

Automated Classification of Modes of Moral Reasoning in Judicial Decisions

Nischal Mainali¹
NYU Abu Dhabi
nischal.mainali@nyu.edu

Liam Meier*
NYU Abu Dhabi
liam.meier@nyu.edu

Elliott Ash
ETH Zurich
ashe@ethz.ch

Daniel Chen
Toulouse School of Economics
daniel.chen@iast.fr

Abstract

What modes of moral reasoning do judges employ? We attempt to automatically classify moral reasoning with a linear SVM trained on applied ethics articles. The model classifies paragraphs of text in hold out data with over 90 percent accuracy. We then apply the classifier to a corpus of circuit court opinions and find a significant increase in consequentialist reasoning over time. We report rankings of relative use of reasoning modes by legal topic, by judge, and by judge law school. Though statistical techniques inherently face significant limitations in this task, we show some of the promise of machine learning for understanding human moral reasoning.

1. Introduction

The legal profession is undergoing a great transformation. The tools of machine learning and causal inference can be used to increase efficiency and fairness of the law. In this article, we discuss how these tools can also be used to detect how judges motivate their decisions. What is the role of moral reasoning in judicial decision-making? Law is divided between the consequentialist view that optimal policy should be based on calculations of costs and benefits and a non-consequentialist view that policy should be determined deontologically: from duties we derive what is the correct law—what is right and just. One way of quantifying this divide empirically is to identify and measure the use of different modes of moral reasoning in judicial decisions. The goal of this project is to use computational techniques to automatically classify judicial decisions by the type of moral reasoning employed.

Computational linguistics, typically referred to by computer scientists as natural language processing (NLP), utilizes computational techniques to translate, make sense of, and produce

¹ These authors contributed equally.

material in human languages. Human language is complex, full of ambiguities, encoded knowledge, and variety. Though state of the art NLP systems still struggle tasks that are simple for humans (disambiguation, for example) statistical techniques that make use of large data sets have been highly successful in sentiment analysis, classification, and more [1].

Two broad moral frameworks most often used by philosophers are consequentialism and deontology. For a consequentialist, what one ought to do is whatever brings about the best consequences. The canonical form of consequentialism is utilitarianism, according to which ethical agents are obligated to do whatever brings about the most utility. For hedonic utilitarians like J.S. Mill and Jeremy Bentham, pain is bad and pleasure is good. While philosophers have debated about how to measure utility, the idea is broadly in line with preferring happiness over unhappiness [2].

In a deontological framework, an act is right if it conforms to a moral norm. For Kant, this is the categorical imperative, the first formulation of which holds that one should act only according to a maxim which they can will to be a universal law [3]. The idea is that morality is a matter of conforming to ethical law instead of acting in order to bring about certain consequences.

Applied ethicists argue about the morality of various issues from these positions. Take the permissibility of lying, for example. A consequentialist might argue that it would be permissible to lie if the consequences of telling the lie would be better than not telling the lie. In contrast, a deontologist instead might argue that it's immoral to lie because one could not will the acting of lying to be a universal law.

Law commonly operates in correspondence with morality. Some actions are made illegal not because of practical considerations, but because a society believes that the action is morally wrong. For example, laws against sex work are often justified on moral grounds.

In the legal system, we can observe when judges reason according to either of these moral frameworks. In the case of a contract, a deontological judge may hold that breach is always illegal, since it is a break of a promise. A consequentialist judge may reason that certain breaches of contract are acceptable, if, for example, a breach of contract would lead to a better outcome for the relevant parties. Such reasoning is recognized as "efficient breach" in law and economics.

In this paper we build a classifier using tools from natural language processing and machine learning, trying to identify modes of moral reasoning. Moral reasoning is often studied in relation to political ideology [4] [5] [6]. Recently researchers [7] employed computational techniques to measure texts amongst the five moral dimensions posited by Jonathon Haidt [8]. To the best of our knowledge, our work is the first attempt to computationally classify moral reasoning into the conventional theoretical categories of ethics.

Here we operate on the assumption that patterns in written language reflect, however imperfectly, different types of reasoning. For example, an individual reasoning consequentially would use language associated with ends. We might also expect language that attempts to infer the results of different types of action and a higher-frequency of words that designate

consequence. In contrast, an individual reasoning deontologically might tend use more absolute language and employ words like duty and obligation more often.

