Conflict Analytics: When Data Science Meets Dispute Resolution

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Dispute settlement is fundamentally about "bargaining in the shadow of the law,"[4] where lawyers resolve disputes by speculating on what would happen if a court were to decide the matter. Evaluating how a case maps onto the existing set of published historical court decisions is a challenging task, insofar as a legal issue can be shaped by hundreds (or thousands) of judicial factors. Recent progress in data science and artificial intelligence (AI) has helped develop predictive tools capable of determining how courts will rule a specific legal issue[5] and the odds of winning a case.[6]

Data science is exerting a substantial influence on most industries. Law and dispute resolution are not immune from this transformational change. Data science and AI are starting to affect various aspects of dispute resolution, including tasks that historically relied on human judgment, such as predicting court outcomes.[7] Data science has the potential to improve legal transparency, make dispute resolution more efficient, and increase access to justice; but at the same time will challenge the traditional functioning of the legal industry and the way disputes are negotiated and resolved.

This article does not intend to present a comprehensive overview of data-driven methods used in dispute resolution. Instead, it focuses on the use of analytics to both legal and non-legal disputes, including customer, insurance, trademark, and employment disputes. First, we explore the ways in which data science is likely to influence the practice of law. Many areas of dispute resolution will be affected – legal search, document generation, and prediction of case outcomes.[8] We mainly focus on how data science can help pursue a data-driven negotiation strategy, notably by assessing the merit of a legal case but also on how to optimize dispute resolution processes based on past negotiated outcomes.[9] Second, we assess the current limitations of data science research in the legal field, and the fact that many legal questions are not always predictable. Furthermore, we argue that in order to produce accurate results, data-driven models must be trained using both legal and negotiation data, as opposed to only legal data. Making predictions solely based on legal precedent will likely produce inaccurate results and undesired biases as most disputes are resolved via negotiation, and hence unobserved in the data. Finally, we explore cutting-edge innovation in AI

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[4] R. Cooter, S. Marks and R. Mnookin, "Bargaining in the Shadow of the Law: A Testable Model of Strategic Behavior" (1982) 11 The Journal of Legal Studies 225.

[5] For a comprehensive overview of legal technology see, N. Lettieri, A. Altamura and D. Malandrino, "The Legal Macroscope: Experimenting with Visual Legal Analytics" (2017) 16 Information Visualization 332.

[6] J. G. Conrad and L K. Branting, "Introduction to the Special Issue on Legal Text Analytics" (2018) 26 Artificial Intelligence and Law 99; M. Dunn et al., "Early Predictability of Asylum Court Decisions", Proceedings of the 16th Edition of the International Conference on Articial Intelligence and Law (ACM 2017), accessed July 2019. Several companies have broken new grounds by using cutting-edge analytics to make legal predictions based on precedents (LexMachina by Lexis, BlueJ Legal).

[7] B. Alarie et al., "How Artificial Intelligence Will Affect the Practice of Law" (2018), 68 University of Toronto Law Journal 106.

[8] We mainly focus on case prediction which has become an extensive area of research and has raised a significant interest from practitioners.

[9] To our knowledge, this area is under-researched as most legal technology firms focus mainly on legal data. While this is understandable given that legal data is publicly available, case law represents only the tip of the iceberg insofar as most disputes are resolved via negotiation.

research. Specifically, we discuss deep-learning models for law and negotiation that aim to develop a comprehensive dispute resolution system capable of understanding legal concepts.

1. Analytics: A Game-Changer for Dispute Resolution

Recent advances in data science have created unprecedented opportunities for lawyers and litigants to approach the task of dispute settlement differently, notably by moving from a speculative strategy to a data-driven strategy. AI has the potential to shed light on how legal decisions are made and to improve the consistency (and predictability) of judicial decisions.[10] As mentioned, leading legal technology companies, including Lex Machina, BlueJ Legal, and Ross,[11] have used analytics to develop predictive tools capable of determining how courts will rule on a specific legal issue and the odds of winning a case. Once the facts relevant to the case are identified, an algorithm can situate these facts within the domain of applicable legal precedents and predict what a court would decide if the negotiation were to fail. This constitutes a significant advance for the legal field given that determining litigation outcomes is key in helping litigants decide whether they should settle or litigate–that is, in negotiation terms, to identify their Best Alternative to a Negotiated Agreement (BATNA).[12]

