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Predicting Chapter 11 Bankruptcy Case Outcomes Using the Federal Judicial Center IDB and Ensemble Artificial Intelligence

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PREDICTING CHAPTER 11 BANKRUPTCY CASE OUTCOMES USING THE FEDERAL JUDICIAL CENTER IDB AND ENSEMBLE ARTIFICIAL INTELLIGENCE

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INTRODUCTION

Over 100,000 Chapter 11 bankruptcy cases were filed in the United States over the ten-year period from 2008–2017.[1] These cases represent a cross section of society; from large, public corporations to small mom-and-pop stores to individuals trying to work out real estate investments.[2] Regardless of whether the filer was a corporation or an individual, a large entity or a small business, each case shared a common goal—to use the provisions of Chapter 11 of the United States Bankruptcy Code to reorganize its assets, operations, and financial affairs and hopefully return to profitability.[3] Despite large investments in judicial resources, more than half of these cases failed to achieve their goals.[4]

Understanding how a case is likely to end has very real value for practitioners. Chapter 11 bankruptcy cases almost always resolve in

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1. This information was calculated using data obtained from the Federal Judicial Center, downloaded from its Integrated Database at https://www.fjc.gov/research/idb/interactive/IDB-bankruptcy. *See also Statistics From Epiq Systems*, AM. BANKR. INST., https://www.abi.org/newsroom/bankruptcy-statistics [https://perma.cc/WF6E-UYXT] (last visited Feb. 22, 2019).

2. Edith H. Jones, *Chapter 11: A Death Penalty for Debtor and Creditor Interests*, 77 CORNELL L. REV. 1088, 1088–89 (1992).

3. *Id.*

4. *Id.* At one point, only 10% of Chapter 11 cases resulted in confirmed plans of reorganization. *Id.* More recent studies show a confirmation rate between 30% and 33%, depending on the sample. Elizabeth Warren & Jay L. Westbrook, *The Success of Chapter 11: A Challenge to the Critics*, 107 MICH. L. REV. 603, 615 (2009). Our analysis of ten years of case data taken from the IDB suggests a confirmation rate of up to 45%, although this statistic is qualified by the caveat that confirmation of a Chapter 11 plan must be inferred when using the IDB. S*ee Statistics From Epiq Systems*, *supra* note 1.

one of three ways. Some cases end up dismissed by the court.[5] Others end up converted into Chapter 7 cases, where operations cease, and assets are liquidated for distribution to creditors.[6] The remaining cases achieve some level of success: either obtaining confirmation of a plan of reorganization or managing to operate under the protection of Chapter 11 long enough to liquidate in an orderly fashion as an operating entity.[7] The attorneys, financial advisors, credit managers, and others involved in Chapter 11 cases often face difficult decisions about how to respond to these businesses in crisis.

In this project, the authors obtained public data on over 100,000 Chapter 11 bankruptcy cases and used machine and deep-learning methodologies to explore whether models could be designed to predict Chapter 11 case outcomes. The data used was obtained from the Federal Judicial Center's bankruptcy Integrated Database and included information about case filing dates, the court where the case was filed, the type of business entity, and basic information about assets and liabilities. Using this information, the authors initially sought to predict whether a particular case was dismissed, converted to another Chapter under the Bankruptcy Code, or closed with a plan. Cases that had not yet closed at the end of the dataset's period, but had been open in Chapter 11 for at least two years, were treated as viable Chapter 11 cases. Of the cases used for the project, about 55% were dismissed or converted. The authors also created models to predict between two outcomes—dismissal or conversion, as opposed to case viability.

The authors used most commonly known and reasonably applicable machine learning algorithms and deep-learning optimizers in an attempt to create a robust model. The general-purpose AI platform, Decision Options®, was utilized to explore the data and build meta-models. We achieved an accuracy of about 75% for the selected models. These results show the ability of AI systems to

5. *See* 11 U.S.C. § 1112 (2018) (governing conversion and dismissal of Chapter 11 bankruptcy cases).

6. *See* 11 U.S.C. §§ 701–84 (2018).

