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Centrality Scores and Precedent Value in Legal Network Analysis

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Abstract.
Courts commonly rely on precedents to guide their judgments. Centrality measures have been used to calculate precedence value in citation networks of judgments, yet it remains largely unknown whether and which centrality measures correlate well to precedent value. An analysis of European Court of Human Rights (ECtHR) judgments offers a unique opportunity to uncover this relationship, as the ECtHR publishes an importance score for its judgments and the branch of court that dealt with them. These scores, although not perfect, may serve as proxies for a case's precedent value. Various network centrality measures correlated reasonably with these proxies, with Degree being a stable measure across the (sub)networks. An ordinal regression model with network centrality among other predictor variables performed reasonably when Importance Score was used as an outcome variable ($F1 \approx .655$). The results support that network centrality, to an extent, indicates case precedent value, and that Degree seems to be a stable proxy for precedent value across different networks. The data, code, and additional results are made available.

Keywords. legal network analysis, precedents, network centrality, case law, European Court of Human Rights (ECtHR)

1. Introduction

A precedent is a rule, set in a prior legal case, that may be used to decide subsequent cases [1]. A famous precedent in European human rights law is the Marckx case, where a rule stipulating that no legal bond between an unmarried mother and her child resulted from the mere fact of birth was considered a violation of the right to private and family life [2].

Network analysis has been used to retrieve precedents in case law. Treating court judgments as nodes (also called vertices) and citations from one court decision to another as edges (also called arcs or links) allows for creating a precedent network and for exploring how central precedents are in a given network [3]. Network analysis thus leverages the citations from and to court judgments. Centrality scores can serve as prox-

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ies for the precedent value of judgments. The idea of using centrality as a proxy for the precedent value of court judgments is that those cited more frequently are more likely to be important compared to judgments that are cited less frequently.

Studies have reported on the use of different centrality measures in legal network analysis, as mentioned in Section 2. The outcomes that the measures produce have been found to be different for networks of different sizes and densities [4]. Although each centrality may measure a particular type of relevance, there is a lack of a ground truth (i.e., a benchmark or reference point for evaluating the performance of a centrality measure) that is a stable proxy for measuring precedent value across different networks.

In this study, we compare the scores of different centrality measures to ground truth scores for the entire body of case law as well as for subsets of case law of the European Court of Human Rights (ECtHR). The contributions to the body of knowledge can be summarized as follows:

- Introduction of two ground truths for the precedent value of ECtHR judgments.
- Comparison of a variety of network centrality measures in their ability to measure precedent value
- Network modification to test potentially different relationships between precedent value and network centrality
- Modeling the relationships between network centrality and ground truths to predict precedent value.

2. Related Work

A vast number of studies that apply network analysis in a legal context, focus on identifying precedents in case law [5]. In this respect, case law of the ECtHR, the Court of Justice of the European Union (CJEU), the International Criminal Court, courts in individual European member states, the US, and Canadian courts has been analyzed [6]. Legal network analysis studies have also focused on other areas than case law, such as legal services, statutes and regulatory codes, patent citations, criminal behavior, and terrorists [6]. Methodological works have focused on improving the use of legal network analysis by focusing on, among other things, community detection methods and centrality measures that capture the relevance of precedents [4].

3. Data and Methods

The code, datasets, and analyses (reported and unreported) are made available at https://doi.org/10.34894/FDGGDZ.

3.1. Data

All ECtHR judgments of the Grand Chamber (seventeen judges), the Chamber (seven judges), and of Committees (three judges) published on the HUDOC website were collected on 17 May 2023.[2] The available metadata include the date of the judgment, the

[2] https://hudoc.echr.coe.int/.

articles that have been invoked, whether a violation was found, the court branch, and importance scores. Metadata was collected for 25,937 judgments in the English language, which mostly overlapped with the number reported on the HUDOC website.

The preprocessing of the metadata involved extracting the citations from the metadata. In the metadata, each judgment has an attribute 'scl,' i.e., the Strasbourg Case Law, which stores the outgoing citations, and an attribute 'extractedappnos', which stores the judgments extracted from the full text. A citation in 'scl' commonly consisted of the case title, a judgment date, and an application number, and 'extractedappnos' of a list of application numbers.