However, using analytics and natural language processing (NLP) methods for dispute resolution is not possible for every dispute, especially when there is no case law or when the court's determination of a legal question does not lend itself to an identifiable set of factors. Even when it is possible, using analytics in the legal field is often challenging because law and negotiation texts are unstructured data. In fact, while most judgments follow a structured template – recitation and application of facts – they vary considerably from one another. If the data is not structured properly, machine-learning algorithms may yield inaccurate results. Transforming unstructured legal data to structured data is a research-intensive endeavour that requires significant computing power along with a skilled team of researchers in law, operations research, and computer science.[13]

Several leading research institutions such as CodeX at Standford Law, Cyberjustice at the University of Montreal, SMART law at HEC Paris, the Tilburg Institute for Law, Technology, and Society, and the Conflict Analytics Lab (CAL) – have also engaged in data analytics research. It is important to note that these institutions have mainly focused on using technology to improve access to justice or have undertaken a more theoretical agenda. The Conflict Analytics Lab (CAL), a Canadian-based consortium of academic institutions and industry partners hosted at Queen's University Smith School of Business, has undertaken a slightly different endeavour: applying analytics to dispute resolution. The CAL started with an open-source prediction project for employment, insurance, and antitrust litigations including: (1) trademark risk of confusion, (2) personal injury, (3) calculation of employment notice, and (4) determining whether a worker is an employee or an independent contractor. The consortium has also worked on the development of a prototype AI-powered tribunal platform for small claims in Canada.[14] The pilot platform aims to offer a pre-trial analytics system to help guide self-represented litigants at the outset of the process. Users first answer a set of questions regarding their circumstances. Then, the system analyzes past relevant cases and negotiation agreements to provide a tailored prediction regarding how a court is likely to resolve the dispute.

While these innovations have already significantly affected the practice of law, more advanced AI research is on its way. It can be argued that advanced analytics, if adopted by litigants, will radically alter pre-trial

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[10] R. Guimerà and M. Sales-Pardo, "Justice Blocks and Predictability of U.S. Supreme Court Votes" (2011), Plos One.

[11] Note that several European startup companies offer similar products, including Predictice and Doctrine,fr.

[12] R. Fisher et al., "Getting to Yes: Negotiating Agreement without Giving In" (Houghton Mifflin Harcourt 1991).

[13] For detailed explanations on how unstructured legal data are transformed to structured data, and how NLP and machine learning are used to make predictions, see Alarie, Niblett and Yoon (n 3) 118–119; S. Dahan et al., "Predicting Employment Notice Period with Machine Learning: Promises and Limitations" (2020), Working paper.

[14] "Putting the AI in Legal Aid" (*Queen's Gazette*, 2019) <https://www.queensu.ca/gazette/stories/putting-ai-legal-aid> accessed Nov. 2019.

strategies. For instance, it is possible to predict how a specific judge might rule on a summary judgment motion or which argument a judge on the bench may find the most persuasive. Such predictions can be critical for the outcome of a trial.[15] Consider for example, a case in which the European Commission may fine a company for several millions or billions of euros for anticompetitive practice. If the litigant brings an appeal before the European Union's Court of Justice and the case is assigned to a Chamber of the Court whose historical data suggest a strong confirmation bias towards the Commission's decision, it is reasonable to reconsider moving forward with the litigation. The use of such data to inform pre-trial strategies may ultimately become standard practice in the legal industry. That said, while the prospect of applying AI methods to the legal field has raised high expectations, it has also raised concerns, notably regarding the reliability and explicability of predictions.[16]

2. New Frontiers in Negotiation and Legal Language Modeling

In this section, we first discuss the limitations of AI applications in dispute resolution. Particularly, we highlight the fact that many legal questions that could potentially benefit from AI are not always predictable. We then argue that making predictions solely based on past legal precedents can produce inaccurate predictions. Indeed, legal data constitute only the tip of the judicial iceberg, as most disputes are resolved via negotiation.[17] Finally, we explore how more modern techniques, such as deep learning, can help mitigate the limitations of traditional machine-learning methods.

