiguation page. Among the possible usages of steal are “theft”, “steal (basketball)”, “stolen base”, and “steal (film)”. If the document set under analysis is law related, the obvious choice of steal is “theft”. The Wikipedia key term selection algorithm automatically selects “theft” as the correct usage by determining the Wikipedia category membership of each disambiguation choice. Because “theft” is the only term belonging to the Wikipedia law category, the term “theft” is selected to replace the term steal. Thus, disambiguation pages can identify the correct meaning of the term and then convert it into a synonym if necessary. If the synonym itself is already a key term, the term frequency data for the term and its synonym are combined. In this way, disambiguation pages provide a means to reduce dimensionality while preserving semantic information. Otherwise, the term may be added to the Wikipedia term list as a unique term.

An experiment was conducted to compare the key term sets selected by WCKTA with two other well-known key term selection methods (Lippert & Goldsmith, 2014). Document categorization performance and face validity of key terms were used as measures of “goodness” of the resulting term sets. An assumption is that better categorization performance reflects key terms that better represent a document set (Sebastiani, 2005). The face validity of terms was compared by visual inspection. The results of the experiment demonstrated that key terms selected by WCKTA yielded better categorization of documents into their human defined categories than key term sets selected by the two other methods. In addition, the face validity of selected key terms was higher in terms selected by WCKTA. These two findings suggest WCKTA provides a good key term set for use in creating SCOD networks.

For this dissertation, the category name of "Law" was the initiating category. Thus, all fifty-four subcategories and fifty-three pages on the Wikipedia category page for Law (Figure A1) were first recorded as part of the potential key term set. Next, all subcategories and pages of each of these fifty-four subcategories from the Wikipedia law category page were recorded as potential key terms. After collecting the page and subcategory names from the law category page and then collecting the pages and subcategory names from each subcategory name on the law category page, there were 4,096 potential, non-unique key terms. This set included any number of grams. Then, the terms from the page "Index of Law Terms" were added to this list, so the number of non-unique potential key terms was 7784. The set had terms ranging from one grams to 13-grams. After keeping only terms that were either one, two or three grams, the set was reduced to 6,703 terms. Next, duplicate terms were removed, reducing the number of terms in the potential key terms set to 5675 terms.

Finally, each term was checked to see if it was redirected to another page. If it was redirected, that term in the potential key term list was replaced with the name of the page to which it was redirected (Fig A3). Of the 5,675 terms, 1462 were redirected. Once all redirected terms were replaced by the term corresponding to the page to which they were redirected, the duplicate terms were removed. This resulted in 5349 terms. Finally, if a term was redirected to another term that was neither a one, two or three gram, this term was removed. After removing such terms (there were 84 of them), the count of the potential key term set was 5265.

Further reduction of this term set occurred by identifying terms in this set of 5265 that were terms followed by a parentheses enclosed term, indicating the nature of the term, in order to disambiguate it from the same term with a different meaning. For instance, in the list of the 5265 terms, "Covenant" followed by "(law)" is listed as a single term "Covenant (law)". The

term law in parentheses is used to disambiguate this use of Covenant from others listed by Wikipedia such as “Covenant (biblical)” , or “Covenant (band)”. Because I did not want the key term list to include the disambiguation marker and because it was likely the marker indicated the term was law related, I removed these markers. For example, the term “Covenant (law)” simply became “Covenant”. There were 329 terms that needed to have the disambiguation marker removed. After removing the marker from these 329, some of the terms in the list became non-unique. After removing any duplicate terms, there were 4779 terms left in the potential key term list.