We aimed to match each judgment mentioned in the 'scl' and 'extractedappnos' attribute to an European Case Law Identifier (ECLI). To obtain the correct ECLI, first all application numbers from the 'extractedappnos' were matched with the application numbers from the metadata. Thereafter, the citations from 'scl' were retrieved and each application number was extracted and matched with the application numbers from the metadata. In the event no results were returned, the case title was extracted from the citation and matched to the case titles in the metadata. Often, matching judgments from the metadata resulted in multiple judgments being retrieved. To distinguish the correct judgment, the judgment date from the citation was matched to the judgment dates from the retrieved judgments.

We observed that a significant proportion of the citations included in the dataset were either improperly formatted or contained typographical errors. In fact, among the total of 158,899 citations present, this issue was identified in approximately 21,000 citations. We identified two primary reasons why certain citations could not be located. Firstly, in the metadata we have retrieved, decisions were not included but were frequently present in the citations. The number of decisions omitted were 12,017. Secondly, we encountered instances where the formatting of the citations was incorrect, thereby posing challenges in accurately parsing and retrieving individual citations from the 'scl' attribute. This issue was identified in approximately 8,900 citations. To mitigate this concern, we implemented a preprocessing step wherein we systematically documented the most common typos and patterns observed and utilized them to either replace or remove such citations. In certain instances, it came to our attention that the date to identify a specific ECLI was missing. In these instances, we included all versions as data points to ensure completeness. The final number of citations that were omitted from this study due to errors in the citations was approximately 5,500.

After the preprocessing, a network with nodes (judgments) and unweighted directed edges (citations) was constructed with 25,937 nodes, 141,320 edges, and an approximate density of .000209. It contained 14,328 isolated nodes, and 20,975 connected components, with the largest having size 3,476. The variables of interest for the analysis were the aforementioned court branch (Grand Chamber, Chamber, Committee), importance scores, year of each decision, and invoked articles, as well as whether or not these articles were violated.

3.2. Methods

The following centrality measures were used: In-degree (number of incoming edges) [5], Out-degree (number of outgoing edges) [5], Degree (number of incoming and outgoing edges) [5], Relative In-degree (in-degree corrected for year of decision) [8], Eigenvector (rewards connections to well-connected nodes) [7] (tolerance of 1E-6), PageRank (probability that a random traversal will end at a node) [9] (damping factor of .95 and tolerance of 1E-9), Betweenness (to what extent a node can be seen as a broker) [10], Current Flow Betweenness (betweenness using an electrical flow model instead of shortest paths) [11], Closeness (average distance between a node and all other nodes it can reach) [12], Current Flow Closeness (closeness based on effective resistance of nodes) [11], Harmonic (closeness using inverse of distances) [13], Hub (the extent to which a node connects to nodes with high authority) [14] (same parameters as HITS), Authority (the extent to which a node is connected to by nodes which are hubs) [14] (same parameters as HITS), Hyperlink-Induced Topic Search (HITS) (the sum of authority and hub) [14] (tolerance of 1E-8), Core Number (largest number defining a core in which a node is present) [15], Trophic Level (a concept from ecology) [16], Forest Closeness (closeness using forest distance) [17] (estimated with $\varepsilon = .1$ and $\kappa = .3$), and Disruption (the extent to which a node introduces new information into a network) [18]. For certain measures it was necessary to modify the graph structure. The graph was augmented to compute Trophic Level, and was made undirected on top of this to compute the Forest Closeness, Flow Betweenness, and Flow Closeness. When it was impossible to calculate a centrality score, for example, when a division by 0 was involved, the corresponding judgement was excluded from calculations.

From Articles 28(1)(b), 30, and 43 of the European Convention of Human Rights (ECHR) it follows that Court Branch can be indicative of case importance. Furthermore, the Bureau of the Court has assigned one of the following importance scores to judgments: Key cases (since 1 November 1998),[3] and High/Medium/Low importance. Tables 1 and 2 show the distributions.

