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Using Course-Subject Co-Occurrence (CSCO) to Reveal the Structure of an Academic Discipline: A Framework to Evaluate Different Inputs of a Domain Map

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Using Course-Subject Co-Occurrence (CSCO) to Reveal the Structure of an Academic Discipline: A Framework to Evaluate Different Inputs of a Domain Map

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Abstract
This article proposes, exemplifies, and validates the use of course-subject co-occurrence (CSCO) data to generate topic maps of an academic discipline. A CSCO event is when two course-subjects are taught in the same academic year by the same teacher. 61,856 CSCO events were extracted from the 2010-11 directory of the American Association of Law Schools and used to visualize the structure of law school education in the United States. Different normalization, ordination (layout), and clustering algorithms were compared and the best performing algorithm of each type was used to generate the final map. Validation studies demonstrate that CSCO produces topic maps that are consistent with expert opinion and four other indicators of the topical similarity of law school course-subjects. This research is the first to use CSCO to produce a visualization of a domain. It is also the first to use an expanded, multi-part gold-standard to evaluate the validity of domain maps and the intermediate steps in their creation. It is suggested that the framework used herein may be adopted for other studies that compare different inputs of a domain map in order to empirically derive the best maps as measured against extrinsic sources of topical similarity (gold standards).

Introduction
This article seeks to ascertain the similarity of legal course-subjects in terms of their topical relatedness and to rigorously and in a replicable manner, best distribute those course-subjects in a two-dimensional mapping so that they may be quickly perceived by the viewer using the distance-similarity metaphor (Montello et al., 2003). Once created, domain maps provide cognitive scaffolding for learning (Greenfield, 1984; Wood et al., 1976). These big-picture, global perspectives have the potential to allow a novice to more quickly become familiar with the domain and experts to contextualize their teaching and research in a broader perspective. Additionally, domain maps of legal course-subjects allow for numerous thematic overlays that facilitate insight about legal education in the United States. While it would be possible to create a domain map from the citation interlinkages or lexical overlaps of the scholarly literature, the maps created herein most directly represent how topics are taught and interrelate in almost 200 (ABA & LSAC, 2012) law schools in the United States. The framework used herein may be adopted by other researchers for studies that compare different inputs of a domain map in order to empirically derive the best maps as measured against extrinsic sources of topical similarity (gold standards).

The explanatory power of CSCO networks is premised on the assumption that in the aggregate, and for reasons of efficiency, faculty members specialize and focus their energy teaching courses that are topically similar to other courses they teach. The first research question is whether course-subject co-occurrence (CSCO) can be used to produce topic maps that are consistent with expert opinion and other indicators of the topical similarity of law school course-subjects. The second question is, when using CSCO network data to compare normalization algorithms, spatial layout techniques, and clustering algorithms, which combination of algorithms, tools, and techniques is best at portraying the overall structure of law school course-subjects as compared to an extrinsic 'gold-standard' of similar course-subject pairs.

Related Work

While the course-subject structure of legal academia in the United States has been described in essays (Kennedy, 1983) and other writings on the history of law school education (Stevens, 1983), it has never been revealed through the exploration of large datasets and determined through replicable, empirical means. The most similar studies to this work also involve a spatial mapping analysis of either academic courses or disciplines (Biglan, 1973; White & Calhoun, 1984; White & Nolt, 1987). There have been some studies that compare different domain map production techniques (Boyack et al., 2005; Klavans & Boyack, 2006; Van Eck & Waltman, 2009). There needs to be significantly more of these in order to arrive at a consensus for the best combinations of the constituent domain mapping techniques for specific purposes. The use of CSCO networks to make structural claims about a domain is supported by the numerous uses of co-occurrence data that have been used to create domain maps. The underlying assumption is that items that co-occur together are categorically or substantively more similar than those that do not. This includes co-voting (judicial: (Hook, 2007a, 2014a; Pritchett, 1941, 1942, 1948, 1954; Schubert, 1962, 1963; Sirovich, 2003; Thurstone & Degan, 1951)) (legislative: (Clinton et al., 2004; Clinton & Meirowitz, 2001; Jackman, 2001; Moody & Mucha, 2013; Poole & Rosenthal, 1985)), word co-occurrence (Doyle, 1961, 1962), bibliometric coupling (Kessler, 1963; Price & Schiminovich, 1968), co-authorship (De Solla Price & Beaver, 1966), co-citation (Marshakova, 1973; Small, 1973), co-nomination (Lenk, 1983), co-courses taken (White & Calhoun, 1984; White & Nolt, 1987), co-classification (Hook, 2007b; Spasser, 1997; Todorov, 1989), and co-membership (McCain, 1993).

Data and Evaluative Gold-Standard

Course-subject co-occurrence (CSCO), is the same professor teaching multiple, different course-subjects over some period of time. Used herein, the period of time is one academic year as captured in the annual directories of the American Association of Law Schools (AALS). Furthermore, courses with differing individual course names are controlled through a proscribed subject vocabulary supplied by the AALS. In other words, courses with similar content, but with differing titles, are harmonized through a common course-subject listing. In 2010-11, there were 104 academic course-subjects (AALS, 2010). If a professor teaches two different course-subjects in a given year, those course-subjects are connected by a single link when the two mode network (professors and course-subjects) is collapsed to a single mode network (course-subjects). When two professors teach the same two course-subjects, this results in an edge weight between those course-subjects of two when the network is collapsed from a two mode network to a single mode network. In 2010-11, 536 faculty members taught both Criminal Law and Criminal Procedure—the highest amount of pairwise co-occurrence between any of the 104 course-subjects. At the other end of the spectrum, 1,467 of the 5,356 possible course-subject pairs (((104 x 104) - 104) / 2) were not taught by any of the same faculty members.

Table 1. Distribution of the Amount of Course-Subjects Taught in 2010-11.

Number of Courses Taught by the Same Faculty Member	**Resultant Pairwise Associations** ((X*(X-1))/2)	**Number of Teachers**	**Resultant Pairwise Associations** (course-coupling)
1	0	1143	0
2	1	1531	1531
3	3	2163	6489
4	6	2159	12954
5	10	1665	16650
6	15	847	12705
7	21	294	6174
8	28	116	3248
9	36	34	1224
10	45	12	540
11	55	5	275
12	66	1	66
		9,970	**61,856**

Domain maps should be validated in order to verify their structural accuracy to the furthest extent possible. Validation has traditionally occurred in one of two ways: (1) examination by experts in the domain, and (2) consistency with extrinsic (from outside the data or technique) sources of structure of the domain (McCain, 1985). Ideally, it's best to use both methods as few experts have global knowledge of an entire domain. The evaluative gold-standard used herein is composed of five different sources that indicate the similarity of law school course-subjects: (1) the syndetic structure (cross-references) contained in the AALS directories (AALS, 1931, 2011); (2) the mergence and divergence of AALS course subjects over time; (3) the Jackson and Gee categories of law school courses (1975); (4) the topic categories of the *Current Index to Legal Periodicals* (CILP); and (5) those produced by a card-sorting exercise completed by eighteen experts.