7. Warren & Westbrook, *supra* note 4, at 615.

predict Chapter 11 case outcomes with some level of accuracy with even limited data, exceeding baseline statistics. However, the project also highlighted the deficiencies in the data made publicly available in formats that machine learning systems can easily use and the promise of significantly better results with higher quality information.

I. Chapter 11 Bankruptcy and Potential Case Outcomes

The Chapter 11 bankruptcy process provides a mechanism for businesses and individuals to restructure their debts and other obligations using a flexible mechanism.[8] Although it is used primarily by business organizations, individuals too can seek protection from creditors using Chapter 11.[9] The primary mechanism used to reorganize is the Chapter 11 plan of reorganization. A Chapter 11 plan allows a company to restructure its debt and capital, shed undesired business arrangements and contracts, cure outstanding defaults on valuable contracts, and provide buyers of assets with protection against prior creditors.[10] Sometimes Chapter 11 cases are successful, resulting in a reorganization of business assets and debts to increase stakeholder values. Sometimes, the cases are not successful. Can the results of a bankruptcy case be predicted in advance? A small number of prior studies have addressed this question, using data on a limited number of large bankruptcy cases.

Once a Chapter 11 case commences, four possible outcomes exist. First, the Chapter 11 case may end up dismissed,[11] removing the debtor from the bankruptcy court's protection. Second, the case may be converted to a case under a different Chapter of the Bankruptcy Code—typically Chapter 7, where a trustee is appointed to liquidate the debtor's assets.[12] Both of these outcomes can generally be

8. *See* 11 U.S.C. §§ 1101–16 (2018).
9. 11 U.S.C. § 101(35) (2018) (defining the term "person"); 11 U.S.C. § 109.
10. Jones, *supra* note 2, at 1089.
11. 11 U.S.C. § 1112(b) (2018).
12. 11 U.S.C. § 1112 (2018). Generally, a business debtor cannot operate during a Chapter 7 case. *Bankruptcy: What Happens When Public Companies Go Bankrupt*, U.S. SEC. & EXCHANGE

considered a failure of the reorganization process. Third, a debtor's assets may be sold, either through confirmation of a Chapter 11 plan or through a successful sale process.[13] A sale does not necessarily evidence a failure of the Chapter 11 process; in many cases, a single buyer will purchase substantially all of the debtor's assets through an acquisition entity which then continues to operate the business. To the public, the change in ownership may be completely invisible. Fourth, the Chapter 11 plan process helps to restructure the debtor's finances, allowing the debtor to continue business operations after Chapter 11 or change ownership of the business through a merger or acquisition, with the debtor's business continuing to operate as a separate entity.

In theory, the company that can successfully restructure its finances and operations and stay in business will generate more value for its stakeholders than might be obtained from a straightforward sale of assets.[14] Although many cases result in an asset sale, assets sold out of an operating business will generally obtain better prices than assets sold out of a closed business, and an orderly liquidation obtains better results than a disorderly scramble by creditors. As a result, understanding how a particular bankruptcy case may resolve has value to everyone involved in the process.

Prior studies attempting to predict Chapter 11 outcomes have primarily sorted cases into those where the company continued as an

COMMISSION (Feb. 3, 2009) https://www.sec.gov/reportspubs/investor-publications/investorpubsbankrupthtm.html [https://perma.cc/D697-W3KK]. Typically, business operations end and any remaining assets are simply liquidated. *Id.*

13. 11 U.S.C. § 363 (2018). This sale process is referred to as a "363 Sale" and named after the section of the Bankruptcy Code used to authorize asset sales without using the Chapter 11 plan-confirmation process. *What Is a 363 Sale?*, CORP. FIN. INST., https://corporatefinanceinstitute.com/resources/knowledge/deals/363-sale/ [https://perma.cc/3G3P-YXWG] (last visited Feb. 20, 2019). In larger Chapter 11 cases, the § 363 sale is typically followed by confirmation of a plan addressing disposition of funds and handling of remaining case issues. *Id.* For smaller cases, a 363 sale might be followed by conversion to Chapter 7 to allow the Chapter 7 trustee to distribute the sale proceeds. *Id.*