To train our classifier, we use a corpus of articles from the applied ethics literature. In these articles, philosophers argue about issues like abortion, vegetarianism, and war. The articles are drawn from an archive of philosophical literature, where they were categorized as either consequentialist or deontological. Our trained classifier assign holdout samples to the proper class with over 90% accuracy.

We then apply the classifier to circuit court opinions, where judges outline their reasoning for the decision on a case. We use these opinions (dating back to 1883) to analyze trends in moral reasoning in the U.S. legal system. We look at rates of consequentialist vs deontological reasoning over time, according to where the individual was born, where the individual attended school, their sex, and the party of the president under which they were nominated.

2. Automated Classification of Moral Reasoning

2.1 Training Data

The training corpus comprises all articles from the philosophy paper database PhilPapers.org tagged with “Applied Consequentialism” or “Applied Deontology”. We filtered out papers written in languages other than English, papers that had both consequentialism and deontology tags, and papers that obviously did not conform to either category. The resulting training corpus consists of 14 Consequentialist papers and 11 Deontology papers. These were converted to plain text, and artifacts from the PDF conversion were expunged when possible.

Our data set is composed of a few large texts. But most text classification techniques perform better with larger corpora. Accordingly, we separated each of our Consequentialist and Deontology corpa into 100 equally sized chunks. This introduces risk of overfitting, which we address by verifying performance over multiple random seeds that were used for separation of the data into the training and validation set.

Next we featurize the text. We tried many approaches, including bag of words, various lengths of n-grams, tf-idf and so on for featurizing the text. After some hyperparameter tuning, we chose tf-idf with n-gram featurization, which we found performed best in the holdout test set. The tf-idf statistic is an indicator of the relative importance of a word or phrase to a specific document. We take phrases of up to 3-words-length and adjust them by their document frequency to create a list of tf-idf n-grams. Each document is represented as a sparse vector representing the frequency distribution over these n-grams. The algorithm proceeds by using PCA to reduce the dimensionality of these vectors because the feature vectors in NLP are extremely high dimensional even though they reside in a low-dimensional manifold.

2.2 Model Training

The preprocessing step leaves us with a vector assigned to each of the texts to use for training the machine learning model. A natural choice for classification problems such as ours is Linear

Support Vector Machine (SVM) or Naive Bayes. Initial performance of Naive Bayes was very poor, so we focused our efforts on implementation of the SVM, which is known to be highly effective at text classification [9].

In broad terms, Linear-SVM tries to find a hyperplane that neatly separates the vectors with 'Deontology' labelling and 'Consequentialist' labelling. On one side of the hyperplane we find consequentialist text and on the other side we find deontological texts. The prediction is made by locating the vector of the test text in relation to the hyperplane. We use a multi class SVM, with an additional label 'other', trained on philosophy papers that did not have the consequentialism nor deontological label. This measure reduces spuriously categorizing moral reasoning into the categories when in fact there is no moral reasoning being used at all.

During the initial steps in the training, we separate our data set into training and validation sets. After each training, the model predicts on the validation set and we tweak the training parameters to increase accuracy and get sensible features. Major tuning components in training the model were frequency threshold and stop words. A sensible frequency threshold prevents especially uncommon n-grams from influencing the classification. Stop words are common words filtered out of a dataset before introducing the data to a model.

Our model very quickly approached a 100% prediction accuracy in the validation set, so the main hyperparameter tuning step was finding junk features in the prediction function and removing them. For example, the papers were downloaded on a university license, so we removed the terms that came from the license watermark. There were other overfitting type terms (e.g. “fetus”, from the high-frequency of medical ethics papers), and junk phrases from the PDF conversion such as 'x-86'. These were also removed.

This was done through examination of the prediction function. Linear-SVM predicts by assigning weights (coefficients) to the n-grams. We looked at the top 50 predictors for both Consequentialist reasoning and Deontological reasoning and weeded out obviously irrelevant n-grams.

We also experimented with n-grams by adjusting the number of words per phrase. $N=3$ gave good results. Further increasing N further helped very little and would have introduced risk of further overfitting.

Finally, we used Latent Dirichlet Allocation (a method frequently used to model topics) to check if any unobserved groups or topic bias is influencing our prediction. We found that the topics were varied and uniformly distributed, an indication that there was no such bias.

Figure 1: Most predictive N-grams for identifying consequentialist (top) and deontological



(bottom) reasoning

2.3 Feature Importance

The end product of the training is a weight assignment to each n-gram in the feature set. We rank the n-grams by their weights. In our model an n-gram with a positive weight means that it tends to occur in deontology articles, while a negative weight signals that the text is consequentialist.