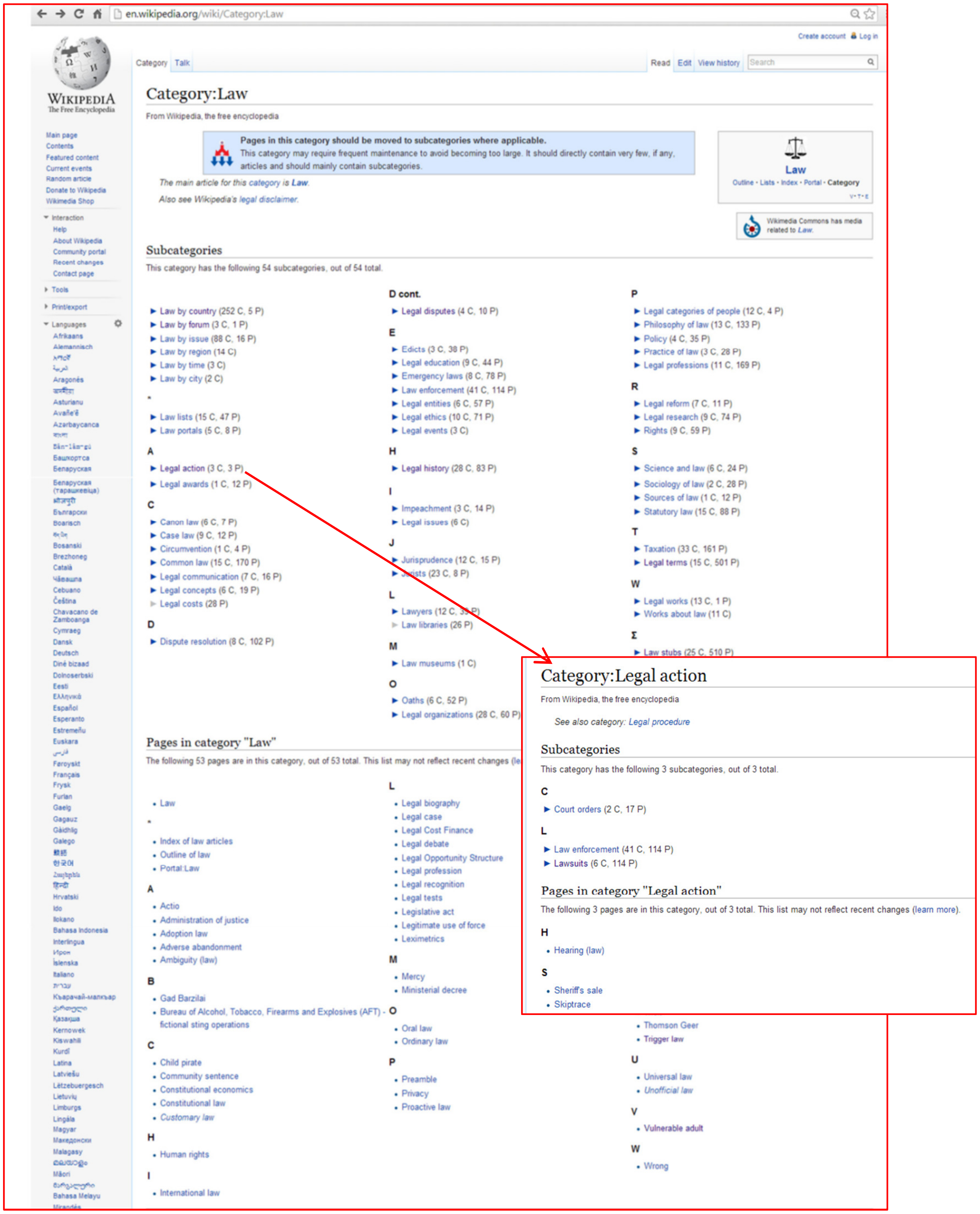

Figure A1. Gathering potential key terms for the domain of Law using Wikipedia categories. The potential key term set is acquired by first recording all subcategories and page names listed on the category page of the specified domain, in this case, Law. Next, each of the subcategories and pages of each subcategory on the law category page were recorded. For example, law subcategory "Legal Action" has three subcategories and three pages, each of which were recorded as potential terms.

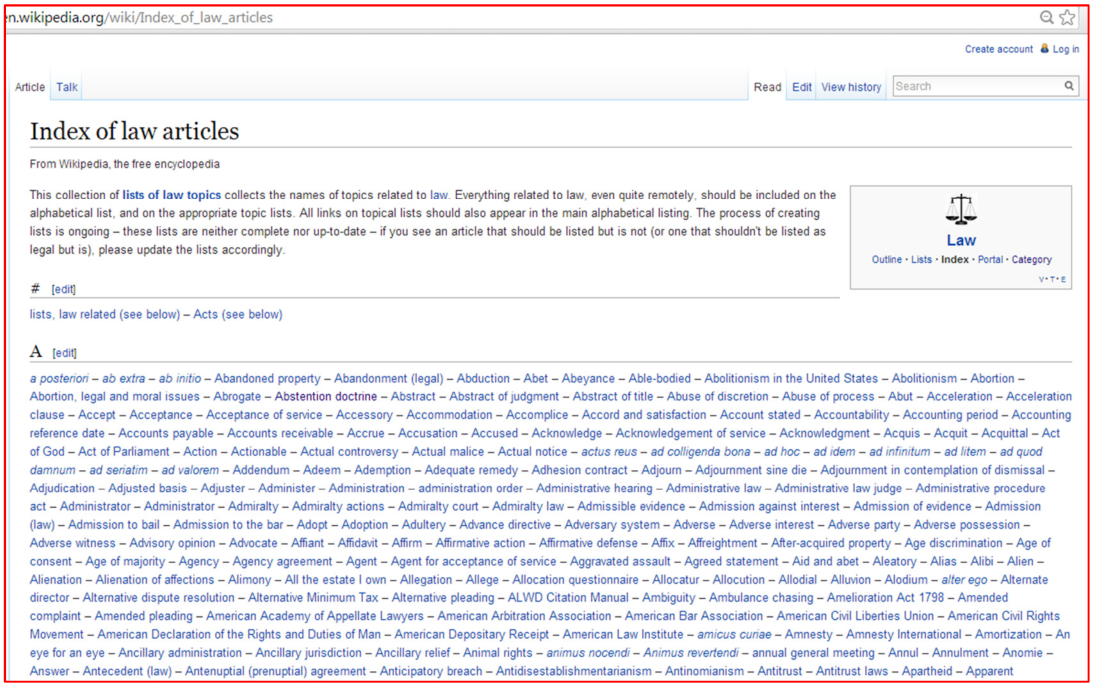

Figure A2. Index of law articles webpage. The terms on this page were also part of the list of potential key terms. Figure A2 only shows the terms beginning with A for brevities sake.

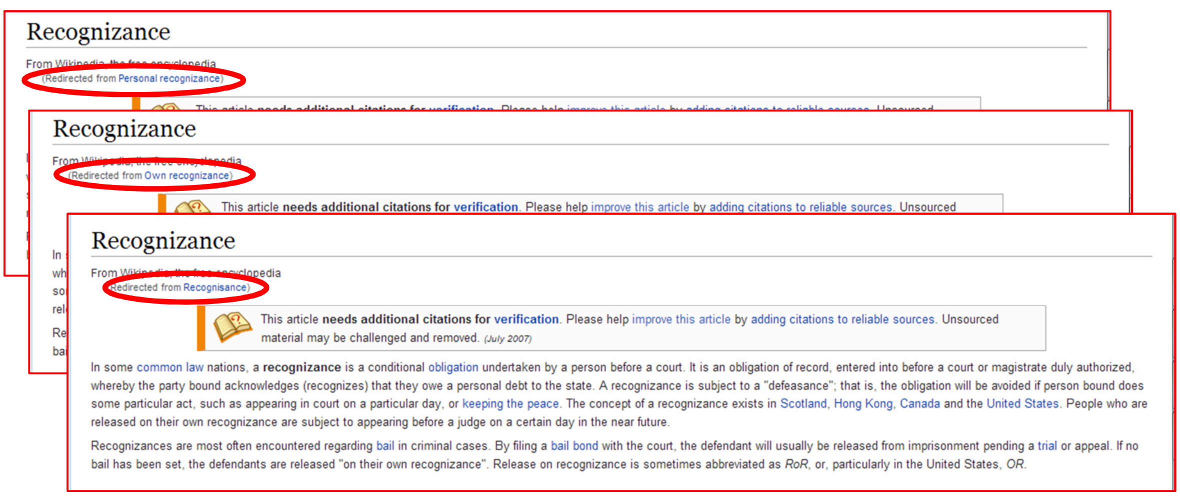

Figure A3. Example of Redirected Terms. Of the initial unique 5688 terms (one grams, bigrams and trigrams), 1376 were redirected to other pages, and allowed for a reducition in the potential key term set. Figure A3 shows how the terms “Personal Recognizance”, ”Own Recognizance”, and “Recognisance” are all redirected to “Recognizance” page. In this way, the potential key term set is reduced by removing the three redirected terms and replacing them with a single term, “Recognizance”.