14. *See* Michael Bradley & Michael Rosenzweig, *The Untenable Case for Chapter 11*, 101 YALE L.J. 1043, 1095 (1992); Robert K. Rasmussen & Douglas G. Baird, *Chapter 11 at Twilight* 1–24 (John M. Olin Program in Law & Econ. Working Paper No. 201, 2003).

operating entity post-bankruptcy and those where assets were sold.[15] This dichotomy may be dictated by the nature of the cases for which data was available: large corporations and primarily public companies. Large public-company cases rarely end up dismissed, and they rarely end up converted to a case under Chapter 7. When a large, public-company case is not successful, the result is usually an accelerated sale of assets through a Chapter 11 plan, or a series of asset sales using § 363 followed by a Chapter 11 plan that controls the remainder of the company's winding-down process.

The most useful data set for examining large-company Chapter 11 outcomes was assembled by Professor Lynn LoPucki and the UCLA School of Law. Known as the Bankruptcy Research Database (BRD), it contains information on a little over 1,000 large public company cases. In 2015, using the BRD, Lynn LoPucki and Joseph Doherty published *Bankruptcy Survival*, which sought to build a regression-based prediction model for evaluating whether a particular case would result in a continuing operating business or liquidation.[16] The study examined a subset of 634 cases from the BRD, of which 70% were classified as surviving.[17]

LoPucki and Doherty ran a series of logistic regressions[18] on about seventy variables tracked within the BRD using survival as the dependent variable.[19] Subsets of these seventy variables were tested in hundreds of combinations to ascertain the combination of variables that best correlated with corporate survival in the Chapter 11

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15. Lynn LoPucki & Joseph Doherty, *Bankruptcy Survival*, 62 UCLA L. REV. 970, 979 (2015); Jairaj Gupta & Mariachiara Barzotto, Insights on Bankruptcy Emergence (Aug. 19, 2018) (unpublished manuscript) (on file at https://ssrn.com/abstract=3216433 [https://perma.cc/P44M-BT4Q]).

16. *Id.* at 978.

17. *Id.* at 983.

18. *Id.* at 978. Logistic regression is a form of regression analysis designed to predict categorical choices, such as, in this instance, whether a particular company "survived" Chapter 11. *Id.* For more on logistic regression, see *Lesson 6: Logistic Regression*, PA. STATE EBERLY COLL. OF SCI., https://onlinecourses.science.psu.edu/stat504/node/149/ [https://perma.cc/7X4A-9RAC] (last visited Feb. 22, 2019).

19. LoPucki & Doherty, *supra* note 15, at 979. In most prediction models, a series of data points referred to as "independent variables" or "features" are used to predict the "dependent variable" or "label." *Id.* In other terms, the independent variables are the things that you know, and the dependent variable is the thing that you want to know. *See id.*

process.[20] They identified three different models that did equivalent jobs of predicting case survival. All three models contained ten independent variables:

- Whether the company provided advance notice of an intention to sell its assets;
- Whether the company's EBIT[21] was positive;
- The shareholder to equity ratio;[22]
- Whether the company was in the manufacturing sector;
- The prime rate of interest one year prior to the petition date;
- The distance between the company's headquarters and its local bankruptcy court;[23]
- Whether a plan was pre-negotiated;
- Whether a debtor-in-possession loan was obtained;[24]
- Whether a creditors' committee was appointed; and
- The size of the company in asset value.[25]

In addition to the ten variables used in all three models, one model added the log value of the judge's years of experience, one added whether the case was filed in Delaware or New York as opposed to

20. LoPucki & Doherty, *supra* note 15, at 981.

21. *Id.* at 1000. EBIT means Earnings Before Interest and Taxes, which is a measure of operational profitability. *Id.*

22. *Id.* at 1004.