The set of most predictive n-grams for each category are visualized in Figure 1's word clouds. Some of the features are somewhat intuitive. For example, "pleasure" is a consequentialist value, while "duty" is a deontological value.

3. Application to U.S. Circuit Courts

The application corpus is the universe of U.S. Circuit Court Opinions from the years 1883 through 2013. Besides the text of the opinions, we have some relevant metadata, such as biographical details of the judges writing the opinions.

3.1 Prominent Paragraphs

In order like to better understand how our classifier works in the judicial corpus, we ranked the paragraphs in the corpus by the mode of moral reasoning used. We list some of those paragraphs here. We can read these paragraphs and see how our classifier works in the new context.

Strongly Deontological Prediction

The following paragraphs are considered deontological by the prediction model with high confidence:

Second, after determining that Congress intended "special dumping duties" to be treated differently than normal customs duties, Commerce compared 201 safeguard duties to both normal customs duties and antidumping duties in order to determine how Congress would have intended 201 duties to be treated in achieving the purposes of the antidumping objectives. Commerce found several significant similarities between 201 safeguard duties and antidumping duties and determined that 201 duties are "special dumping duties" because they are "more like AD [antidumping duties] in purpose and function than they are like ordinary customs duties." *Id.*

[I]f an insurer who refuses to defend were estopped from asserting the lack of coverage as a defense in a subsequent action, then the insurer's duty to indemnify would be coextensive with its duty to defend. [The Maine Law Court], however, ha[s] repeatedly stated that an insurer's duty to indemnify is independent from its duty to defend and that its duty to defend is broader than its duty to indemnify.

By reason of its nature as a public institution St. Elizabeths Hospital owes a duty to the public in carrying out its difficult responsibilities. We have no occasion now to decide, however, whether its public duty included an entirely separate duty to Mrs. Morgan. There was a particular duty to the Court of General Sessions, and in the circumstances of this case it was intertwined with a duty to her. See *infra*, note 12.

3.2 Strongly Consequentialist Prediction

The following paragraphs are considered Consequentialist by the predication function with high confidence:

No rule of bankruptcy practice and procedure is designed to be considered in isolation. Each rule is to be considered in conjunction with every other rule. What the entire body of rules makes available to the practitioner and the bankruptcy judge is a gestalt designed to constitute a functional whole. The rules are not a melange of independent parts. The Advisory Committee alluded to this in its preface to the rules: "The proposed rules are not divided into chapters related to the different types of debtor relief chapters in the Code. These rules apply in all chapter cases except as a particular rule otherwise provides." Preface to Rules and Forms, 11 U.S.C. XXI. One of the trustee's most vigorous arguments, therefore, is explicitly contradicted by the Preface to the Rules. He argues that Rule 1019(4) does not apply to Chapter 7 cases. This is the rule that specifies that claims filed in the superseded case shall be deemed filed in the Chapter 7 case. The Advisory Committee's preface clearly reveals that the rules apply in all chapter cases "except as a particular rule provides otherwise." Rule 3002(a), requiring the filing of a claim in a Chapter 7 case, does not "provide[] otherwise." So construed, there is but one proper resolution of this case.

Besides the nonrestrictive nature of the ordinary meaning of the claim term "code," the doctrine of claim differentiation provides a powerful argument against construing the term "code" restrictively, to mean "spreading [**1615] code." Independent claim 1 of the '966 patent uses the term "code," and dependent claim 5 recites, in full, "The subscriber unit of claim 1 wherein the same code is a spreading code." The clear implication of narrowing the term "code" in dependent claim 5 by limiting the claim scope to cases in which the claimed code "is a spreading code" is that the term "code" in the independent claim is not limited to a spreading code.}

However, the evidence submitted by Clark does not stand alone. Critically, Jerlene Bush and Mildred Bobo, both within job code 1433, testified that at the time of the RIF, they trained two employees, Carolyn Muse and James Russell Hunter, who then replaced them in their positions. See Appellants' App. at 496-98. Yet Hunter was placed in job code 1432, see id. at 171, and Muse in 1402, see id. at 170.10 Muse's placement in another job code generally raises questions about the claimed functional differences between job codes. But Hunter was placed into the very job code that plaintiffs argue was pretextually separated from their own code for purposes of discrimination. On the basis of personal observation, two witnesses from job code 1433 testified that they trained someone to perform their jobs and that the person they trained was placed in job code 1432. That is sufficient for a reasonable jury to find Seagate's differentiation of the two codes pretextual.