Appendix B

The list of 2647 key terms rank ordered by tf-idf score

TERM	TF-IDF SCORE
Court	1
Law	0.29903
Tax	0.23179
Jury	0.21165
Trial	0.21008
Statute	0.20977
Government	0.20494
Evidence	0.19681
Public	0.18664
Petitioner	0.17823
district court	0.17534
Opinion	0.17083
Rights	0.16276
Justice	0.16132
Property	0.15237
Jurisdiction	0.15037
Judgment	0.14826
Interest	0.14549
Defendant	0.13589
Use	0.13053
Respondent	0.12974
Death	0.12428
Issue	0.12206
Review	0.11777
Fact	0.11717
Police	0.11228
Authority	0.11105
Sentence	0.1102
Counsel	0.10948
Discrimination	0.10803
Damages	0.10605
Title	0.10577
Laws	0.10442
Constitution	0.10441
Service	0.10277
Judge	0.10256
Regulation	0.10168
Person	0.10143

Income	0.099009
Party	0.098458
Contract	0.097802
Provision	0.097058
Business	0.094426
Relief	0.093424
Policy	0.093423
due process	0.092877
Information	0.092284
F	0.08933
supreme court	0.088736
appeal	0.088309
liability	0.087934
brief	0.086895
hearing	0.086063
employment	0.084028
particular	0.082664
crime	0.082315
conviction	0.081664
arbitration	0.081609
attorney general	0.080335
code	0.080308
proceedings	0.080066
majority	0.079736
testimony	0.079281
bankruptcy	0.077487
patent	0.0765
child	0.074212
holding	0.074211
capital	0.074056
matter	0.073697
result	0.072884
report	0.07201
bank	0.071224
defense	0.070339
company	0.070086
insurance	0.0699
petition	0.068738
complaint	0.068665
injury	0.068472
education	0.067847
enforcement	0.067222
notice	0.066858
reason	0.065994

bill	0.065306
murder	0.065088
arrest	0.064805
test	0.064735
life	0.064385
warrant	0.064374
privilege	0.064201
security	0.064065
construction	0.063272
certiorari	0.063192
ordinance	0.062881
discretion	0.062331
plaintiff	0.06205
corporation	0.060813
prison	0.059942
sales	0.059301
witness	0.058834
injunction	0.058531
award	0.057879
habeas corpus	0.057724
abortion	0.057391
duty	0.056718
guilty	0.056427
commissioner	0.056404
finding	0.056034
legislation	0.056007
grand jury	0.054882
reservation	0.054567
error	0.054205
decree	0.054175
privacy	0.05406
failure	0.053687
executive	0.052749
fair	0.052602
take	0.05236
standing	0.051719
charge	0.051639
probable cause	0.051473
fee	0.051473
legislative history	0.05121
trade	0.051173
indictment	0.05112
stock	0.051066
consent	0.05066

bar	0.050242
payment	0.049886
official	0.04962
writ	0.04959
confession	0.049493
copyright	0.049394
consideration	0.04924
parole	0.049161
conspiracy	0.049122
verdict	0.048861
dissent	0.048844
alien	0.048838
money	0.048506
force	0.04767
taxpayer	0.047262
presumption	0.047135
candidate	0.047091
legislature	0.046721
grant	0.046083
plea	0.045912
liberty	0.045661
federal law	0.045434
risk	0.045186
war	0.044331
common law	0.04418
commerce clause	0.043979
trial court	0.043819
license	0.043446
estate	0.04327
possession	0.042523
deportation	0.042122
good	0.041707
fraud	0.041531
answer	0.041147
preemption	0.041134
waiver	0.041028
reading	0.04101
double jeopardy	0.040914
treaty	0.040866
filing	0.040268
tort	0.040093
immigration	0.039609
administration	0.039285
illegal	0.039272

summary	0.039264
discharge	0.038567
cause of action	0.037521
faith	0.037472
family	0.037358
establishment clause	0.037334
disability	0.037015
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prohibition	0.036963
obligation	0.036875
negligence	0.036752
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prosecutor	0.036534
remand	0.03646
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felony	0.036192
guilt	0.035851
apportionment	0.035732
detention	0.035071
punitive damages	0.034972
harm	0.034918
collateral	0.034853
interrogation	0.034533
settlement	0.034477
admiralty	0.034357
debtor	0.034335
admission	0.034179
lien	0.033954
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sovereign immunity	0.033512
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discovery	0.032874
controversy	0.032508
letter	0.032479
face	0.032404
event	0.032162
attempt	0.032083
element	0.03197
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equity	0.031938

in re	0.031512
equal protection clause	0.031469
constitutionality	0.031465
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principal	0.031178
lawyer	0.03114
ordinary	0.030888
of counsel	0.030852
color	0.030461
master	0.030323
violence	0.030125
performance	0.029986
public interest	0.029985
retirement	0.029602
trustee	0.029596
share	0.029442
ban	0.0293
reasonable doubt	0.02914
parent	0.029105
objection	0.029104
enactment	0.029019
solicitor	0.028922
applicant	0.028872
ownership	0.028567
justification	0.028523
page	0.028335
acting	0.02823
probation	0.027972
appear	0.027944
debt	0.027769
accept	0.02752
judiciary	0.027412
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robbery	0.027279
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deference	0.026521
adjudication	0.026448

obscenity	0.026424
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solicitor general	0.026343
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belief	0.025
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demand	0.024724
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ex rel	0.02188
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emergency	0.020654
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customs	0.019676
rape	0.01966
prima facie	0.019504
expense	0.019382
street	0.019297
assault	0.018824
declaratory judgment	0.018794
en banc	0.018784
divorce	0.018776
creditor	0.018651
assignment	0.018513
passenger	0.018333
discipline	0.018312
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chairman	0.015077
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police power	0.008835
garnishment	0.008772
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nuisance abatement	0.000305
forensic science	0.000305
impossibility defense	0.000305
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hostile witness	0.000304
law society	0.000304

tax break	0.000304
tort reform	0.000304
witness protection	0.000304
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westlaw	0.0003
cumulative sentence	0.000299
mental health law	0.000299
per stirpes	0.000299
unenumerated rights	0.000298
acceleration clause	0.000298
humanism	0.000298
legal advertising	0.000298
legal malpractice	0.000298
precommitment	0.000298
black letter law	0.000295
business ethics	0.000295
position of trust	0.000295
jurisdictional fact	0.000291
prior review	0.000291
women lawyers	0.000291
education policy	0.000291
asset forfeiture	0.000288
constructive fraud	0.000286
lead plaintiff	0.000286
contingent interest	0.000281
alluvion	0.00028
frontage	0.00028
letters of administration	0.00028
quran	0.00028
war crime	0.00028
putative father registry	0.000279
trial in absentia	0.000279
rectification	0.000276
police lineup	0.000276
notice of default	0.000273
right of passage	0.000273
civil disobedience	0.000273
duplicity	0.000273
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totalitarianism	0.000273
conservatorship	0.000272
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fealty	0.000269