23. LoPucki & Doherty, *supra* note 15, at 992. The log value of the distance was used. *Id.* at 986. The distance is calculated to the local bankruptcy court, not the court where the case was filed. *Id.* at 992. The paper suggests that the variable served as a substitute for whether the company was geographically isolated. *Id.*

24. *Id.* at 1001. A DIP, or debtor-in-possession, loan refers to specialized post-petition financing obtained to capitalize operations during the Chapter 11 process. *Debtor-In-Possession (DIP) Financing Can Help Turn a Company Around Following Bankruptcy*, PARAGON FIN. GROUP, https://www.paragonfinancial.net/how-factoring-works/articles-resources/factoring-articles/debtor-in-possession-dip-financing-company-bankruptcy/ [https://perma.cc/GYY2-FYBN] (last visited Jan. 23, 2019). A DIP loan requires court approval and typically provides greater protection for the lender than the typical non-bankruptcy lending transaction. *Id.*

25. LoPucki & Doherty, *supra* note 15, at 1008 (the log of the asset value was used).

another jurisdiction, and the third model added a variable indicating whether the judge had presided over at least six prior large cases.[26] Each model presented a pseudo-R-squared value of about .26,[27] but there was no information about each model's prediction accuracy.

The article *Insights on Bankruptcy Emergence*—proposing the use of a regression-based model to predict the likelihood of a company emerging from Chapter 11 successfully—built on the LoPucki-Doherty study and examined the correlation between a variety of variables and success in Chapter 11 cases.[28] The analysis was based on examining 401 Chapter 11 filings using data collected from the BRD, coupled with relevant financial data obtained from Compustat.[29] The created model used eight features to achieve a classification performance of 94%.[30] Relevant factors identified in this study include filing in a debtor-friendly jurisdiction, having a high asset-to-debt ratio, being outside the retail industrial business sector, replacing the CEO after filing, having a pre-negotiated or pre-packaged plan, and a high debtor-in-possession loan-to-assets ratio.[31] This study, conducted by Jairaj Gupta and Mariachiara Barzotto, also found that filers are significantly less likely to emerge from Chapter 11 intact when they announce, at the start of the case, an intent to sell substantially all assets and when a significant amount of time passes before plan confirmation.[32]

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26. *Id.* at 985, 990–91.

27. *Id.* at 986. The R-squared statistic is a measure of the relationship between the independent values used and the dependent variable. *Lesson 1.5: The Coefficient of Determination*, PA. STATE EBERLY COLL. SCI., https://onlinecourses.science.psu.edu/stat501/node/255/ [https://perma.cc/VL9K-USC3] (last visited Feb. 22, 2019). The closer the R-squared number is to one, the stronger the relationship. *Id.* An R-squared value of .26 can be interpreted as meaning that the eleven data points considered explain 26% of the variation in success outcomes. *Id.*

28. *Id.* at 2–3.

29. *Id.* at 3. Made available through Standard & Poor's, the Compustat database contains financial, statistical, and market information on active and inactive global companies throughout the world. *Fundamental Data*, S&P GLOBAL, https://www.spglobal.com/marketintelligence/en/solutions/fundamental-data [https://perma.cc/LUH6-A2DV] (last visited Apr. 9, 2019).

30. Gupta & Barzotto, *supra* note 15, at 4. The performance was measured using an AUC (area under the curve) metric. *Id.* The Gupta-Barzotto model also had a pseudo R-squared of .55, compared with the .26 metric for the LoPucki-Doherty model. *Id.*

31. *Id.*

32. *Id.* at 4–5, 14.

Gupta and Barzotto's project built a prediction model to tell whether a company filing Chapter 11 would emerge successfully, defined as when the confirmed Chapter 11 plan either had the company continuing as an independent entity or being acquired through a merger or stock acquisition.[33] The project deemed a Chapter 11 case unsuccessful when the company's Chapter 11 case was dismissed or converted to Chapter 7, or the company's assets were sold in lieu of a merger.[34]

Gupta and Barzotto built their model using multivariate probit regression[35] applied to groups of potential features and then using the features showing the most predictive value.[36] The final model used eight features.[37] Although the classification accuracy of the model was an impressive 94%, the inclusion of one feature in particular calls into question its true predictive power.[38] The model included the length of time, measured in years, from the start of the case to case disposition.[39] This is not information available at the beginning of a Chapter 11 case and, thus, is inappropriate to include in a model attempting to predict, in advance, case results. Also, although not explicitly stated, the 94% accuracy statistic appears to derive from applying the model to the same data used to build the model. In machine-learning terms, the statistic is from the training set instead of a separate-test set.[40] Regression models, like any type of machine-learning model, can easily overfit to the data available. In other words, a model that is overfit to its data simply describes what is going on with the data used to create the model but fails to accurately predict results when applied to new cases. Because the model was built on 401 data samples, this draws into some question the model's