First, we see that the statements considered deontological all contain the word "duty," which is intuitive. The statements categorized consequentialist include phrases like "Each rule is to be considered in conjunction with every other rule", clearly emblematic of consequential reasoning.

Time Series for Consequentialist Reasoning

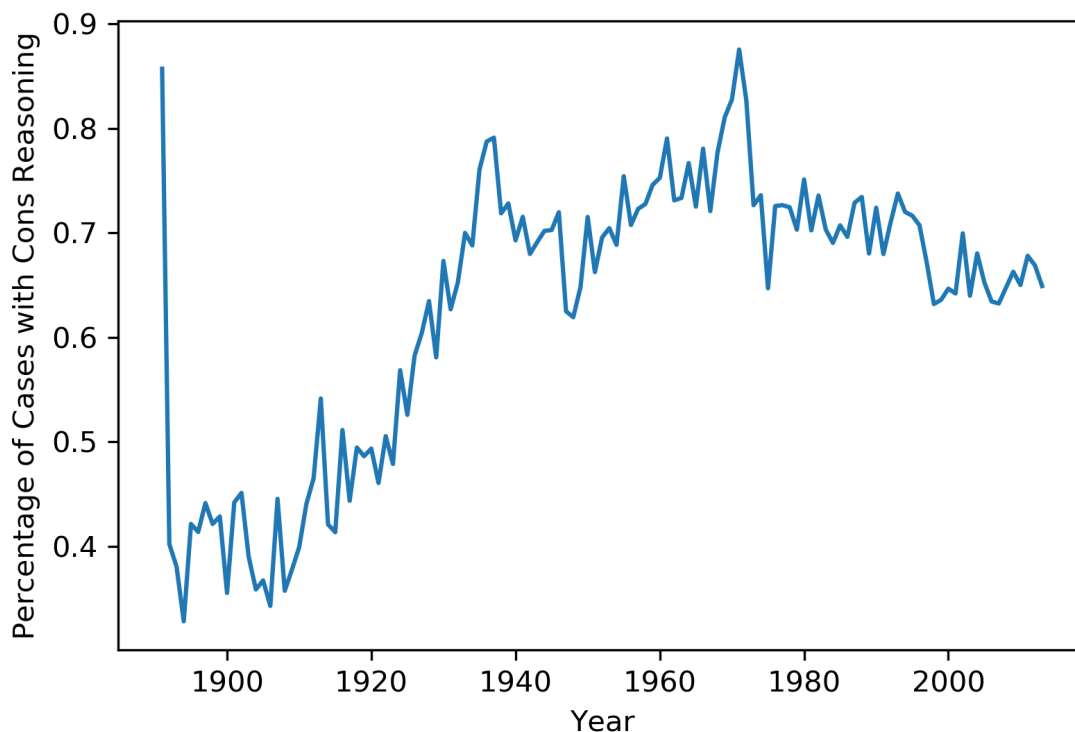


Figure 2: Consequentialist reasoning in the Circuit Courts, 1891-2013

Next we examine trends in consequentialist versus deontological reasoning over time (Figure 2). We see there is a discrete jump in consequentialism in the 1930s, indicating a major switch in thought at the time.

There could be many factors driving this change. One possibility is that the hardships of the depression brought disenchantment with prevailing norms; so moral attitudes shifted toward a focus on better outcomes, rather than strict adherence to laws regardless of outcomes. Another potential factor is the legal realism movement of the 1920s and 30s, which viewed law as a mean towards an end, rather than an end in itself [10].

Another explanation for the trend we observe is that over time the language of circuit court opinions has shifted to that of the consequentialist articles. For example, words that are weight

samples consequentialist like ‘code’ and ‘rule’ might be appearing more often now compared to the past because there are more cases being decided on statutory grounds instead of common law grounds.

In the appendix, we report rankings of legal topics by moral reasoning. Opinions written in estate law and family law have a deontological bent, while administrative law tends to be more consequentialist. As the popularity in topics have changed over time, some of the rankings may reflect when opinions in that topic were being written, because reasoning has become more consequentialist (e.g. the fact that there’s been more administrative law in more recent times explain why more opinions in this topic are consequentialist). This effect could be disentangled in future work.

3.3 Judge Rankings

It might also be illuminating to learn which judges are most consequentialist or most deontological. For example, we might expect pragmatist judges such as Richard Posner to be consequentialist. To ensure a large enough sample size, we filter out all judges that have less than 50 opinions in our dataset.