2.1. Predictability and Consistency of Legal Outcomes

While analytics has produced successful results when it comes to gaining insight into judges' preferences or opposing counsel's strategy, in many instances it cannot (and should not) yield a perfect prediction. This does not mean that predicting legal outcomes with high accuracy is not possible in some cases.[18]

In many cases, however, predictive models produce modest results – but can still be useful for gaining insight into judicial trends and delivering value to human decision makers. For instance, the question of Employment Notice – that is, how much of a notice period an employee should receive in case of work termination – is a difficult outcome to predict. A recent study shows that machine-learning algorithms can predict the actual notice period with an average error of 2.79 months (with a standard deviation of 2.2), and with 75% of accuracy.[19] Namely, it is hard to predict exactly how much notice an employee will receive. Consider the simplified example of an employee who worked for a duration of ten years. A typical notice for such a case lies between 8 and 11 months. The crucial question is thus whether a judge will choose 8 or 11 months and based on which attributes. In that regard, analytics cannot really help, given that each case is very specific.

In the same vein, limitations in the predictive power can be partially explained by the approximative and inconsistent application of the relevant judicial factors, and perhaps by the influence of external factors such as personal attributes (e.g., age, gender). Considering that predictive analytics learns from previous cases, if the judges did not weigh attributes consistently, it is hard to make a perfect prediction, and little

[15] G. Carothers et al., "Legal Analytics Based on Party, Judge, or Law Firm"; J. Dixon, "Review of Legal Analytics Platform" Litigation World (2016).

[16] D. Chen, "How Artificial Intelligence Can Help Us Make Judges Less Biased" *The Verge* (2019).

[17] American Bar Association, "How Courts Work" (2019), https://www.americanbar.org/groups/public_education/resources/law_related_education_network/how_courts_work/cases_settling/

[18] For example, the working paper B. M. Tehrani et al., "Independent Contractor vs Employee: Worker Classification with Machine Learning" (2020) predicts whether a worker is an employee or an independent contractor with more than 90% accuracy.

[19] S. Dahan et al., "Predicting Employment Notice Period with Machine Learning: Promises and Limitations" (2020), Working paper.

correlation will be found among these attributes. Predictive models cannot be more accurate than the accuracy of the datasets that underlie them.

While AI can be used to generate predictions of case decisions, it can also be used to search for inter-judge disagreements and to reduce the number of undetected disagreements. This is quite relevant insofar as consistency of case law is a prerequisite to legal certainty, a central component of the concept of the Rule of Law.[20] The principle of legal certainty is an essential aspect of many legal systems as it strongly contributes to public confidence in the court system. Conflicting court decisions, especially at the appellate-court level, can trigger breaches of the due process requirement, as observed by the European Court of Human Rights, “justice must not degenerate into a lottery.”[21]

That said, moderate predictability and a certain level of inconsistency do not necessarily signal unfair judicial decision making. In fact, evidence suggests that some level of inconsistency is inevitable as it constitutes an inherent component of most judicial processes. While general rules, either imposed through legislation or precedent, aim to protect against inconsistency in decision making, these rules are often poorly suited for application.[22] For instance, the process of determining reasonable notice – or any other complex legal issue – is far from being a science. While it can be argued that notice should be sufficiently predictable, “there is no right and exact figure.”[23] In Canada, for example, judges need to consider the Bardal factors[24] and then decide “what appears to be logical, judicious, fair, equitable, sensible, and not excessive” according to the presiding judge. Actually, research on notice calculation does not show striking evidence of systematic bias in decision making, that is, instances in which the outcome of a case depends on factors unrelated to its merits.