Importance Score	Pre 1998 Frequency	Post 1998 Frequency	Total Frequency
Low Importance	179 ($\approx 21.4\%$)	18282 ($\approx 72.8\%$)	18461 ($\approx 71.2\%$)
Medium Importance	238 ($\approx 28.4\%$)	5123 ($\approx 20.4\%$)	5361($\approx 20.7\%$)
High Importance	419 ($\approx 50.1\%$)	666 ($\approx 2.65\%$)	1085 ($\approx 4.18\%$)
Key Cases	1 ($\approx 0.119\%$)	1029 ($\approx 4.10\%$)	1030 ($\approx 3.97\%$)
Total	837	25100	25937

Table 1. Importance Score frequencies before and after the 1st of November 1998.

Ground Truth Value	Importance Score Frequency	Court Branch Frequency
3	18461 ($\approx 71.2\%$)	5262 ($\approx 20.1\%$)
2	5123 ($\approx 19.8\%$)	20175 ($\approx 77.8\%$)
1	2115 ($\approx 8.15\%$)	500 ($\approx 1.93\%$)

Table 2. Court Branch and merged Importance Score frequencies.

Because 'Key cases' were introduced later than the High/Medium/Low importance categories, we merged the 'Key cases' and 'High importance' (merged approach) into a single category when using Importance Score, which preserves the inclusion of pre-1998 judgments in the analysis. We compared the results with an unmerged approach that treated the two as separate categories and discarded judgements from before November 1998 to avoid a shift in the distribution of cases before and after this cutoff date. In gen-

[3] With the exception of Case of Goodwin v. the United Kingdom, ECLI:CE:ECHR:1996:0327JUD001748890. The reason for this anomaly is unknown.

eral, the same centrality measures were strong for both approaches. The correlation coefficients in the unmerged approach tended to indicate slightly stronger relationships. For the regression, the merged approach significantly outperformed the unmerged approach. All results, also the ones not reported in this paper, can be found in our repository.

Both Importance Score and Court Branch are ordinal in reversed order (the higher the importance/court branch, the lower the importance/court branch score), whereas all centrality measures are continuous. One of Kendall's rank-based correlation coefficients, Kendall's τ_b, was selected for the correlation analysis because it is suitable for handling these relationships. Two correlation coefficients were computed for each centrality measure, one for each ground truth. This was done across all judgements as well as for various sub-networks, which were constructed by first computing centrality scores on the full network and selecting nodes which fit certain criteria. This was done to avoid overly sparse sub-networks. Correlation coefficients were also computed for the relationship between the ground truths. Finally, ordinal probit regression models were constructed that made use of promising centrality measures in combination with other metadata to predict precedent value via the proxies.

4. Results

Table 3 shows the correlation coefficients. The fact that the maximum centrality scores, which were all 1 due to normalization, exceed the means suggests that the scores for each centrality measure follows a Power Law distribution (many nodes with few adjacent edges, few nodes with many adjacent edges).

Metric	Importance Score τ_b	Court Branch τ_b	μ	σ
Degree	**-.636**	**-.448**	.00880	.0229
In-degree	**-.649**	-.387	.00961	.0210
Core Number	-.631	**-.446**	.125	.168
Relative In-degree	**-.647**	-.382	.000158	.00759
Eigenvector	**-.637**	-.382	.0162	.0551
PageRank	**-.640**	-.381	.000984	.00878
Current Flow Betweenness	-.626	**-.445**	.00464	.0143
Forest Closeness	-.627	**-.443**	.394	.376
HITS	-.511	**-.397**	.00574	.0348
Trophic Level	-.618	-.378	.238	.303
Betweenness	-.630	-.313	.000575	.00807
Current Flow Closeness	-.574	-.340	.394	.376
Out-degree	-.473	-.349	.00441	.0189
Hub	-.437	-.336	.00493	.0445
Authority	-.486	-.309	.00543	.0371
Harmonic	-.435	-.333	.145	.216
Disruption	-.189	-.336	-.618	1.19
Closeness	-.434	-.332	.160	.237

Table 3. Correlations between each centrality measure and both ground truths (top 5 in bold), along with descriptive statistics for each measure. Centrality scores were normalized, except for Disruption. All trends were statistically significant by a one-tailed Mann-Kendall test with 99% confidence.