Included in the AALS lists of "Teachers by Subject" are cross-references between some of the course-subjects. Cross-referenced course-subjects are one indication that the course-subjects are topically similar. Changes in the canon of AALS course-subject lists may also be indicators of topical similarity. For instance, when two course-subjects are merged into one, this may be taken as an indicator that they are related. Similarly, two course-subjects that diverge from a common course-subject may also be considered similar. Jackson and Gee published a report on the type and frequency of electives offered at law schools in the United States (1975) and analyzed law school courses by placing them in 33 categories. Inclusion in the same Jackson and Gee category is evidence of topical similarity between the course-subjects. Another source of topical similarity for law school course-subjects is the *Current Index to Legal Periodicals* ('CILP') (Wolotira, 2012). It is a current awareness service (table of contents service) for legal academics and provides a listing of recent legal articles by subject. To aid the process of subject selection, there are twelve 'topics' that allow one to subscribe to several related subjects at once. These super categories are indicators of similarity for their constituent subjects and indicate pairwise similarity between each of the included subjects. The expert derived course-subject pairings included all pairings that at least ten out of the eighteen experts indicated were related. The resultant evaluative gold standard consists of 115 course-subject pairs that at least two of the five methods indicate are similar. (Three pairs involving Forensic Medicine were not used because, in this extreme case, only one person was listed as teaching that course-subject.) For a complete description and analysis of the component parts of the evaluative gold standard *see* (Hook, 2014b).

Methods

Using CSCO data, this work evaluates three different normalization treatments, three different ordination treatments, and two different clustering treatments (plus QAP analysis). See Figure 1. The treatment most consistent with the gold-standard from each step in the analysis was determined as best performing and noted for the reader. .

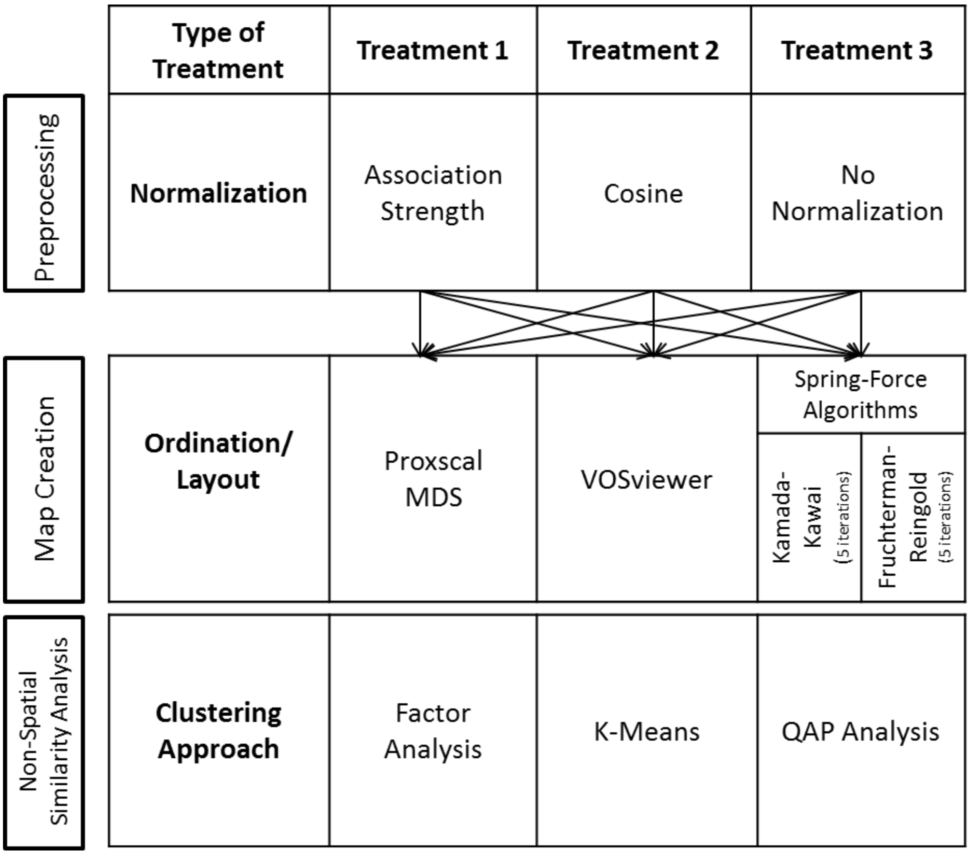

Figure 1: Different treatments applied to the domain map making steps.

Normalization

Normalization is a mathematical transformation of one's data in order to more fairly and accurately compare items that occur in varying frequencies (Van Eck & Waltman, 2009). Three different normalization treatments were evaluated: (1) Association Strength, (2) Cosine, and (3) no normalization (raw). Van Eck and Waltman (2009) define Association Strength as one of two variations: (1)

$$\frac{\text{total number of co-occurrences between objects } i \text{ and } j}{(\text{total number of occurrences of object } i) \text{ x } (\text{total number of occurrences of object } j)}$$

or (2)

$$\frac{\text{total number of co-occurrences between objects } i \text{ and } j}{(\text{total number of co-occurrences involving object } i) \text{ x } (\text{total number of co-occurrences involving object } j)}.$$

Variation (2) involves column summations of the co-occurrence matrix for each object *i and j* in the denominator. Van Eck and Waltman assert that "[b]oth [methods of calculating the denominator] are used in scientometric research … but [variation 1] seems to be more popular" (2009, p. 1637). Klavans and Boyack identify another consideration applicable to variation (2)—whether or not to include the matrix diagonal (the amount an item occurs in the dataset, or in other words, co-occurs with itself) in normalization calculations (2006, p. 255). As most scientometricians treat the diagonal as missing when calculating normalization, the practice is followed herein. As applied to CSCO data used in this work, the two versions of the Association Strength normalization techniques are as follows:

Association Strength (2009): Total Occurrences Method

$$\frac{\text{(co-occurrence counts between course-subjects a and b)}}{\text{(count of people teaching course-subject a) x (count of people teaching course-subject b)}}$$

Association Strength (2009): Column Totals Method

$$\frac{\text{(co-occurrence counts between course-subjects a and b)}}{\text{(total co-occurrences involving course-subject a) x (total co-occurrences involving course-subject b)}}$$

Similarly, cosine normalization also has two variants (Van Eck & Waltman, 2009):

Cosine Total Occurrences Method

$$\frac{\text{(co-occurrence counts between course-subjects a and b)}}{\sqrt{\text{(count of people teaching course-subject a) x (count of people teaching course-subject b)}}}$$

Cosine Normalization: Column Totals Method

$$\frac{\text{(co-occurrence counts between course-subjects a and b)}}{\sqrt{\text{(total co-occurrences involving course-subject a) x (total cooccurrences involving course-subject b)}}}$$

Similar to the analysis used in (Boyack et al., 2005; Klavans & Boyack, 2006), a rankings analysis of all normalized co-occurrence values was used to assess the different normalization techniques and their denominator variants against the gold-standard. This approach was used because it is not possible to directly compare the values from different normalization techniques as the values vary greatly in magnitude between any two techniques while being consistent in magnitude within a particular technique. For each normalization technique and variant, the values in the upper half of the normalized matrix were sorted by the highest normalized value and assigned a ranking (1,2,3 etc.). 5,356 (((104x104)-104)/2)) pairwise co-occurrence values for the course-subjects were thus placed in rank order. The same values (ties) resulted in the same ranking number (1,2,3…1247, 1248, 1248, 1250, etc.). However, there were very few ties with the exception of the 1,467 course-subject pairs that were never taught by the same faculty member and had a normalized value of zero. The average of the rankings values for each of the pair of course-subjects identified as related by the gold-standard were then used to evaluate the success or deficiencies of each normalization technique and their variants.

Ordination

Once pair-wise similarity has been obtained in a normalized co-occurrence matrix or edge list, an ordination or spatial layout must be performed to visualize the data. While there are many different spatialization techniques, three specific approaches are commonly used in the production of domain maps: multidimensional scaling (MDS) (Kruskal & Wish, 1978); the VOS mapping technique (visualization of similarities) and its corresponding software platform, VOSviewer (Van Eck & Waltman, 2010); and spring force layout algorithms (Fruchterman & Reingold, 1991; Kamada & Kawai, 1989). Each of the normalization treatments above were used as inputs for each of these ordination treatments. While producing two-dimensional maps, each treatment also resulted in a matrix of distances between each of the course-subjects. As done with the normalization analysis, each of these distance matrixes was converted to an edge list with rankings of the distances—from closest (most similar, highest ranking) to furthest apart (least similar, lowest ranking). These rankings were then compared against the gold-standard to ascertain which of the ordination techniques, with which of the different normalization treatments, produced the lowest average of the ranked values of the gold-standard pairs.

The version of MDS used herein is Proxscal (Commaneur & Heiser, 1993) as implemented in SPSS version 19 (IBM Corp., 2010). For replicability, the applicable decision points in the implementation of the software are set out in the following note.[1] SPSS allows one to save out Viewer Files (.spv) that includes the "Final Coordinates" (x,y) of each of the course-subjects. Using this formula:

$$\sqrt{((\mathrm{X1} - \mathrm{X2})^2 + (\mathrm{Y1} - \mathrm{Y2})^2}$$

distances were calculated for each of the 5,356 course-subject pairs. Rank values were given for each of these distances—1 being the closest and 5,356 being the furthest. The average of the ranking values was calculated for each of the 115 gold-standard pairs and this average was used to compare results amongst the five different normalization approaches.

The version of VOS used was that implemented in VOSViewer version 1.5.4. For replicability, the applicable decision points in the implementation of the software are set out in the following note.[2] Once created, a map file (.txt) may be saved out of VOSViewer that contains x,y coordinates for each of the course-subjects. A similar analysis as that performed for the MDS distances was used to obtain the average ranking of the VOS distances of the gold-standard pairs for each of the five normalization input methods.

The layout of the CSCO data using spring force algorithms was accomplished through the implementation of those algorithms in the network analysis software, Pajek (Batagelj & Mrvar, 1998), version Pajek64 3.14. The two algorithms used were: Fruchterman-Reingold (1991) and Kamada-Kawai (1989). For replicability, the applicable decision points in the implementation of the software are as follows. In the draw function, the "meaning of the lines" (edge weights) is "similarities" as the normalization procedures produced higher edge weights for the more similar course-subjects. All ordinations using the spring force algorithms, both initially, and as export files were two-dimensional rather than three-dimensional. Kamada-Kawai Free was used instead of Kamada-Kawai Separate Components as the dataset did not have any separate, disconnected components. To obtain x,y coordinates, the rendered layouts were exported as SVG files (SVG General). As spring force algorithms are stochastic, five iterations were performed for each of the two types of spring force algorithms and each of the five different normalization variant input values, (2 x (5 x 5)) or 50 treatments total. Additionally, there are two methodological variants from which to ultimately compare the results of the spring force ordinations. In Method 1, for each of the normalization variants being tested, the results were fully calculated for each of the five iterations similar to the methodological technique used for the MDS and VOS results. Afterwards, the five separate iteration results were averaged together to make comparisons between the different normalization approaches as rendered by the specific spring force algorithm. In other words, this is an average of averages approach. In Method 2, for the five different iterations, all five distances obtained for each of the 5,356 possible course-subject pairs were averaged. Then, the averaged distances were ranked (1 to 5,356), and the average of the 115 gold-standard pair ranking values was determined and compared.

Cluster Analysis

Cluster analysis, or aggregation, is a means of achieving insight through simplification, *see* (Fortunato, 2010) and facilitates cognitive chunking. Well-defined regions on a domain map allow a viewer to perform regional chunking and to develop hierarchical memory structures based on those regions (MacEachren, 2004). This, in turn, facilitates image memory and the learnability of the domain map. Two common cluster techniques used in the scientometrics literature are factor analysis (Harman, 1976) and k-means clustering (Zitt et al., 2011). Additionally, QAP analysis is a means of comparing two matrices of similarity data to obtain how similar the underlying networks are in terms of their structure (Lawler, 1963).