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privy council	0.000269
compurgation	0.000267
general partnership	0.000267
inherent jurisdiction	0.000267
irresistible impulse	0.000267
legal age	0.000267
truancy	0.000267
title search	0.000267
arbitral tribunal	0.000262
bail bondsman	0.000262
territorial integrity	0.000262
police radio	0.000262
comparative law	0.000262
defalcation	0.000262
franking	0.000262
oyer and terminer	0.000262
age of consent	0.000257
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catechism	0.000257
civil recovery	0.000257
perverse incentive	0.000257
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tax expense	0.000254
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short title	0.000253
indecent exposure	0.00025
mutation	0.00025
general strike	0.000248
secret trial	0.000248
estray	0.000248
substantial performance	0.000248
service mark	0.000245
executioner	0.000243
bankruptcy discharge	0.000238
grounds for divorce	0.000238
investiture	0.000238
tacking	0.000238
bona vacantia	0.000236
fa	0.000236
state of emergency	0.000236
chain of title	0.000234

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parol	0.000234
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articles of impeachment	0.0002
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trial by combat	0.00019
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land tenure	0.000178
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res gestae	0.000178
toll bridge	0.000178
undisclosed principal	0.000178
tax treaty	0.000174
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churning	0.000174
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rights of englishmen	0.000174
torah	0.000174
will and testament	0.000174
irish law	0.000171
religious text	0.000171
universal jurisdiction	0.000171
decriminalization	0.000171
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law report	0.00017
policy studies	0.00017
retributive justice	0.00017
statute book	0.00017
trial by ordeal	0.00017
game law	0.000163
idem	0.000163
statement against interest	0.000163
indefinite imprisonment	0.000163
internal affairs doctrine	0.000163

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world trade organization	0.000163
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crimes against humanity	0.000157
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fieri facias	0.000157
grievous bodily harm	0.000157
guest statute	0.000157
land reform	0.000157
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struck jury	0.000157
wrongful dismissal	0.000157
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forced heirship	0.000155
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letter rogatory	0.000155
war powers resolution	0.000155
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courtship	0.000153
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irreconcilable differences	0.000153
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will contest	0.000153
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request for production	0.000149
social control	0.000149
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law of japan	0.000143
misprision of felony	0.000143
panamanian law	0.000143
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coming into force	0.000136
hypothecation	0.000136
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accord and satisfaction	0.000131
champerty and maintenance	0.000131
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delegated legislation	0.000131
fair division	0.000131
fair trade law	0.000131
force majeure	0.000131
frivolous or vexatious	0.000131
grazing rights	0.000131
imperium	0.000131
inspection of documents	0.000131
law enforcement operations	0.000131
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legal nullity	0.000131
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legal realism	0.000127
legal treatise	0.000127

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natural order	0.000127
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privacy law	0.000127
proposed laws	0.000127
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integration clause	0.000124
law of belgium	0.000124
paraphilia	0.000124
presumption of paternity	0.000124
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best evidence rule	0.000109
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crime of passion	0.000109
diminished responsibility	0.000109
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disability law	0.000109
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geis	0.000109
glossator	0.000109
international law association	0.000109
last clear chance	0.000109
mock trial	0.000109

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pauperism	0.000109
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publishing rights	0.000109
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energy law	0.000105
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golden rule	0.000105
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legal debate	0.000105
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legal science	0.000105
limited liability company	0.000105
manhunt	0.000105
medieval law	0.000105
misprision of treason	0.000105
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parallel construction	0.000105
parliamentary procedure	0.000105
patriot act	0.000105
peerage	0.000105
plagiarism	0.000105
police escort	0.000105
prime suspect	0.000105

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social class	0.000105
social issue	0.000105
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reception statute	$9.3x10^{-5}$
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school resource officer	$9.3x10^{-5}$
specimen charges	$9.3x10^{-5}$
unlawful combatant	$9.3x10^{-5}$
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ad quod damnum	**3.1×10^{-5}**
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empty chair	**3.1 x 10^{-5}**
entertainment law	**3.1 x 10^{-5}**
epileptic seizure	**3.1 x 10^{-5}**
erectile dysfunction	**3.1 x 10^{-5}**
erratum	**3.1 x 10^{-5}**
ethnic cleansing	**3.1 x 10^{-5}**
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fashion law	**3.1 x 10^{-5}**
firm offer	**3.1 x 10^{-5}**
fisheries law	**3.1 x 10^{-5}**
fishing net	**3.1 x 10^{-5}**
fleta	**3.1 x 10^{-5}**
forged endorsement	**3.1 x 10^{-5}**
form book	**3.1 x 10^{-5}**
fratricide	**3.1 x 10^{-5}**
free license	**3.1 x 10^{-5}**
frustration of purpose	**3.1 x 10^{-5}**
gibbeting	**3.1 x 10^{-5}**
good conduct time	**3.1 x 10^{-5}**
good governance	**3.1 x 10^{-5}**

government gazette	**3.1×10^{-5}**
grand inquisitor	**3.1×10^{-5}**
gross floor area	**3.1×10^{-5}**
haitian law	**3.1×10^{-5}**
hardship clause	**3.1×10^{-5}**
harmonisation of law	**3.1×10^{-5}**
heir apparent	**3.1×10^{-5}**
hereditament	**3.1×10^{-5}**
housekeeping provision	**3.1×10^{-5}**
identity change	**3.1×10^{-5}**
illegal drug trade	**3.1×10^{-5}**
in situ	**3.1×10^{-5}**
incidental damages	**3.1×10^{-5}**
indigenous law	**3.1×10^{-5}**
information privacy	**3.1×10^{-5}**
informed refusal	**3.1×10^{-5}**
intellectual property infringement	**3.1×10^{-5}**
intimate part	**3.1×10^{-5}**
invitation to treat	**3.1×10^{-5}**
judicial murder	**3.1×10^{-5}**
juris doctor	**3.1×10^{-5}**
jury stress	**3.1×10^{-5}**
jus gentium	**3.1×10^{-5}**
language tax	**3.1×10^{-5}**
law and gospel	**3.1×10^{-5}**
law and religion	**3.1×10^{-5}**
law of denmark	**3.1×10^{-5}**
law of france	**3.1×10^{-5}**
law of germany	**3.1×10^{-5}**
law of uruguay	**3.1×10^{-5}**
legal benefit	**3.1×10^{-5}**
legal citation	**3.1×10^{-5}**
legal english	**3.1×10^{-5}**
legal information institute	**3.1×10^{-5}**
legal organizations	**3.1×10^{-5}**