As such, one may argue that predicting legal outcomes such as the notice period with 75% accuracy is not only tolerable, but it also suggests a judicial system that strikes a good balance between predictability and flexibility: it is sufficiently flexible to adapt to the specific circumstances of a case, while being mostly driven by legally relevant variables. While legal certainty is essential to the Rule of Law, a judicial system that is too predictable is overly ambitious and suggests the existence of a rigid status quo. This may be problematic, especially if the status quo is unfair or if the decision making is heavily influenced by extraneous factors that seem inequitable. Another consideration is that data-driven models are inherently backward looking: using statistical predictions of past decisions to inform future decisions necessarily tethers future decisions to the status quo. This tethering to the past may be problematic if past decisions become incompatible with current values. Similarly, making future decisions exclusively based on historical data can create and accentuate systematic errors that will ultimately lead to unfair outcomes, such as favoring a specific group of individuals. This bias has recently been addressed in the 2018 European Union's General Data Protection Regulation (GDPR).[25]

Furthermore, while advanced algorithms can help predict the big picture, it would be surprising if they could predict exact figures (e.g., with 90% accuracy within +/- 1 week), as long as judges have sufficient flexibility to adapt their decisions to specific situations. It may also be argued that AI algorithms should not aim to predict every aspect of a judicial decision, as this may crystallize the status quo and stall case-law development. If the status quo happens to be unfair, this would be highly problematic. But even if the status

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[20] The principle of legal certainty is implicit in all the articles of the European Convention on Human Rights and constitutes one of the basic elements of the rule of law; see Beian v. Romania (No. 1), 30658/05, judgment of 6 December 2007, para. 39.

[21] Şahin and Şahin v. Turkey, 13279/05, judgment of 20 October 2011, Joint dissenting opinion para. 17.

[22] C. R Sunstein, "Problems with Rules" (1995) 83 Calif. L. Rev. 953.

[23] Minott v. O’Shanter Development Company Ltd. (1999), 168 DLR 4th 270 (Ont. CA), at para. 62.

[24] http://www.bardalfactors.ca/whats-reasonable

[25] https://eur-lex.europa.eu/eli/reg/2016/679/oj

quo is fair, changes in society may trigger the need for a new precedent or an adaptation of the law to societal changes. This phenomenon is coined as bridging the gap between law and society.[26]

This discussion leads to another important question: Are legal precedents the right data to predict the outcome of a dispute? Having access to a data-driven system that helps anticipate litigation outcomes can be essential to mitigate the cost and emotional stress of legal proceedings. As mentioned, however, making predictions solely based on legal data can only provide a partial representation since most disputes are resolved via negotiation.

2.2. Negotiation Analytics: Learning from the Full Picture

To our knowledge, cutting-edge data science and AI research have not yet explored pre-trial settlement and negotiation agreements in the judicial context.[27] The current research paradigm is mainly concerned with clearly defined areas of law, such as tax and patent law, areas where data is openly accessible.

In light of these observations, several researchers have undertaken the task of developing intelligent negotiation systems for consumer and insurance disputes. These systems are not only based on legal trends but also on negotiation data. This unconventional marriage of law, negotiation, and data science aims to address the problem that many organizations face by conducting negotiations based on intuitive and speculative strategies. Negotiators are often unable to capitalize on the negotiation precedents relevant to the specific issue at stake. Accordingly, there is an opportunity to develop data-driven models that would rely on traditional similarity mechanisms.[28] Drawing from a large dataset of negotiation precedents, once a new dispute situation is presented, the algorithm will search for the most similar past situation. The retrieved agreement is then adapted to the present conflict, since the rationale behind this heuristic is that similar conflict situations should yield similar outcomes.

One example is the New York No-Fault insurance arbitration administered by the American Arbitration Association (AAA) to handle reimbursement disputes for medical expenses in the wake of motor vehicle accidents.[29] In this caseload, medical service providers and insurance companies can resolve disagreements around appropriate reimbursement amounts for medical treatments delivered in the context of automobile accidents. In order to divert these cases from the New York courts (where they took on average 3-5 years to resolve), the New York state insurance regulator created an expedited online resolution process administered by AAA, to resolve these cases through negotiation and arbitration (where resolution takes on average 3-5 months). All of the redacted awards delivered under this framework are available and full-text searchable, and the data is structured by arbitrator, date, and issue type.[30] Some of these cases are resolved via negotiation (called “conciliation” in the process design) whereas others are decided by arbitrators in expedited (15-30 minute) hearings. Because of the consistency of each case type and the structured data generated by the administrative platform, this caseload is promising for training algorithms to recognize patterns in new cases, apply rules gleaned from closed cases, and predict an appropriate resolution.