The centrality measures most strongly correlated with precedent value depended on the proxy that was selected. Certain measures performed decently for both proxies. Degree, for example, was in the top 5 for both ground truths. Figure 1 plots the centrality measures responsible for the strongest and weakest correlation coefficient for each proxy (more results can be found at https://doi.org/10.34894/FDGGDZ).

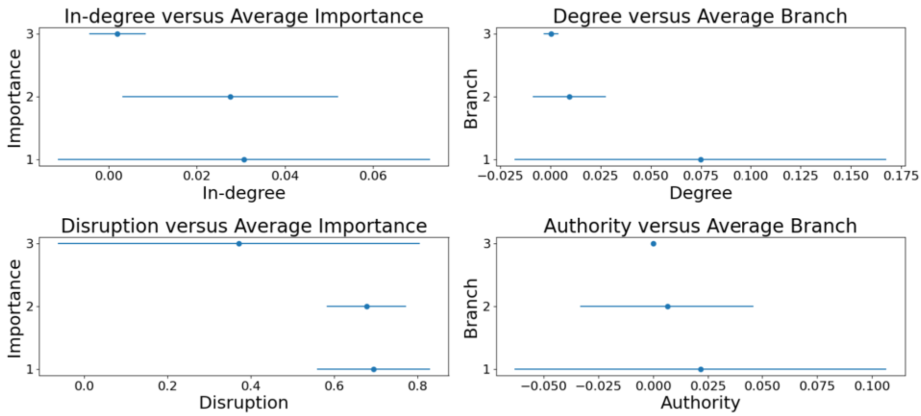

Figure 1. Plots of the two most strongly correlated centrality measures with each proxy on the top row, and the two least strongly correlated centrality measures with each proxy on the bottom. The plots shows average centrality scores and the error bars show standard deviation.

Because the scores for Importance and Court Branch are reversed (the higher the importance or court branch, the lower the score), one would expect negative correlations (higher centrality score are associated with lower proxy values), as Figure 1 displays. Interestingly, the weakly correlated measures according to the rank-based metric sometimes show a downward trend that appears more linear than the strongly correlated measures. Seeing as the coefficients measure monotonicity, however, this is entirely possible. Table 2 indicates that, although each category contains a sufficiently large number of observations for considering these patterns robust, the data are distributed unevenly amongst the ground truth categories. Because of this, centrality measures that capture the downward trend for the most populated category in relation to the other categories will have stronger correlation coefficients.

The error bars show the standard deviation of the centrality scores in each ground truth category, and indeed, high scoring measures have smaller error bars for the majority class (class ’3’) than the low scoring measures. Certain centrality measures have lower correlation coefficients than other measures because of their inability to distinguish the majority class effectively, but are better at distinguishing minority classes. For example, the bottom left plot in Figure 1 corresponds to Disruption, which has the weakest correlation coefficient with Importance Score due to a wide error bar for the Low importance category compared to the plot for In-degree, which performed the best for this ground truth. Similarly, in the bottom right the plot for Authority, which was the worst performing measure for Branch, the error bar for the category Chamber is wider than that of the best performing measure, Degree.

Table 2 shows that Low importance and Chamber are the majority classes for the two ground truths. While the bottom two plots are for measures which have weaker correlation coefficients, they have smaller error bars for the minority classes High importance and Grand Chamber than the best performing measures on the top row. This indicates that they are better at distinguishing these categories even though their correlation coefficients are weaker.

Correlation coefficients were also computed for various sub-networks. First, only judgements from one ground truth category were considered at a time. Consequently, with Importance Score as a ground truth, sub-networks were built with only Grand Chamber, Chamber, and Committee judgements in turn. With Court Branch as a ground truth, sub-networks were built with only key or high importance, medium importance, and low importance cases in turn.