Factor analysis was performed on the best performing normalized data using SPSS Version 21.0 (IBM Corp., 2012) to identify principle components, or factors, that aggregate the course-subjects into larger groupings.[3] Comparisons were then made to the groupings identified by the eighteen human subjects as well as a similar factor analysis performed on the matrix of course-subjects identified as similar by the human subjects. K-means clustering was performed using the algorithm implemented in SPSS Version 21.0 (IBM Corp., 2012). As K-means analysis is sensitive to the selection of each of its component variants, it is important to note the decision points made in the analysis.[4] Once again, the CSCO cluster analysis results were compared against the human subject card sort data to see differences in how the two datasets cluster. The clustering algorithm was run on both datasets at increasing numbers of predetermined cluster sizes (15, 20, and 25). QAP analysis was used to compare the best performing CSCO normalized network to the card sort matrix of expert determined related course-subjects. The implementation of the algorithm was that used by UCINET (Borgatti et al., 2002). Both matrixes were loaded into UCINET after selecting the following path: Tools -> Testing Hypotheses -> Dyadic (QAP) -> QAP Correlation (old). (Note: The new version of the QAP Correlation did not produce an observed Pearson correlation value. The MR (multiple regression) options were not appropriate as there were only two matrices being compared.) The amount of random permutations to test against for significance was changed from 2500 to 5000.

Results and Discussion

The gold-standard created for this work allows for a comparison of domain map production techniques and an assessment as to which is best performing relative to the CSCO data.

Normalization

Generally, most gold-standard pairs are in the top quintile of the normalized CSCO data. This is consistent with expectations if: (1) the gold-standard is an accurate reflection of course-subject topical similarity; and (2) in general, faculty members teach course-subjects that are topically similar such that topically similar course-subjects will have a higher normalized similarity value. Based on the variety of the gold-standard inputs and the manner of their selection, it is assumed that the gold-standard for each map year is an accurate representation of the topical similarity for the course-subject pairs included in the gold-standard. (The gold-standard does not purport to be an exhaustive list of all similar course-subjects.) As to 2010-11, 83% to 92% (depending on the technique and variant) of the gold-standard course-subject pairs are in the first quintile of normalized CSCO data. This is strong support for the hypothesis that generally, faculty members teach course-subjects that are topically similar.

Table 2: Amount of Gold-Standard Course-Subject Pairs in the Top Quintile of Ranked CSCO Values.

	Amount (out of 115) **of Gold Standard Course-Subject Pairs in the Top Quintile** (1-1,071 out of 5,356**) of Ranked CSCO Values**	**Percentage of All Gold Standard Pairs in the Top Quintile**	**Mean Ranking of All Gold-Standard Co-Occurrence Pairs Applied**	**Average of Rankings is in the top __% of all Co-Occurrence Pairs**
Association Strength (2009) Total Occurrences Method	106	92%	438.97	8%
Association Strength (2009) Column Totals Method	105	91%	438.51	8%
Cosine Total Occurrences Method	95	83%	586	11%
Cosine Column Totals Method	95	83%	610	11%
Non-Normalized Co-Occurrence Values	71	62%	1054	20%

Table 2 provides the average rank value of all gold-standard course-subject pairs for each of the normalization treatments. (Note: Lower values equate with higher rankings—1 being best.) The data provides some support for the assertion of Van Eck and Waltman (2009) that the Association Strength normalization technique is better than the Cosine normalization technique. (For years 1931-32 and 1972-73, the data is inconclusive (Hook, 2014b)). Both normalization techniques and their variants far outperform the non-normalized CSCO data. This indicates that CSCO data should be normalized before drawing meaningful comparisons as to how often any two course-subjects are taught by the same professor.

The data supports the assertion of Van Eck and Waltman (2009, p. 1646) that the Association Strength technique does a better job than the Cosine technique and other set-theoretic similarity measures as the later "do not properly correct for the size effect and, consequently, do not properly normalize co-occurrence data." This can also be seen in the vastly different averages of the ranked Cosine normalized values when comparing data from different quintile ranks of the amount that a particular course-subject was taught. When both course-subjects of the gold-standard pairs are in the top 20% of the amount that a particular course-subject was taught, the average ranks for the Cosine normalized values are very high (low numbers). The reverse is true when both gold-standard course-subject pairs are in the lowest quintile (lowest 20%) of the amount that a particular course-subject was taught. The difference is even more pronounced for the non-normalized (raw) data and lends further support to the assertion that the data should be normalized before making comparisons of the co-occurrence values. In contrast, and true to the assertion of Van Eck and Waltman, the Association Strength normalization technique is more consistent and does a better job, across the vastly different amounts that the course-subjects were taught. In other words, with the Association Strength, there is less variance than with the Cosine technique in the average rank of the 'gold-standard' course-subject pairs between the different quintile ranks (Hook, 2014b).

Ludo Waltman and Nees Jan Van Eck note the following:

> [There is a] tendency of the association strength to give very high values for combinations of items that both have very low total occurrences (or very low column totals). In our experience, often the pairs of items with the highest association strengths have very low total occurrences/column totals. The reliability of these very high association strengths then is relatively low (i.e., adding or removing a single co-occurrence would directly lead to a

quite different association strength value) (email correspondence with the author on August 14, 2013).

This may be seen with the course-subject, Forensic Medicine. In the 2010-11 CSCO data, Forensic Medicine was only taught by one individual who happened to teach four other course-subjects as well. As to both of the Association Strength normalization variants, the course-subject pair (1) Forensic Medicine & (2) Labor Law appears on each list of top five most similar course-subjects. The same pair is absent from the top five list for each of the Cosine variants (Hook, 2014b).

The comparison with the gold-standard of the two different denominator variants of each normalization technique ((1) total occurrences and (2) column totals) reveals calculable differences and a possible explanation for those differences. As might be reasoned a priori, the column totals method will be significantly different than the total occurrences method for those subjects that are taught in large numbers but are frequently the only course-subject that a particular instructor is teaching. This can be seen in the top ten list (fourteen because of ties) of 2010-11 course-subjects with the highest percentage of being the only course-subject taught by an instructor. Eight of these fourteen course-subjects happen to be amongst the 27% of course-subjects not included in any of the gold-standard pairs. However, Legal Research and Writing as well as Legal Drafting, both within the top ten percentages of being the only course-subject taught by a professor, have great differences for each normalization technique denominator variant. These two course-subjects are included in four of the top ten greatest differences in normalized values between the two Association Strength variants but in only one of the top ten greatest differences in the normalized values between the two Cosine variants. As to the top ten biggest differences between the Cosine denominator variants, more of these are from the lowest quintiles of how many teachers teach a particular course-subject (Hook, 2014b).