Judge	Percent Consequentialist
Trieber, Jacob	21.2
Van Devanter, Willis	21.9
Cotterall, John H.	24.4
Reed, Henry Thomas	24.6
Kenyon, William	25.3
McDowell, Henry Clay	25.8
Hawley, Thomas Porter	26.6
Booth, Wilbur F.	27.5
Philips, John Finis	27.6
Pritchard, Jeter C.	28.1

Table 2: Top 10 Deontological Judges

Judge	Percent Consequentialist
Gorsuch, Neil M.	92.4

Judge	Percent Consequentialist
Moore, Kimberly Ann	91.3
Martin, Beverly B.	90.2
Tatel, David Stephen	88.8
Madden, Joseph	88.1
Clevenger, Raymond Charles, III	87.9
Wilkey, Malcom R.	87.8
Rich, Giles Sutherland	87.6
W Starr, Kenneth W.	87.5
Patterson, Robert P.	87.3
Chambers, Richard H.	87.0

Table 3: Top 10 Consequentialist Judges

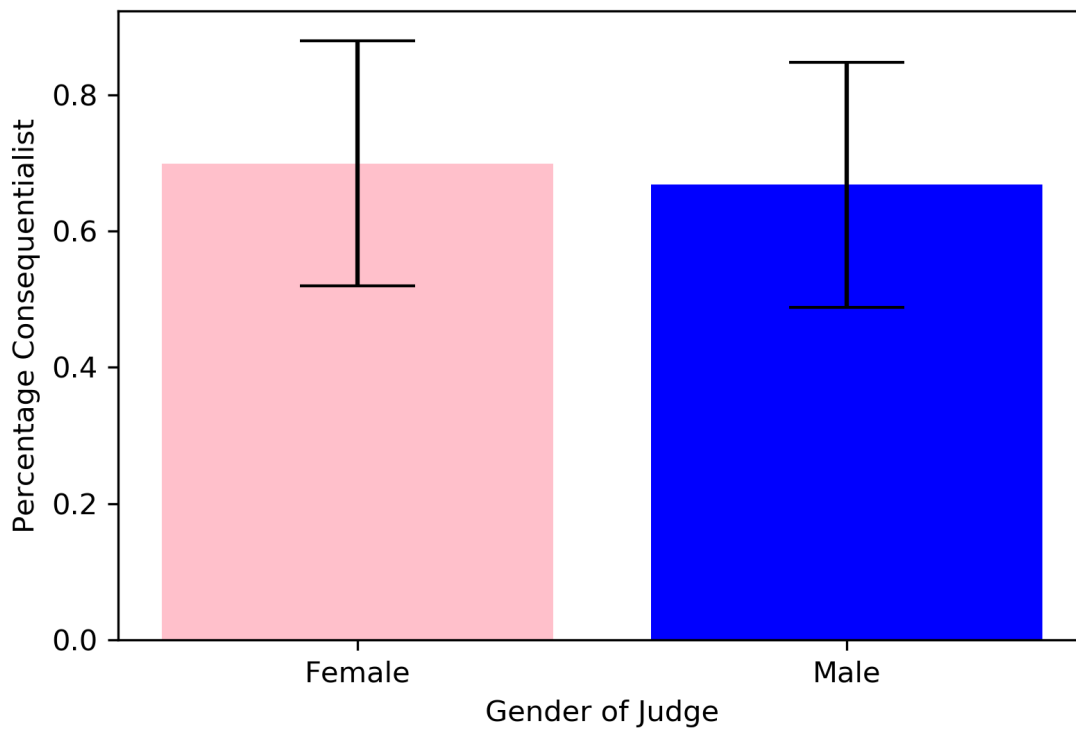


Figure 3: Consequentialist reasoning by gender

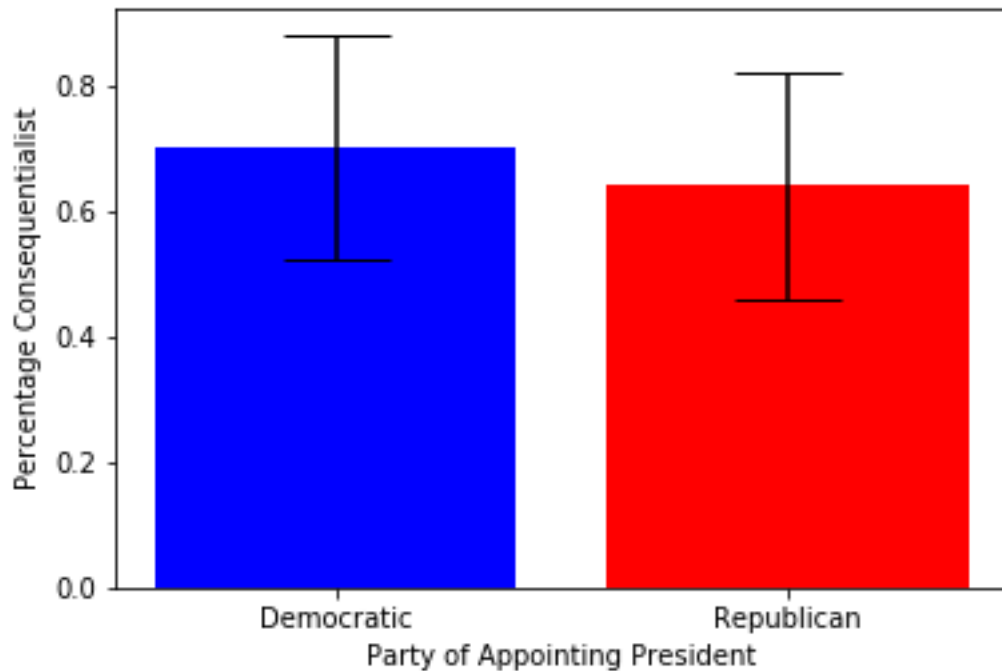
Table 2 has the most deontological judges. Table 3 has the most consequentialist judges. We can see that this appears to be driven by judge cohorts and time effects. Interestingly, the most consequentialist judge, Neil Gorsuch, was recently promoted to the U.S. Supreme Court.

3.4 Moral Reasoning and Judge Characteristics

Here we look at what biographical characteristics of judges are associated with the use of more consequentialist versus deontological language.

First, we show in Figure 3 that there seems to be very little difference across gender in moral reasoning. While, it appears that females are more likely to reason consequentially, the difference is too small to be a reliable signal. This is also likely due to more female judges being in office in later years, after the upward shift.

Figure 4: Consequentialist reasoning by Political affiliation



Next, we ask in Figure 4 whether political party affiliations matter for modes of reasoning. There appears to be almost no difference in consequentialist reasoning across party affiliations of the President who appointed the judge.