legal pluralism	**3.1×10^{-5}**
legal psychology	**3.1×10^{-5}**
legal recourse	**3.1×10^{-5}**
legal transplant	**3.1×10^{-5}**
legal writing	**3.1×10^{-5}**
list of taxes	**3.1×10^{-5}**
mare clausum	**3.1×10^{-5}**
marketable title	**3.1×10^{-5}**
material adverse change	**3.1×10^{-5}**
mature minor doctrine	**3.1×10^{-5}**
medieval jurists	**3.1×10^{-5}**
middle temple	**3.1×10^{-5}**
mishnah	**3.1×10^{-5}**
mitra	**3.1×10^{-5}**
morganatic marriage	**3.1×10^{-5}**
motor vehicle exception	**3.1×10^{-5}**
multiple citizenship	**3.1×10^{-5}**
muniment	**3.1×10^{-5}**
negative pledge	**3.1×10^{-5}**
nota bene	**3.1×10^{-5}**
nuclear law	**3.1×10^{-5}**
nulla bona	**3.1×10^{-5}**
numerus clausus	**3.1×10^{-5}**
nuremberg code	**3.1×10^{-5}**
oath of supremacy	**3.1×10^{-5}**
obstructing government administration	**3.1×10^{-5}**
offshore company	**3.1×10^{-5}**
outrageous government conduct	**3.1×10^{-5}**
papal infallibility	**3.1×10^{-5}**
parliamentary sovereignty	**3.1×10^{-5}**
patent pending	**3.1×10^{-5}**
per minas	**3.1×10^{-5}**
person of interest	**3.1×10^{-5}**
peruvian law	**3.1×10^{-5}**
phill kline	**3.1×10^{-5}**

plumbing code	**3.1×10^{-5}**
police code	**3.1×10^{-5}**
police prosecutor	**3.1×10^{-5}**
political law	**3.1×10^{-5}**
positive obligations	**3.1×10^{-5}**
practising law institute	**3.1×10^{-5}**
prepared testimony	**3.1×10^{-5}**
preventive police	**3.1×10^{-5}**
primary legislation	**3.1×10^{-5}**
primogeniture	**3.1×10^{-5}**
prisoners and detainees	**3.1×10^{-5}**
property manager	**3.1×10^{-5}**
provisional order	**3.1×10^{-5}**
reform judaism	**3.1×10^{-5}**
regional policy	**3.1×10^{-5}**
reid technique	**3.1×10^{-5}**
religious oaths	**3.1×10^{-5}**
riot control	**3.1×10^{-5}**
royal assent	**3.1×10^{-5}**
rylands v fletcher	**3.1×10^{-5}**
secured transaction	**3.1×10^{-5}**
simony	**3.1×10^{-5}**
simultaneous death	**3.1×10^{-5}**
social law	**3.1×10^{-5}**
south african law	**3.1×10^{-5}**
south korean law	**3.1×10^{-5}**
specific legacy	**3.1×10^{-5}**
statism	**3.1×10^{-5}**
stock transfer agent	**3.1×10^{-5}**
street law	**3.1×10^{-5}**
subordination agreement	**3.1×10^{-5}**
surrebuttal	**3.1×10^{-5}**
table of authorities	**3.1×10^{-5}**
tallage	**3.1×10^{-5}**
tax amnesty	**3.1×10^{-5}**

tax haven	**3.1×10^{-5}**
tax profit	**3.1×10^{-5}**
taxor	**3.1×10^{-5}**
terra nullius	**3.1×10^{-5}**
test act	**3.1×10^{-5}**
the old bailey	**3.1×10^{-5}**
think tank	**3.1×10^{-5}**
thomas raeburn white	**3.1×10^{-5}**
time and materials	**3.1×10^{-5}**
timeshare	**3.1×10^{-5}**
tobacco smoking	**3.1×10^{-5}**
totten trust	**3.1×10^{-5}**
trademark attorney	**3.1×10^{-5}**
trademark examiner	**3.1×10^{-5}**
truces	**3.1×10^{-5}**
twelve tables	**3.1×10^{-5}**
unitary state	**3.1×10^{-5}**
utilitarianism	**3.1×10^{-5}**
vacated judgment	**3.1×10^{-5}**
vice admiralty court	**3.1×10^{-5}**
victimology	**3.1×10^{-5}**
violent disorder	**3.1×10^{-5}**
visiting judge	**3.1×10^{-5}**
Volens	**3.1×10^{-5}**
Vulgate	**3.1×10^{-5}**
war measures act	**3.1×10^{-5}**
watered stock	**3.1×10^{-5}**
witness box	**3.1×10^{-5}**
wordmark	**3.1×10^{-5}**

Appendix C

Fit of Regression models to Court Data

Table C1

Civil Liberties/ Conservative

Vinson

Model: f(x) = a*exp(b*x) + c*exp(d*x)

Coefficients (with 95% confidence bounds):

a = 0.4069 (0.3171, 0.4968)
b = -0.06319 (-0.09097, -0.03541)
c = 0.06724 (-0.004819, 0.1393)
d = -0.006963

Goodness of fit:

SSE: 0.003434
R-square: 0.979
Adjusted R-square: 0.9751
RMSE: 0.01465

Warren

Model:

f(x) = a*exp(b*x) + c*exp(d*x)

Coefficients (with 95% confidence bounds):

a = 0.3316 (0.09925, 0.564)
b = -0.03238 (-0.07479, 0.01003)
c = 0.03732 (-0.2279, 0.3026)
d = -0.00303 (-0.04016, 0.0341)

Goodness of fit:

SSE: 0.03996
R-square: 0.8489
Adjusted R-square: 0.8222
RMSE: 0.04848

Burger

Model:

f(x) = a*exp(b*x) + c*exp(d*x)

Coefficients (with 95% confidence bounds):

a = 0.2489 (0.09452, 0.4032)
b = -0.03207 (-0.06934, 0.005213)
c = 0.1416 (-0.03467, 0.318)
d = -0.002939

Goodness of fit:
SSE: 0.01773
R-square: 0.9173
Adjusted R-square: 0.9027
RMSE: 0.0323

Rehnquist
Model:
f(x) = a*exp(b*x) + c*exp(d*x)
Coefficients (with 95% confidence bounds):
a = 3.246 (-8.982, 15.47)
b = -0.5089 (-1.269, 0.2517)
c = 0.2962 (0.2437, 0.3488)
d = -0.008112 (-0.011, -0.005221)

Goodness of fit:
SSE: 0.03083
R-square: 0.9021
Adjusted R-square: 0.8848
RMSE: 0.04259

Roberts
Model:
f(x) = a*x^b
Coefficients (with 95% confidence bounds):
a = 1.938 (1.152, 2.725)
b = -0.79 (-0.9602, -0.6199)

Goodness of fit:
SSE: 0.0462
R-square: 0.8774
Adjusted R-square: 0.8709
RMSE: 0.04931