Next, four sub-networks were constructed for each proxy based on whether or not articles were violated. Only judgements in which at least one article was violated were considered first, then only judgements in which an article was violated and none of the pertaining articles were marked as not violated. Then, only judgements that had pertaining articles which were marked as not violated were considered, followed by judgements that had pertaining articles which were not violated as well as an absence of violated articles. Finally, sub-networks were constructed containing judgements pertaining to individual articles for each proxy. Results for the 10 most frequently occurring articles and protocols were considered to ensure that the sub-networks contained a sufficient number of nodes. From most to least frequent, these were articles 6 and 41, followed by Protocol 1, and then articles 3, 5, 13, 35, 8, 29, and 10. The top 5 measures are shown for the first five of these articles in Table 4. Of all 24 sub-networks, Degree was amongst the top 5 most strongly correlated measures 19 times. The strengths of the relationships were typically worse in the sub-networks than for when the full network was used. Table 4 contains some exceptions.

	Art. 6	Art. 41	Pro. 1	Art. 3	Art. 5
Importance	Betweenness -.586	Degree -.553	Betweenness -.591	In-degree -.791	In-degree -.724
	Degree -.575	Forest Closeness -.544	Rel. In-degree -.588	Rel. In-degree -.783	Relative In-degree -.719
	Core Number -.569	Core Number -.543	In-degree -.587	Eigenvector -.780	PageRank -.711
	Current Flow B. -.567	Current Flow C. -.543	Degree -.585	PageRank -.778	Eigenvector -.708
	Forest Closeness -.566	Current Flow B. -.530	Core Number -.582	Trophic Level -.770	Trophic Level -.705
Branch	Degree -.419	Degree -.232	Degree -.413	Degree -.562	Degree -.512
	Core Number -.418	Current Flow B. -.230	Core Number -.412	Core Number -.561	Core Number -.510
	Current Flow B. -.417	Forest Closeness -.229	Current Flow B. -.411	Current Flow B. -.558	Current Flow B. -.508
	Forest Closeness -.415	Current Flow C. -.228	Forest Closeness -.409	Forest Closeness -.557	Forest Closeness -.508
	In-degree -.378	Out-degree -.224	In-degree -.394	Current Flow C. -.539	HITS -.461

Table 4. The top 5 most strongly correlated measures for both ground truths for sub-networks built from the 5 most frequently occurring articles. All trends were statistically significant by a one-tailed Mann-Kendall test with 99% confidence.

The correlation coefficient between the two proxies was $\tau_b \approx .362$. At least a weak correlation was to be expected, as the reasons for the ECtHR to assign cases to the Committee, Chamber, or Grand Chamber are likely to overlap, at least in part, with the motivation to assign a certain importance score to a judgment. Correlation coefficients were also computed for the relationships between the proxies and the decision year. For Importance Score, there was no indication of a relationship, however, for Court Branch, the resulting coefficient was $\tau_b \approx .441$, which may suggest that the way a case is assigned to a branch of court has not remained completely consistent over time. In addition, sub-networks were constructed each containing judgements from within spans of 5 years to investigate if the correlation strengths between centrality score and the ground truths had changed over time. This, as well as the number of judgements per year, is shown in Figure 2.

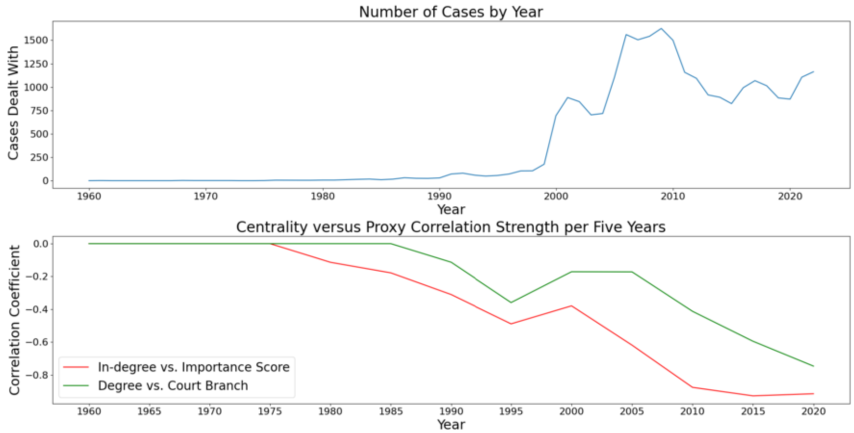

Figure 2. The number of judgements per year (top) and the correlation coefficient for the strongest measures for each proxy in sub-networks composed of cases in spans of 5 years.