Another factor determining differences across judges in the mode of reasoning is their legal training. Are there differences between judges that come from different law schools? To answer this question we took the average use of consequentialism for the judges trained at each law school and then ranked them. This ranking is reported in Table 1, along with the percentage difference of that school from the global average. So, for example judges who attended law school at Washington and Lee are on average reason consequentially about 20% less often than the average judge. There are large differences by law school attended.

Table 3: Ranking of Judge Consequentialism by Law School Attended

School	Percentage
Washington and Lee University School of Law	-19.6
University of North Carolina School of Law	-9.9
University of Wisconsin Law School	-9.5
University of Oxford	-3.5

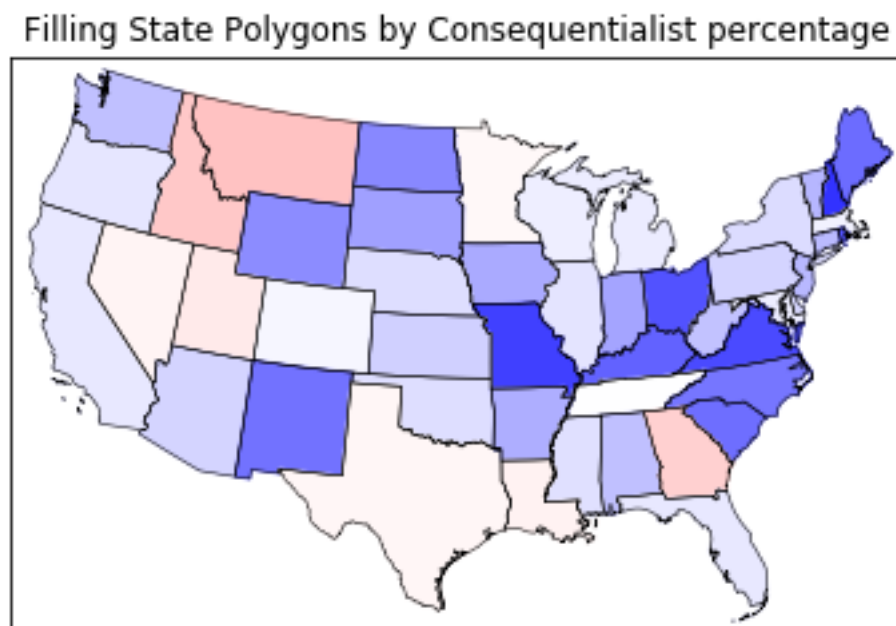
School	Percentage
University of Nebraska College of Law	0.5
St. Louis University School of Law	1.2
University of California, Berkeley	1.7
New York University School of Law	2.3
Columbia Law School	2.8
Cornell Law School	3.1
Syracuse University College of Law	3.6
Fordham University School of Law	4.0
University of Arkansas School of Law	4.3
University of Alabama School of Law	4.5
Harvard Law School	5.9
George Washington University Law School	5.9
Notre Dame Law School	6.0
Northwestern University School of Law	6.1
University of Utah College of Law	7.2
University of Washington School of Law	7.4
University of Southern California Law School	7.6
University of Virginia School of Law	7.8
Louisiana State University Law School	8.4
Yale Law School	8.4
University of Minnesota Law School	8.5
University of Chicago Law School	9.6
Tulane University Law School	9.6
University of Texas School of Law	11.1
University of Mississippi School of Law	11.7
University of Montana School of Law	11.7