As between the two denominator variants of each normalization technique, the data is inconclusive as to which is best performing. More studies with larger and different datasets and gold-standards should be conducted. However, the differences are striking and scientometricians should be aware of them, the reason for them, as well as the sensitivity (both positive and negative) of the Association Strength to items occurring only a few times. The fact that the Association Strength performs the best for the 2010-11 data suggests that a higher proportion of its gold-standard course-subject pairs involve individual course-subjects that are not frequently taught or come from pairs of course-subjects that are not frequently taught. This is indeed the case (Hook, 2014b). Compared to 1931-32 and 1972-73, the 2010-11 gold-standard is more skewed towards those course-subjects that are taught less frequently. Based on the analysis above, it is not surprising that the two normalization techniques are less distinguished for map years in which the gold-standard co-occurrence pairs are derived more often from the most frequently occurring items. As the Association Strength normalization technique does a better job than Cosine in data years with widely varying occurrences of course-subjects (or is skewed to including more items from the less frequently occurring items), and just as good as Cosine in years without a wide variance, Association Strength is the preferred normalization technique (either variant) to use with co-occurrence data.

Ordination

The next step in the evaluative process is to see how three popular ordination, or layout, techniques compared relative to the gold-standard. The different normalization inputs produced vastly different ranks of distances both within the same ordination technique and between the different ordination techniques. As discussed above, these differences are most likely attributable to the differing amounts that some course-subjects are the only course-subject taught by an instructor and how this phenomena causes great fluctuations between the normalization techniques and their individual variants. The range of fluctuations once again emphasizes how crucial the choice is between normalization techniques as the different normalization inputs result in vastly different layouts.

Compared to Proxscal MDS, the VOSviewer ordination technique resulted in less variance both between the different denominator variants for each normalization technique and between the Association Strength and Cosine normalization techniques. This consistency is a good thing for an ordination algorithm as the results produced will be more uniform and less variable. Contrary to MDS and VOS, the Cosine normalization input used with both spring force algorithm variants outperformed the Association Strength normalized data. However, the top five adjacencies for each of the best of the five iterations for each normalization input and spring force algorithm pairing created strange course-subject pairings that would cause a domain expert to question the results (Hook, 2014b). While the overall accuracy (global accuracy) for the Cosine normalization input used with both spring force algorithms may be better than that for the Association Strength normalized data, the local accuracy leaves much to be desired. Also, the two different spring force methodologies produce substantially different results.

As can be seen in Figure 3, the different ordination techniques, with different normalization inputs, vary substantially in their general appearance and sensitivity to outliers. All Proxscal MDS ordinations were circular and evenly filled the space. However, the VOSviewer ordination using Cosine normalization was much more affected by the anomaly that Forensic Evidence was only taught by one instructor who also taught four other course-subjects. The notable variations in the visual appearance of the ordinations suggests that they should be studied and compared in order to be better understood and selected for the purposes for which they are best suited. This article is one contribution towards that goal.

Course-subject co-occurrence (CSCO) can be used to produce topic maps that are consistent with expert opinion and other indicators of the topical similarity of law school course-subjects. The average rank of distances of all CSCO gold-standard identified edges are within the top 15% of all possible edges when using the best performing normalization (Association Strength Total Occurrences) and ordination (VOS) techniques. Until demonstrated that a different combination is superior, the author will use it for all future domain maps. It is also important to note that the ordination results are not as good as the best performing normalized edge lists as stress has been introduced during the process of reducing the multidimensional space to two dimensions and locating those topically central course-subjects that are pulled in many different directions.

Table 3: All ordination techniques gold-standard average rank of distances by normalization method.

Normalization Technique	MDS Proxscal	VOSviewer	Spring-Force Algorithms (Pajek)			
			Kamada-Kawai		Fruchterman-Reingold	
	Average of Rankings of Distances / Average of Rankings is in the top __% of the 5,356	Average of Rankings of Distances / Average of Rankings is in the top __% of the 5,356	Average of Rankings of Distances (Method 1)/ Average of Rankings is in the top __% of the 5,356	Average of Rankings Distances (Method 2) / Average of Rankings is in the top __% of the 5,356	Average of Rankings of Distances (Method 1) / Average of Rankings is in the top __% of the 5,356	Average of Rankings of Distances (Method 2) / Average of Rankings is in the top __% of the 5,356
Association Strength (2009) Total Occurrences	1053 20%	828 15% **(Most Consistent with Gold-Standard)**	2459 46%	2354 44%	1902 36%	1764 33%
Association Strength (2009) Column Totals	1292 24%	857 16%	2483 46%	2417 45%	1918 36%	1765 33%
Cosine (2009) Total Occurrences	1385 26%	1264 24%	1539 29%	1285 24%	1672 31%	1440 27%
Cosine (2009) Column Totals	1400 26%	1328 25%	2390 45%	2281 43%	1867 35%	1716 32%
Non-Normalized	1889 35%	2020 38%	2026 38%	2028 38%	2633 49%	2639 49% **(Least Consistent with Gold-Standard)**

Figure 2: CSCO map most consistent with the gold-standard.