Civil Liberties/ Liberal

Vinson

Model:
f(x) = a*exp(b*x) + c*exp(d*x)
Coefficients (with 95% confidence bounds):
a = 0.3803 (0.2462, 0.5144)
b = -0.04022 (-0.07321, -0.007234)
c = 0.02889 (-0.09275, 0.1505)
d = -0.001817 (-0.02448, 0.02084)

Goodness of fit:
SSE: 0.01823
R-square: 0.9087
Adjusted R-square: 0.8916
RMSE: 0.03376

Warren
Model:
f(x) = a*exp(b*x) + c*exp(d*x)
Coefficients (with 95% confidence bounds):
a = 0.7911 (0.6131, 0.9692)
b = -0.06762 (-0.0991, -0.03615)
c = 0.1251 (-0.06375, 0.3139)
d = -0.00829 (-0.02042, 0.00384)

Goodness of fit:
SSE: 0.02406
R-square: 0.9713
Adjusted R-square: 0.9663
RMSE: 0.03762

Burger
Model:
f(x) = a*exp(b*x) + c*exp(d*x)
Coefficients (with 95% confidence bounds):
a = 0.2062 (0.124, 0.2883)
b = -0.05441 (-0.0991, -0.009725)
c = 0.1779 (0.1111, 0.2446)
d = -0.00234 (-0.004561, -0.0001184)

Goodness of fit:
SSE: 0.009578
R-square: 0.9199
Adjusted R-square: 0.9058
RMSE: 0.02374

Rehnquist
Model:
f(x) = a*exp(b*x) + c*exp(d*x)
Coefficients (with 95% confidence bounds):
a = 0.2617 (0.06402, 0.4594)
b = -0.02496 (-0.07393, 0.02402)
c = 0.05008 (-0.1788, 0.279)
d = 0.001315 (-0.01955, 0.02218)

Goodness of fit:
SSE: 0.07285
R-square: 0.6294
Adjusted R-square: 0.564
RMSE: 0.06546

Roberts
Model:
f(x) = a*exp(b*x) + c*exp(d*x)
Coefficients (with 95% confidence bounds):
a = 0.9016 (0.7216, 1.082)
b = -0.1015 (-0.1384, -0.06454)
c = 0.1141 (0.01526, 0.2129)
d = -0.00653 (-0.01384, 0.0007842)

Goodness of fit:
SSE: 0.0201
R-square: 0.9664
Adjusted R-square: 0.9605
RMSE: 0.03438

<u>Economic Activities/ Conservative</u>

Vinson
Model:
f(x) = a*exp(b*x) + c*exp(d*x)
Coefficients (with 95% confidence bounds):
a = 0.7138 (-0.02688, 1.454)
b = -0.221 (-0.3648, -0.07716)
c = 0.04375 (0.0217, 0.0658)
d = 0.009358 (0.000287, 0.01843)

Goodness of fit:

SSE: 0.001932
R-square: 0.9335
Adjusted R-square: 0.9153
RMSE: 0.01325

Warren
Model:
f(x) = a*exp(b*x) + c*exp(d*x)
Coefficients (with 95% confidence bounds):
a = 0.407 (0.0783, 0.7356)
b = -0.1183 (-0.262, 0.02539)
c = 0.07712 (-0.01092, 0.1652)
d = 0.005777 (-0.01326, 0.02482)

Goodness of fit:
SSE: 0.007191
R-square: 0.8538
Adjusted R-square: 0.8139
RMSE: 0.02557

Burger
Model:
f(x) = a*exp(b*x) + c*exp(d*x)
Coefficients (with 95% confidence bounds):
a = 0.1822 (0.1384, 0.2261)
b = -0.002415 (-0.007788, 0.002958)
c = -2.676e+13 (-1.432e+16, 1.427e+16)
d = -4.736 (-81.06, 71.59)

Goodness of fit:
SSE: 0.008732
R-square: 0.5116
Adjusted R-square: 0.3785
RMSE: 0.02817

Rehnquist
Model:
f(x) = a*exp(b*x)
Coefficients (with 95% confidence bounds):
a = 0.3029 (0.2583, 0.3475)
b = -0.01621 (-0.02, -0.01241)

Goodness of fit:

SSE: 0.002292
R-square: 0.907
Adjusted R-square: 0.8977
RMSE: 0.01514

Roberts
Model:
f(x) = a*exp(b*x) + c*exp(d*x)
Coefficients (with 95% confidence bounds):
a = 2.089e+04 (-1.352e+05, 1.77e+05)
b = -1.687 (-2.764, -0.6105)
c = 0.1398 (0.1094, 0.1702)
d = -0.009855 (-0.01514, -0.004571)

Goodness of fit:
SSE: 0.002512
R-square: 0.9449
Adjusted R-square: 0.9311
RMSE: 0.01447

Economic Activities/ Liberal

Vinson
Model:
f(x) = a*x^b+c
Coefficients (with 95% confidence bounds):
a = 2.04 (-5.997, 10.08)
b = -1.338 (-3.428, 0.753)
c = 0.07132 (0.0111, 0.1315)

Goodness of fit:
SSE: 0.01416
R-square: 0.6955
Adjusted R-square: 0.6447
RMSE: 0.03435

Warren
Model:
f(x) = a*exp(b*x) + c*exp(d*x)
Coefficients (with 95% confidence bounds):
a = 0.407 (0.0783, 0.7356)

b = -0.1183 (-0.262, 0.02539)
c = 0.07712 (-0.01092, 0.1652)
d = 0.005777 (-0.01326, 0.02482)

Goodness of fit:
SSE: 0.007191
R-square: 0.8538
Adjusted R-square: 0.8139
RMSE: 0.02557

Burger
Model:
f(x) = a*exp(b*x) + c*exp(d*x)
Coefficients (with 95% confidence bounds):
a = 1.074 (-0.08378, 2.232)
b = -0.1372 (-0.3206, 0.04612)
c = 0.1839 (-0.04604, 0.4138)
d = 0.001245 (-0.0206, 0.02309)

Goodness of fit:
SSE: 0.04502
R-square: 0.8627
Adjusted R-square: 0.8252
RMSE: 0.06397

Rehnquist
Model:
f(x) = a*exp(b*x) + c*exp(d*x)
Coefficients (with 95% confidence bounds):
a = 2.365e+10 (-2.334e+19, 2.334e+19)
b = -2.958 (-1.097e+08, 1.097e+08)
c = 0.1387 (0.104, 0.1734)
d = 0.004401 (-0.0003995, 0.009201)

Goodness of fit:
SSE: 0.003307
R-square: 0.5199
Adjusted R-square: 0.3599
RMSE: 0.01917

Roberts

Model:

f(x) = a*exp(b*x) + c*exp(d*x)

Coefficients (with 95% confidence bounds):

a = 17.55 (-50.28, 85.39)
b = -0.7184 (-1.274, -0.1633)
c = 0.1359 (0.0908, 0.1811)
d = -0.01597 (-0.02451, -0.007427)

Goodness of fit:

SSE: 0.003021
R-square: 0.9418
Adjusted R-square: 0.9273
RMSE: 0.01587

Appendix D

Network Stability Analysis

The purpose of this analysis was to determine the minimum number of documents necessary to create a stable network. A population of networks is stable if the similarity between two randomly selected networks from the population is high, and this similarity is not consistent with being due to chance alone.