The application of data science to non-legal data and especially dispute settlement will significantly disrupt the way in which small-claims disputes are resolved – such as, consumer disputes in the banking, hospitality, and airline industries – as well as how to approach customer service more generally. This is particularly important, as most consumer issues are resolved via negotiation. In other words, this research

[26] A. Barak, "The Judge in a Democracy" (Princeton University Press 2009).

[27] J. Zeleznikow, "Can Artificial Intelligence and Online Dispute Resolution Enhance Efficiency and Effectiveness in Courts" *IJCA* (2016) 39–40.

[28] M. S. Abdel Wahab et al., "Online Dispute Resolution: Theory and Practice: A Treatise on Technology and Dispute Resolution" (Eleven International Pub 2012) 342; K. P. Sycara, "Machine Learning for Intelligent Support of Conflict Resolution" (1993) 10 Decision Support Systems 121; V. Julián et al., "Agreement Technologies for Conflict Resolution", Interdisciplinary Perspectives on Contemporary Conflict Resolution (2016); I. Marsa-Maestre et al., "From Problems to Protocols: Towards a Negotiation Handbook" (2014) 60 Decision Support Systems 39; Zeleznikow (n 8).

[29] https://aaa-nynf.modria.com/, accessed December 2019.

[30] https://aaa-nynf.modria.com/loadAwardSearchFilter, accessed December 2019.

could transform our understanding of how parties negotiate within “the shadow of the law.” For example, iCan Systems, an electronic negotiation specialist, became the first company to resolve a dispute in a public court in England and Wales using a “robot mediator.”[31] A second example is the Chinese company iFlytek who is developing an AI-enabled system to assist courts in judging criminal cases. A third example is the high volumes of eCommerce disputes in online marketplaces like eBay. eBay’s Resolution Center now resolves more than 60 million disputes per year, all without relying on the courts or legal precedent.[32] This high volume of cases has enabled eBay to develop a heuristic approach that helps customer service representatives identify the appropriate solution for each case. eBay’s data-driven resolution process, informed by analysis of hundreds of millions of closed disputes, guides cases into appropriate resolution pathways, providing less expensive and more efficient (and scalable) redress. For example, the use of clustering helps to triage incoming caseloads by classifying the different types of conflicts based on historical data. In addition, algorithms can learn a customer’s needs and preferences by searching and identifying similar other customers (e.g., using collaborative-filtering methods). eBay is also increasingly relying on chatbots leveraging natural language processing, so that customers will be able to find the appropriate resolution pathway within seconds. Using these approaches, eBay can resolve more than 50% of its annual dispute caseload by mutual agreement between the parties, and 90% of cases are resolved via algorithms, meaning that no human employee from eBay has to touch the case to be resolve it.[33]

2.3. Analytics 2.0: Generalized Intelligence for Dispute Resolution

AI researchers interested in dispute resolution and language modeling have already attempted to tackle more complex problems, such as assessment of similarity in trademark law. By using cutting-edge deep learning models, they could overcome the limitations of basic machine-learning models and create a more powerful, intelligent system for dispute resolution. We are referring here to a system that would supplement existing machine-learning models with a comprehensive understanding of legal reasoning and dispute resolution processes.[34]

Early iterations of machine-learning models lacked the necessary computational power to learn difficult tasks. These models typically require exhaustive feature engineering and human intervention to pre-process the data into meaningful representations.[35] The predictive power of these systems have become dependent on how well humans could extract the useful information and convert it into a machine-readable format such as a vector. In addition, machine learning typically works well in recognizing patterns hidden in large datasets but is often less successful when it comes to logical reasoning. In the context of dispute resolution, machine-learning algorithms often fail to capture the nuances or underlying sentiments of individual cases which are essential for an accurate legal analysis.