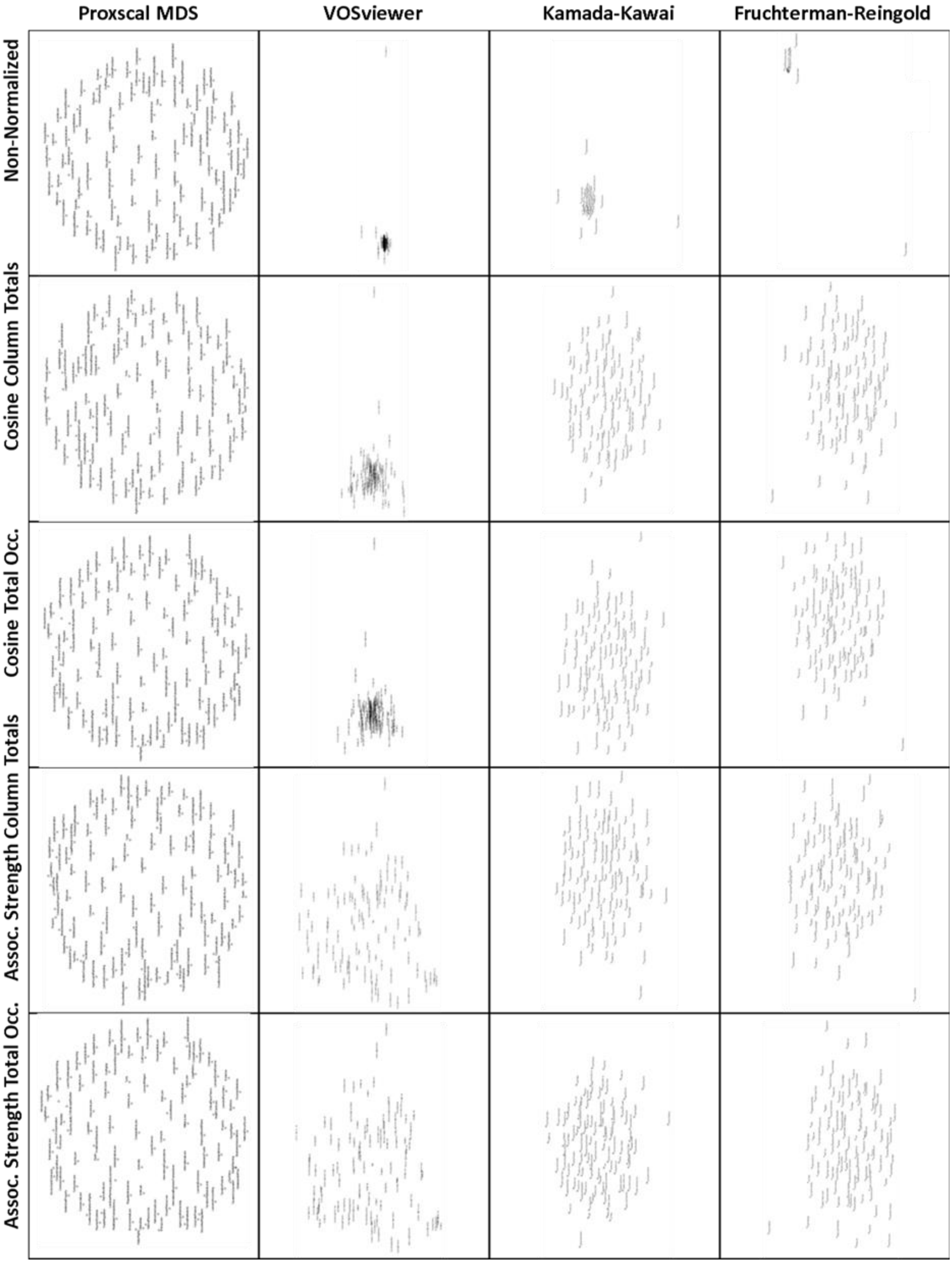

Figure 3: All ordination results (small multiples).

Cluster Analysis

Two clustering approaches were analyzed and compared using the course-subject data: factor analysis and k-means clustering. Additionally, QAP analysis was used to compare the matrix of CSCO data with that of the human subjects' card sort data. A priori, a good clustering treatment satisfies four basic criteria: (1) all of the course-subjects are assigned to groups, (2) there are few or no groupings with only one course-subject, (3) there are few or no mega-clusters that include too many course-subjects to be interpretable as to their general, unifying theme, and (4) a course-subject can only be included in one, and only, one cluster.

For purposes of comparison, a factor analysis was performed on two datasets: (1) the CSCO data, and (2) the human subject matrix of topically similar course-subjects. This allowed for a comparison of groupings from the incidences of what law faculty members taught (CSCO data) and what the human experts identified as topically similar (card sort data). A factor analysis was performed on the association strength (2009) total occurrences normalized CSCO data. The factor analysis identified 28 factors (categories) with eigenvalues above an absolute value of 1.00 (Kaiser's stopping rule (1960)) that accounted for 79% of the variance in the data. However, not all of these are interpretable. In other words, a person knowledgeable about the domain cannot always succinctly summarize the higher level factor that explains the included course-subjects. Traditional scree plot analysis (Cattell, 1966; Leydesdorff & Rafols, 2009) of the CSCO data reveals that the first 15 factors should be maintained (a 15 factor solution). Each course-subject has a factor coefficient of an absolute value of .3 or higher. This is a common threshold when deciding what items to include in a particular factor (Bryant & Yarnold, 1995). As factor titles are not supplied by the statistical software, they must be supplied by the interpreter of the factor analysis. The factor labels were supplied by the author based on the top 25 category names given by the human subjects as well as the author's experience with legal education (Hook, 2014b). With factor analysis, a course-subject may appear in more than one factor category. However, course-subjects were only included with the factor in which their factor coefficient is the highest—the factor on which the course-subject most 'loads.'

A similar factor analysis was conducted on the matrix of card sorting data. The factor analysis identified 14 factors (categories) with eigenvalues above 1.00. These 14 factors account for 74% of the variance in the data. Additionally, a scree plot analysis revealed that all 14 factors with eigenvalues above 1.00 should be maintained. The maintaining of all 14 factors with eigenvalues above 1.00 as determined by the scree plot analysis probably indicates that, as compared to the CSCO data, the expert determined similarity of the course-subjects is less multidimensional and fractured.

While it may be that CSCO analysis is a demonstrably valid way to produce domain maps of the academic discipline of law in the United States, it may not be the best way. For instance, a map derived from the similarity matrix of the human identified similar course-subjects may be better. However, the latter is much more laborious to produce and may be questionable for distant academic years of which contemporary experts have little familiarity. Additionally, cluster groupings made from CSCO data incorporate the vagaries of scheduling in which some faculty members are obligated to teach course-subjects outside of their main field of teaching and research. Taken in their entirety, the author would choose the 14 factors from the card sort data over the 28 factors from the CSCO data. The former better satisfy the a priori desired characteristics of a clustering approach that avoids the existence of many small groupings of only one or two course-subjects. However, a more nuanced analysis reveals that some groupings may be better derived from the CSCO data. For instance, human experts may be biased by course-subject names. It is easy to group the taxation course-subjects together as they all have taxation in their name. However, the CSCO grouping reveals a more topical approach that also includes those course-subjects that exist largely to reduce tax obligations—the estate planning course-subjects as well as Employee Benefit Plans. These course-subjects were placed in other categories by the experts.