Ordinal probit regression was conducted to test the relationships between network centrality and the ground truths while controlling for other variables. To avoid multicollinearity, each regression analysis was conducted with only one centrality measure as a predictor variable. Results reported here use Degree and results from other measures are available in our repository. The 10 most frequently invoked articles were included as binary predictor variables. The year of each judgement was not included as models utilizing this information performed worse than the ones which excluded it. The metrics balanced accuracy, F1 score, and the area under the precision recall curve were computed by averaging across 5 runs of 5-fold cross validation, with undersampling performed after the creation of training and testing sets to deal with class imbalance.

The scores are shown in Table 5 and the contributions of the independent variables summarized in Table 6. For more results, see `https://doi.org/10.34894/FDGGDZ`.

	Balanced Accuracy	F1	Area Under Precision Recall Curve
Importance	.665	.655	.637
Branch	.707	.514	.473

Table 5. The performance of the regression model for both ground truths.

	Degree	Art. 6	Art. 41	Pro. 1	Art. 3	Art. 5	Art. 13	Art. 35	Art. 8	Art. 19	Art. 10
Importance	**-.033**	**.417**	**-.621**	−.012	**.433**	**.339**	-.017	**-.203**	**-.351**	**.176**	**-.094**
Branch	**-.040**	.162	**-.542**	-.132	.323**	**.439**	**.471**	−.211	−.281*	.068	.249

Table 6. Regression table for a single run of the model. DVs: Importance, Court Branch. IVs: Degree, Invoked Articles. The learned decision boundaries were at −1.48 and 0.268 for Importance Score and −1.53 and 0.481 for Court Branch. Note that in ordinal probit regression, the coefficients contribute to a latent variable and not directly to the output. As such, interpretation of how much a variable contributes to the output requires consideration of these boundaries (Degree is measured on a different scale and should not be directly compared). In bold = $p < .001$, ** = $p < .01$, * = $p < .05$.

5. Limitations

The proxies used in this study are imperfect captures of precedent value. When an importance score is assigned to a case, it is without knowledge of how relevant that case will be in the future, and whether or when the judgment will lose relevance, for example, because it is replaced or updated by another, more recent judgment. The decision of which branch of court will deal with a case can have a variety of reasons in addition to the substantive relevance (e.g., policital reasons, societal impact, expected media coverage). The extent to which a judgment has precedent value is contextually determined, making possibly every ground truth limited.

6. Discussion and Conclusion

Degree showed promise both in terms of correlation and as a predictor in the regression model, and seems to be a stable proxy for precedent value. This is surprising, as Degree is one of the more naive measures in that it ignores the directed nature of the network and only considers its neighboring edges. Interestingly, the results reveal that not only the correlation score is important for measuring the precedent value, but also the error bars for the respective categories in the ground truth variables. Future research could further explore the error rates of the centrality measures in relation to ground truths.

Another relevant pattern is that Degree and HITS consistently outperform the measures that they are made up of, which are In-degree and Out-degree, and Authority and Hub, respectively, for both ground truths. It seems that using an electrical flow model is a better way to measure distance in this legal network than shortest path, as evidenced by Current Flow Betweenness and Current Flow Closeness outperforming their counterparts, Betweenness and Closeness.

The correlations are different for Importance Score and Court Branch. It may be that the findings reveal a somewhat different type of relevance that Importance Score and Court Branch reflect. The higher scores relative to the other measures for some betweenness-like and closeness-like measures when using Court Branch compared to Importance Score could suggest that the branches serve as key bridges in a network of judgments, whereas a more diverse and distributed pattern of influence can be observed when considering Importance Scores.

The findings contribute to the understanding of how network analysis can assist in identifying landmark cases and determining the precedent value of court decisions, and consequently to the automated retrieval of landmark cases. Future work could include adding additional ground truths (preferably ones not created at the time of the judgments), investigating why certain articles were better at predicting the proxies for precedent value better than others, using other models, adding more centrality measures, and exploring the error rates in the relationship between the centrality measures and the categories within a ground truth.

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