School	Percentage
Stanford Law School	12.1
Georgetown University Law Center	17.2

Rankings of judge schools by consequentialism. Only includes law schools where at least 1000 opinions by attendees are included in the data set.

Perhaps moral reasoning style is determined by where one grew up as well as where one attended law school. In Figure 5, we look at differences by birth state. We find that judges from coastal states seem to have a relatively deontological leaning.

Figure 5: Consequentialist reasoning by state. Red corresponds to highly consequentialist states, blue corresponds to highly deontological states.



4. Conclusion

Utilitarian vs. Deontological modes of reasoning is a classic divide in moral philosophy and in economics and law. To understand human values, AI systems will likely need to be able to detect and annotate when an argument is utilitarian or deontological. This paper has demonstrated the use of computational linguistics and machine learning techniques for the problem of classifying moral reasoning in written texts. We show that even a small corpus of training articles works can be utilized to reasonably infer patterns of moral reasoning. Such tools can then be used to help understand the practice of law.

That said, we must caution against interpreting these results too strongly. How people reason, morally and otherwise, is always difficult to infer. Oftentimes the reasoner herself cannot correctly identify how they came to some conclusion. To do so from an outside perspective presents even more of a challenge.

Machine learning techniques are far from able to engage in the sophisticated and robust patterns of inference and reasoning that humans exhibit. Current machine learning techniques should be understood as effective but limited, essentially statistical methods that can be used to draw insights from data. This work demonstrates how these techniques might be used to try and answer especially difficult questions in law and elsewhere. We think that the major conclusions suggested by our classifier are reasonable. It's difficult to assess how accurate the more specific findings might be.

There is room for plenty of future work. One approach might be to classify assignments of obligations and authority: e.g., “the right is vested in party 1”, “party 1 has the right”, “the duty is assigned to party 1”, “party 1 must”, etc., or to classify conditional language: “if A, then B” constructions. Another could be to observe whether economics-trained judges use different features of defendants consistent with cost-benefit analysis when obtaining sentences. A larger corpus of training data could be obtained, for example, by hand labelling instances of judges reasoning in a specific way in court opinions. Topic modeling and dimensionality reduction should be further pursued in order to better understand how different populations reason morally.

References

[1] Hirschberg, J., and C. D. Manning. “Advances in Natural Language Processing.” *Science*, vol. 349, no. 6245, 2015, pp. 261–266.

[2] Sinnott-Armstrong, Walter. "Consequentialism", The Stanford Encyclopedia of Philosophy (Winter 2015 Edition), Edward N. Zalta (ed.), URL = <https://plato.stanford.edu/archives/win2015/entries/consequentialism/>.

[3] Alexander, Larry and Moore, Michael. "Deontological Ethics", The Stanford Encyclopedia of Philosophy (Winter 2016 Edition), Edward N. Zalta (ed.), URL = <https://plato.stanford.edu/archives/win2016/entries/ethics-deontological/>.