The k-means clustering algorithm was used to compare the CSCO data against the human subject card sort data to see differences in how the two datasets cluster. The analysis revealed structural differences in the relationships between the course-subjects in each dataset. As required by the algorithm, three predetermined cluster amounts were used (15, 20, and 25 clusters) to see how each dataset responded to the k-means treatment. Repeated running of the CSCO and card sort k-means analysis produced the exact same results at all three cluster intervals. The specific implementation of the K-means algorithm in SPSS appears deterministic.

The CSCO k-means cluster analysis grossly violated some of the desired conditions of a clustering treatment. Over the three predetermined cluster amounts (15, 20, 25 clusters), the k-means algorithm produced numerous clusters consisting of only one member and large and uninterpretable mega-clusters consisting of 38, 41 and 31 course-subjects. Additionally, as the number of clusters increased, it was hoped that the large mega-clusters would break into several interpretable clusters. Instead, with a few exceptions, the already small clusters fragmented into even smaller clusters and there still remained an uninterpretable mega-cluster. Also, there was not a consistent evolution of cluster memberships over the three cluster solutions as course-subjects sometimes went back and forth between otherwise disparate clusters. These same traits were largely absent from the card sort k-means analysis. Again, this is probably a result of the CSCO data being inherently more multi-dimensional than the card sort data.

There is at least one instance in which the experts misunderstood a course-subject—Trade Regulation. Trade Regulation deals with the regulation of business to protect consumers and includes antitrust, Federal Trade Commission guidelines, consumer protections, lemon laws, etc. (Pitofsky et al., 2010). It is not about the governance of international trade. (That is the subject matter of International Business Transactions). A preponderance of experts mistakenly grouped Trade Regulation with international themed course-subjects. This is one instance in which the empirical technique of analyzing what faculty members taught was more correct than the human experts. Furthermore, the grouping of all of the "Law and" course-subjects (Law and Accounting, Law and Economics, Law and Literature, Law and Medicine, Law and Psychiatry, Law and Religion, Law and Science, Law and Social Science) into one or two interdisciplinary categories because they all involve law and one other discipline, is too simplistic. The CSCO data does a better job of revealing how these subjects cluster based on their actual subject matter and not due to the fact that they are simply interdisciplinary in nature. Similarly, Workers' Compensation is more related to Torts than the other Labor and Employment course-subjects as revealed by the CSCO clustering. The human subjects probably grouped Workers' Compensation with other labor and employment law course-subjects because of worker in the title.

QAP analysis was performed on the two networks relied upon in the above clustering analysis—the normalized CSCO data and the card sort data. The Pearson correlation value of 0.535 indicates that the matrixes are halfway between being entirely correlated (1 or -1) and not correlated at all 0. Also, the results are definitely statistically significant well past the 95% confidence interval as none of the 5000 random permutations produced networks that were more highly correlated. This means that CSCO data is about 53% correlated with human subjects' views of the topical relatedness of the course-subjects. The lack of a perfect correlation probably comes from a number of realities. First, teaching assignments (CSCO data) rely on extenuating factors such as shortages, unexpected class enrollment, teachers teaching in more than one general subject area for variety, etc. Second, as discussed above, there were several errors in the human subjects' understanding of the course-subjects. Third, the CSCO data was sometimes more nuanced as in the case of the "Law and" course-subjects.

The following clusters are distilled from the best of the cluster analysis results from the two techniques above. Selection of the clusters and their membership was informed by the analysis of the grouping labels used by the experts (Hook, 2014b). Also, whenever possible, preference was given to CSCO data as clusters on the final CSCO map that are based on the CSCO cluster analysis will be more contiguous than if relying on the card sort cluster data. The clusters have all of the characteristics that are desired in a cluster scheme. Chief among these characteristics are no clusters with only one member (the lowest is two, Entertainment Law) and no disproportionately large clusters (there are two clusters with 9 course subjects each—(1) Taxation / Wealth Preservation, and (2) Jurisprudence. The average amount of course-subjects per cluster is six. While informative, the CSCO k-means cluster treatment created clusters at all three chosen cluster amounts that were unsuited for thematic overlay on a base-map. This was because clusters both had too many constituent course-subjects (38, 41, or 31) and were largely uninterpretable, or there were too many instances of clusters comprised of a single course-subject. The clusters produced by the CSCO factor analysis were more interpretable and more capable of being used for thematic overlay on a base-map than the CSCO k-means analysis. While clustering algorithms will inevitably find clusters, even when none exist, the author's experience working with the eighteen human subjects performing the card sorting exercise lends support that the clusters herein are latent and truly occurring. While some course-subjects were hard to group, not one of the experts questioned the underlying assumption that higher level groupings existed.