Fortunately, in the early 2010s, the introduction of deep learning led to an explosion of AI research that allowed machines to automatically and efficiently extract attributes from raw inputs. Without the reliance on human-extracted representations, deep learning allowed machines to self-learn the entire prediction process. At a high level, deep learning aims to simulate the human thinking process by adding multiple layers of abstraction to learn a task along with its underlying structure. Expressing a person’s case as a structured input fails to capture the minute details of the case, reducing its elements to mere statistics. Deep

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[31] K. Beioley, "Robots and AI Threaten to Mediate Disputes Better than Lawyers" *Financial Times* (2019).

[32] C. Rule and A. Schmitz. “The New Handshake: Online Dispute Resolution and the Future of Consumer Protection” American Bar Association, 2018, page 37.

[33] L. Del Duca, C. Rule, and B. Cressman, "Lessons and Best Practices for Designers of Fast Track, Low Value, High Volume Global eCommerce ODR Systems," (6 Y.B.Arb. & Mediation 204) at the 17th Biennial Meeting of the International Academy of Commercial and Consumer Law held in July 2014 at the Istanbul Bilgi University, Turkey.

[34] G. Olano, "Queen’s Law Partners with European Business School for AI Project" (*Law Times*, 2019).

[35] Y. LeCun et al., "Deep Learning" (2015) 521 Nature 436.

learning, on the other hand learns its own features, automatically determines what is important, and can be trained on an unstructured input of raw text — often discovering latent information.

Researchers at the Conflict Analytics Lab have attempted to train a deep-learning model for law and negotiation. This research will build on cutting-edge existing technology in the area of natural language processing. In particular, it relies on Google Bidirectional Encoder Representations from Transformers (BERT). BERT models code broke several records for difficult language-based tasks, such as predicting the missing words in a corpus in which 15% of the words are masked. Using BERT, one can extract high-quality legal language features from query text data and fine-tune BERT for a specific legal task (e.g., classification) to produce state-of-the-art predictions. Specifically, one promising direction is to fine-tune BERT for legal and negotiation text and create a Generalized Intelligence in Dispute Resolution with Bidirectional Encoder Representations from Transformers (GIDBERT).

One important requirement for deep learning to be successful is that the model requires significant volumes of data. As a result, CAL's researchers have trained a model on a large corpus of legal and negotiation text, which comprises the entire corpus of European and American case law, academic papers, textbooks, legislation, and even Talmudic law. The idea is to feed the model massive volumes of legal and negotiation data so that GIDBERT can train itself and identify existing patterns in law and negotiation.

Note that GIDBERT does not work on its own; it complements pre-existing models trained on annotated data. In particular, it helps increase prediction power. It works by filling in the gaps when faced with new legal facts and using the legal cases and texts it has been trained on. For example, GIDBERT would know that in the phrase "the plaintiff _______ the case," the missing word is likely "appealed."

3. Conclusion

We discussed how data science and AI can help lawyers and litigants to predict legal outcomes, including the recent work on employment, customer, and insurance disputes. We also explored the current limitations of machine-learning models in the legal field, especially the limited predictability of legal outcomes. Finally, we reviewed potential avenues to overcome the limitations of traditional machine-learning research and eventually boost the predictive power of data-driven models. We argued that making predictions based only on legal data can be problematic and may produce inaccurate predictions, since legal data are not a good representation of the way that most disputes are resolved. Finally, we briefly mentioned some of the recent advances at the intersection of deep learning and law.

In addition to a transformative impact on the judicial system, advances in the application of AI to law and negotiation could significantly transform the way we understand dispute resolution. For instance, modeling settlement agreements along with court judgments can improve predictions even further. It would also highlight the points of discrepancy between settlement agreements and court decisions, as well as shed light on the extent to which certain biases may affect judicial decisions. Finally, it may help reveal whether some groups of individuals receive better settlement agreements than others, hence improving fairness and equity.

We expect AI research to also open a new frontier in identifying causal relationships and counterfactual reasoning, a core problem in data science and economics. It will be especially impactful if the learning models can be sufficiently advanced to understand judicial texts and reasoning. We hope that it may contribute to the development of semantic representations of reasoning, particularly because causality and counterfactual reasoning are critical components of legal and negotiation data.