To determine how document set size affects network stability, Monte Carlo experiments were run that compared similarity values across networks created from various sample sizes of randomly selected documents. Each sample of documents was drawn from a population of 1375 documents, where a document corresponded to a single opinion written by Justice Stevens. The logic was that if the number of documents necessary for network stability from a population of Steven's opinions could be determined, then these values could be applied to populations of documents written by other justices.

In addition to varying the number of documents used to create the networks, the network size was varied- that is the number of nodes in the network. This corresponds to varying the number of terms in the term by document matrix. The number of nodes varied from 50 to 10. This range was selected because it is an acceptable range at which network visualization occurs, and network visualization is a primary goal of this research.

To be specific, the each run of the experiment consisted in deriving 100 networks from random samples of n $(50 \leq n \leq 1375)$ documents, drawn from the population of 1375. The number of documents used for network creation, n, began at 1375, then, for each run of the

experiment, n decreased by 25. This allowed me to consider network similarity for networks derived from samples as large as 1375 and as small as 50 documents.

To understand how the size of the network affected these results, I repeated this experiment using several values of network size. I varied the number of nodes in the networks whose similarity was computed from 50 to 10, decreasing network size by 10 nodes in each experiment. Thus, essentially, I ran 5 experiments that analyzed the similarity between networks made from various sample sizes of documents. Each of these experiments differed in the size of the networks whose similarity was being computed. Each run of each experiment differed in the size of the document set used to create the 100 networks.

Figure D1 display the results. Focusing on the 50 node networks, the similarity values remain roughly the same (.2-.3) for most sample sizes until around the number of documents reaches around 85% of the population of documents. At this point, the similarity values increase dramatically as the number of documents increases. This makes sense because as the percentage of documents used to make each network increases, the likelihood of using different documents to make each network decreases. When all the documents in the set are being used, there is only one possible network that will be constructed. Thus, the similarity of 0.2 gives a more realistic look at an average similarity value between two networks drawn from the same document set. To interpret a similarity of 0.2, one could compare it to the similarity values between random networks and SCOD networks. This was done to test hypothesis one. It was shown that the average similarity between two SCOD networks was between 0.2 and 0.3, while the average similarity between a SCOD network and a random network was 0.01. This indicates the degree of semantic similarity among SCOD network opinions, in general, is between 0.2 and 0.3. It would appear, then, that the number of documents necessary to create a stable network is that

number for which where any network derived from this number of documents should, on average, have similarity with any other SCOD network around 0.2 to 0.3.

D1

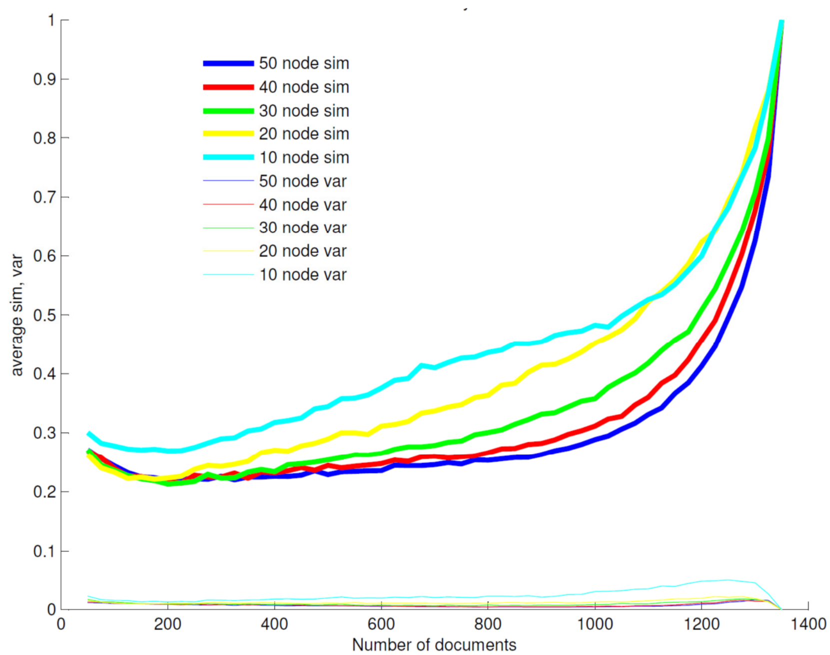

Figure D1. Mean similarity values and variance of similarity values between networks derived from different numbers of documents.