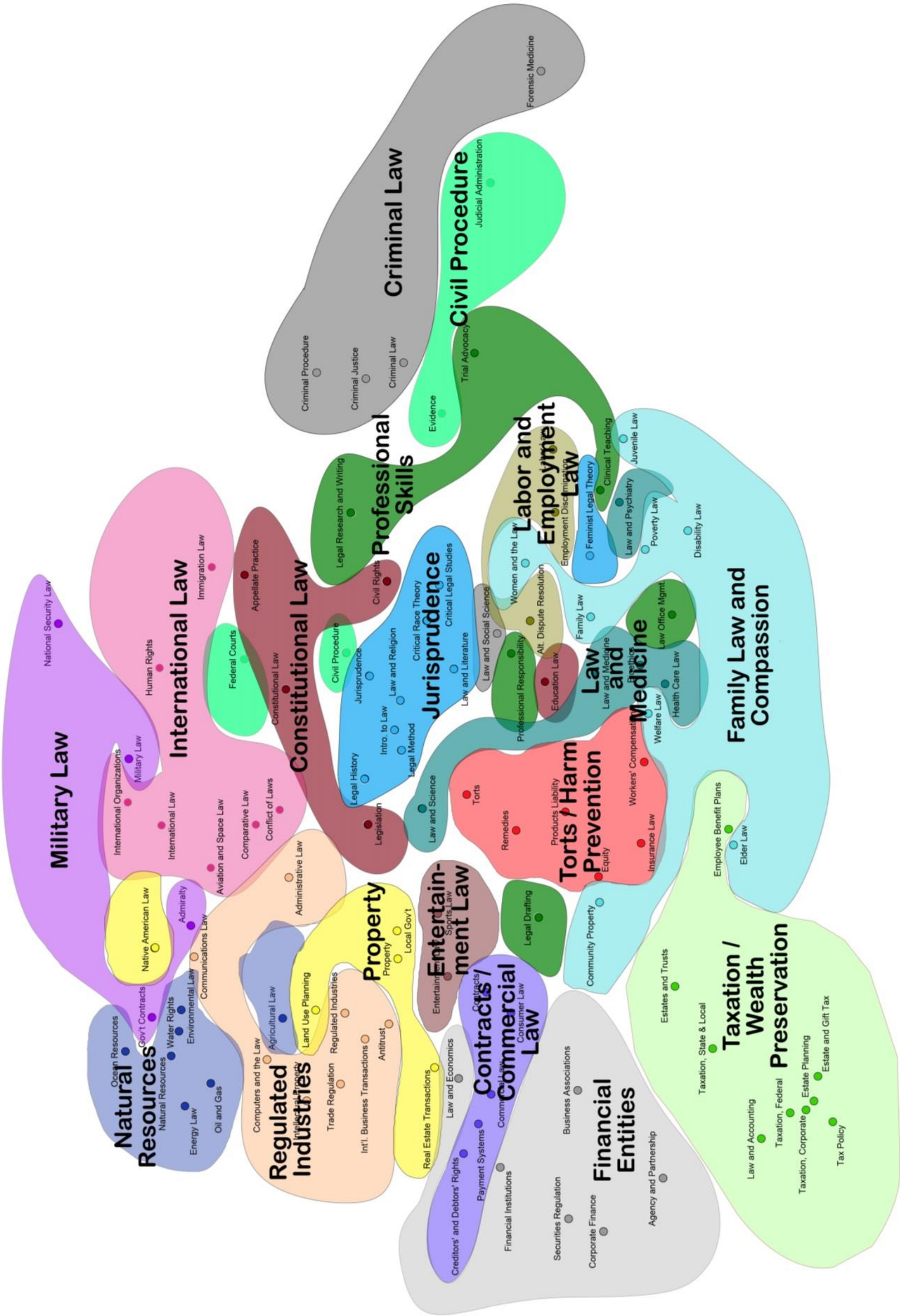

Figure 4: CSCO map most consistent with the gold-standard with clusters.

Conclusions and Future Work

Leydesdorff and Rafols note that: "One should not expect a unique map of science, but a number of possible representations… Each map contains a projection from a specific perspective" (Leydesdorff & Rafols, 2009, p. 350). While there are many different and often competing dimensions to be captured and represented by domain maps, if one articulates criteria or a specific purpose with sufficient specificity, for any given domain map criteria or purpose, there is likely to be a best or most accurate domain map representation relative to that criteria or specific purpose. Domain mapping as a field will not be mature until there have been numerous studies that demonstrate the best techniques for the many different data situations encountered by scientometricians. Perhaps the most significant contribution of this article is the analytic framework to compare multiple different algorithms, tools, and techniques at each stage of domain map production.

In the future, the author would like to conduct similar comparisons with other normalization techniques discussed in the literature. This includes those used in (Boyack et al., 2005; Klavans & Boyack, 2006) as well as indirect similarity measures and other set-theoretic similarity measures identified in (Van Eck & Waltman, 2009). Also, the author would like to replicate the Boyack and Klavens approach of doing the ordination while only using the top 15 co-occurring course-subjects for each individual course-subject (rather than all 103 other course-subjects in 2010-11). Similarly, the author would like to analyze the Top 5, Top10, Top 20, Top 25, and Top 50 co-occurring course-subjects to see the affect this has on the ordination. The author would like to explore other cluster approaches such as hierarchical clustering and that implemented in the VOSviewer software. The infrastructure used to produce the dataset for this article is perhaps a singular occurrence limited to the AALS. However, it may provide an aspirational goal for other communities to maintain such data. Alternatively, sophisticated parsing and scraping of Websites might allow for similar analysis, albeit, not with a rigorously controlled vocabulary. The author would like to apply the CSCO approach to mapping other domains. A number of possible datasets might enable such an analysis. For example, one could use instances of faculty members teaching two or more MOOC's (Massive Online Open Course).

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1. Data Format window: "The data are proximities." Model window: Proximity Transformations, "Interval." Shape, "Full Matrix." Proximities, "Similarities." Dimensions, "Minimum: 2, Maximum: 2." Restrictions window: "No restrictions." Options window: Initial Configuration, "Simplex." Iteration Criteria [defaults], Stress convergence, ".0001." Minimum Stress, ".0001." Maximum iterations: "100." Plots window [all selectable]: "Common space," "Original vs. transformed proximities," and "Transformed proximities vs. distances." Source plots, "All sources." Output window: Display [all selectable].

2. Select: Create map from Pajek.net file. Select: Do not use original coordinates. Minimum total link strength of an item: leave at default of zero. On the Map Tab: Advanced Parameters: Normalization Method: No Normalization. Uncheck Ignore Self Links (although there are not any in the dataset). Random Number Generator (leave defaults). Mapping (leave defaults). Random Starts 1. Convergence 1E-8. Max Iterations 1000. Clustering (not applicable since not run). Run: Mapping Only. Action Tab: Options: Labels: Size .66. Size Variation: zero (all the way to the left). No Overlap (unchecked). Blurred background (unchecked). Gradual Appearance (unchecked). Optimized Screenshots (checked). Lines (leave defaults). Visualization: Item colors: (no item colors).

3. The specific inputs and decision points for the factor analysis performed on SPSS are as follows: Descriptives (leave defaults: Statistics, Initial solution checked; Correlation Matrix, nothing checked); Extraction (Analyze, leave Correlation Matrix checked; Display, uncheck unrotated factor solution, check Scree plot; Extract, Based on Eigenvalue, Eigenvalues greater than 1; Maximum Iterations for Convergence: 25); Rotation (Method, Varimax; Display, Rotated Solution; Maximum Iterations for

Convergence: 300); Scores (leave everything unchecked); Options (Missing Values, Exclude cases listwise; Coefficient Display Format, Sorted by size, leave everything else unchecked. However, the analysis effectively used the threshold, Suppress Small Coefficients, absolute value below: .4—a common threshold when performing factor analysis.)

4. The specific inputs and decision points for the k-means analysis performed on SPSS are as follows: Initial Screen (Method, Iterate and classify; Cluster Centers, leave blank; Number of Clusters, [varies]); Iterate (Maximum Iterations, 100; Convergence Criterion, 0; Use running means, unchecked); Save (check Cluster membership; check Distance from cluster center); and Options (Statistics: check Initial cluster centers, check ANOVA table, check Cluster information for each case; Missing Values, Exclude cases listwise).

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