- [4] Fishkin, James, et al. "Moral Reasoning and Political Ideology." *Journal of Personality and Social Psychology*, vol. 27, no. 1, 1973, pp. 109–119.
- [5] Graham, Jesse, et al. "Liberals and Conservatives Rely on Different Sets of Moral Foundations." *Journal of Personality and Social Psychology*, vol. 96, no. 5, 2009, pp. 1029–1046.
- [6] Emler, Nicholas, et al. "The Relationship between Moral Reasoning and Political Orientation." *Journal of Personality and Social Psychology*, vol. 45, no. 5, 1983, pp. 1073–1080.
- [7] Sagi, Eyal, and Morteza Dehghani. "Measuring Moral Rhetoric in Text." *Social Science Computer Review*, vol. 32, no. 2, 2013, pp. 132–144.
- [8] Haidt, Jonathan, and Craig Joseph. "Intuitive Ethics: How Innately Prepared Intuitions Generate Culturally Variable Virtues." *Daedalus*, vol. 133, no. 4, 2004, pp. 55–66.
- [9] Joachims, Thorsten. Text categorization with Support Vector Machines: Learning with many relevant features. In: Nédellec C., Rouveirol C. (eds) *Machine Learning: ECML-98*. ECML 1998. *Lecture Notes in Computer Science (Lecture Notes in Artificial Intelligence)*, vol 1398. Springer, Berlin, Heidelberg
- [10] Posner, Richard A. "Legal Formalism, Legal Realism, and the Interpretation of Statutes and the Constitution," *Case Western Reserve Law Review* vol. 37, no. 2 (1986-1987): p. 179-217.

5. Appendix

We can rank different legal topics by the percentage of opinions written within the topic that are labelled consequentialist:

Table 4: Topics with Consequentialism Score. Scores are a percentage of the opinions in that category that were classified consequentialist.

Topic	Percentage
Wills, Trusts & Estates	44.7
Negotiable Instruments	50.2
Torts	52.6

Topic	Percentage
Real Property	54.0
Admiralty & Maritime	54.9
Native Peoples	56.7
Judicial Ethics & Conduct	57.1
Natural Resources	57.7
Mortgages & Liens	58.0
Real Estate Investment Truts	58.6
Damages & Remedies	58.8
Landlord & Tenant	59.1
Debtor Creditor	60.1
Bankruptcy Law	60.4
Alcohol & Beverage	61.2
Motor Vehicles & Traffic Law	61.5
Legal Malpractice	61.9
Personal Property	62.3
Eminent Domain	62.6
Corporate Law	62.7
Entertainment Law	63.3
Contracts	63.8
Professional Responsibility	64.9
Civil Procedure	66.1
Civil Rights	66.3
Medical Malpractice	66.6
Agency	66.7
Criminal Law	66.8
Mergers & Acquisitions	67.1

Topic	Percentage
Class Actions	67.6
Transportation Law	68.5
International Trade Law	68.5
International Law	68.8
Art Law	68.9
Appellate Procedure	69.0
Government	69.5
Constitutional Law	69.7
Prisoners' Rights	69.9
Partnerships & Non-Corporate Business Entitites	70.1
Insurance Law	70.5
Employee Benefits	70.6
Postal Service Law	71.6
Alternative Dispute Resolution	72.0
Habeas Corpus	72.8
Gambling & Lotteries Law	72.9
Workers' Compensation	73.2
Elections & Politics	73.7
Securities Law	74.1
Employment Law	74.5
Franchise Law	74.5
Banking & Finance	74.6
Land Use Planning & Zoning	74.8
Uniform Commercial Code	75.2
Evidence	75.2

Topic	Percentage
Environmental Law	75.7
Products Liability	75.7
Agricultural Law	75.9
Government Employees	76.0
Copyright Law	76.1
Military Law	76.2
Consumer Law	76.5
Patent Law	76.7
Education Law	76.8
Construction Law	77.0
Tax & Accounting	77.5
Professional Corporations	77.8
Antitrust & Trade	77.8
Immigration & Naturalization	77.9
Trade Secrets	78.6
Trademark Law	78.8
Intellectual Property Treaties & Conventions	79.2
Conflict of Laws	79.2
Executive Compensation	80.0
Communications & Media	80.3
Religious & Non-Profit Organizations	80.9
Hazardous Material Law	81.3
Health Law	81.7
Government Contracts	81.9
Privacy & Information Law	82.1
Sports Law	82.6

Topic	Percentage
Homeland Security	83.3
Social Security	83.4
Administrative Law	84.6
Labor Law	84.6
Energy Law	92.3
Technology Law	93.9