Appendix E

Comparison of Networks Using Different *q* Parameter

E1

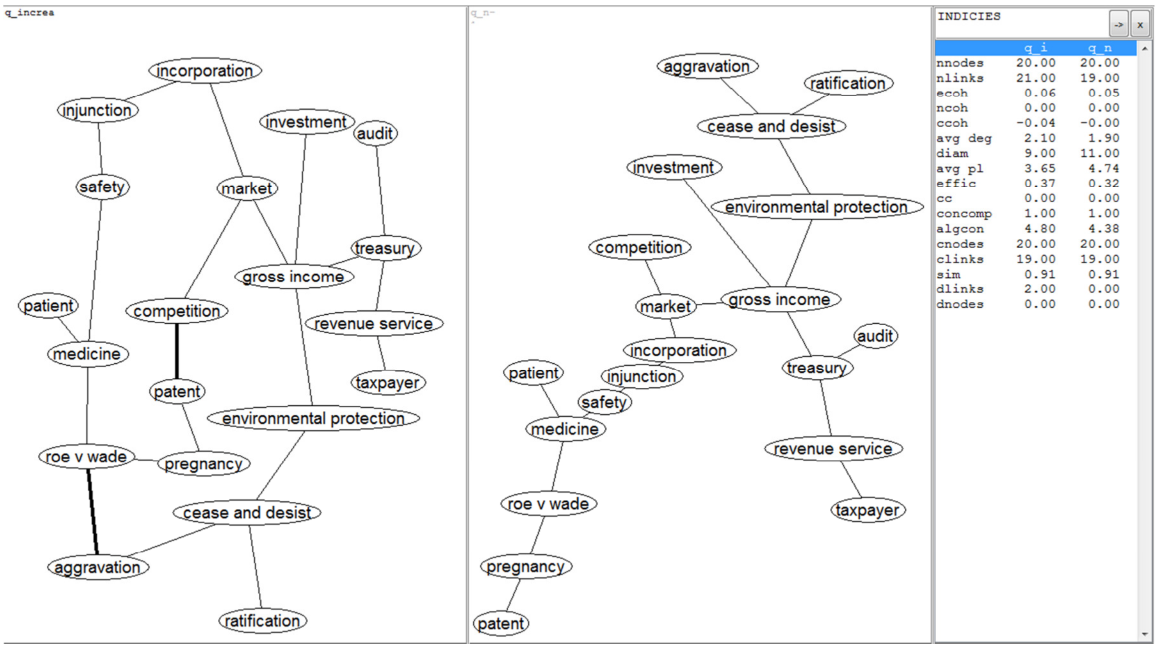

Figure E1. Blackmun's networks from late June, 1970-mid April 1979. Network on left was derived using lower *q* parameter than network on right where *q=n-1*. New links that resulted from decreasing *q* are highlighted in black.

E2

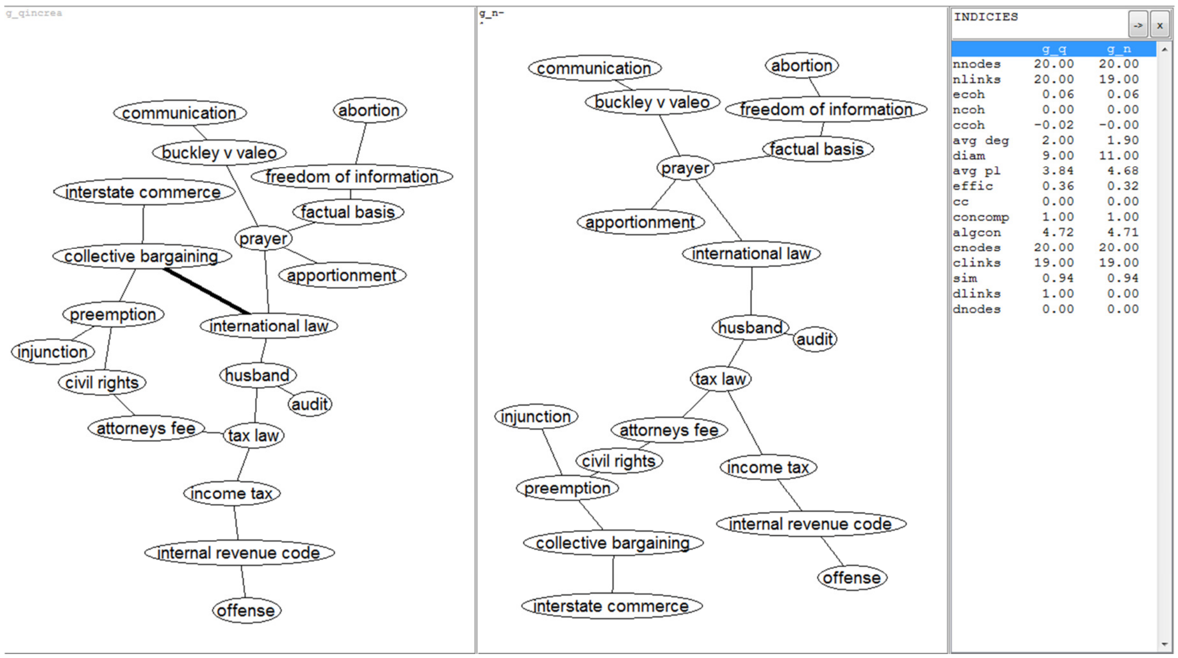

Figure E2. Blackmun's networks from late April 1979-early June1986. Network on left was derived using lower *q* parameter than network on right where *q*=*n*-*1*. New links that resulted from decreasing *q* are highlighted in black.

E3

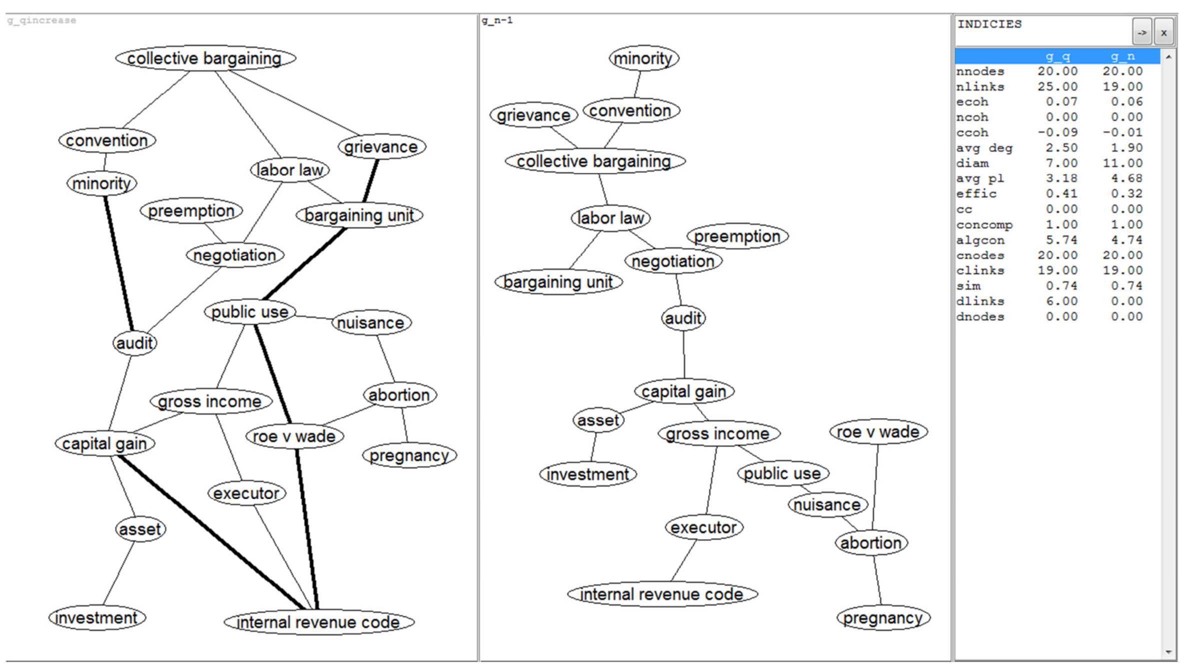

Figure E3. Blackmun's networks for middle June 1986-end of June 1994**.** Network on left was derived using lower *q* parameter than network on right where *q*=*n*-*1*. New links that resulted from decreasing *q* are highlighted in black

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