33. *Id.* at 4–5, 7.
34. Gupta & Barzotto, *supra* note 15, at 15.
35. Multivariate probit regression is a methodology similar to logistic regression, referenced *supra* note 18.
36. Gupta & Barzotto, *supra* note 15, at 21.
37. *Id.* at 22.
38. *Id.* at 31.
39. *Id.* at 7.
40. *Id.* at 31–32.

ability to predict results against new data. Even so, the authors' ability to reach such a high level of accuracy using a limited number of independent variables demonstrates the strong relationships between initial case information and case results, as well as how statistical systems are capable of describing those relationships.

In *What Drives Bankruptcy Forum Shopping? Evidence from Market Data*, Professor Jared Ellias examined factors behind predicting Chapter 11 case outcomes and concluded that insolvency professionals are better able to predict results for cases filed in Delaware and the Southern District of New York.[41] For his study, he examined data collected on 285 large, corporate bankruptcies combined with pricing information for related financial contracts.[42] He calculated the pricing deviation for each financial contract by taking the square of the gain or loss on the investment when purchased at the start of the bankruptcy case.[43] In theory, the lower the pricing deviation, the more accurately the investors were able to price the financial instrument early in the bankruptcy case. So, although Professor Ellias was not trying to predict outcomes, his methodology was designed to identify the case factors that allow for more accurate prediction.

The study used regression models to evaluate the factors that contribute to more accurate prediction of case outcomes.[44] It found a persistent and statistically significant relationship between filing in Delaware or the Southern District of New York and accuracy in predicting outcomes.[45] In other words, financial investors were more accurate predicting outcomes for cases filed in those two judicial districts. Although the paper focused on this aspect of predictability, other statistically significant factors increasing the predictability of a Chapter 11 case were the presence of private equity in the ownership

41. Jared A. Ellias, *What Drives Bankruptcy Forum Shopping? Evidence from Market Data*, 47 J. LEGAL STUD. 119, 119 (2018).
42. *Id.* at 121.
43. *Id.*
44. *Id.* at 146.
45. *Id.* at 122.

structure and the existence of a prepackaged Chapter 11 plan (although pre-negotiated plans did not have the same effect).[46]

These recent studies using the BRD and other smaller datasets apply sophisticated regression techniques to identify linear relationships between company information, details of the Chapter 11 case, and the case outcomes. However, modern software makes available a variety of machine-learning tools that can be applied to identify complex patterns in the data and possibly generate better prediction models.

II. The FDJ and the IDB: The Data Used for this Paper

Prior empirical work analyzing Chapter 11 case outcomes has relied primarily on small samples of the available cases because of the difficulty obtaining usable data for the entire set of Chapter 11 filings. For example, the BRD compiled by Professor LoPucki is probably the most popular data set for researching activity in Chapter 11 cases, but it only contains information on about 1,000 cases.[47] Its contents are limited to those cases filed by public corporations with over $100 million in assets (measured in 1980 dollars) since 1979.[48] However, since 2007, over 100,000 Chapter 11 cases have been filed.[49] Further, obtaining data on a national basis has been difficult in the past. Although anyone can go to a bankruptcy court clerk's office and review case information for free using the PACER access terminals, they must have a PACER[50] account to access case information over the Internet.[51] The court charges a fee for each docket or document obtained over PACER,[52] making a large-scale

46. Ellias, *supra* note 3, at 133.

47. *A Window on the World of Big-Case Bankruptcy*, UCLA-LOPUCKI BANKR. DATABASE, http://lopucki.law.ucla.edu/ [https://perma.cc/U4LE-TVPC] (last visited September 25, 2018).

48. *Id.*

49. *See Statistics From Epiq Systems*, *supra* note 1.

50. *See* PACER, https://www.pacer.gov/ [https://perma.cc/48EL-WN8K]. PACER stands for Public Access to Court Electronic Records and is the system that lets litigants, attorneys, and the public view dockets and filings in federal court cases.

51. *Id.*

52. Currently, documents or dockets cost 10 cents per page, or a maximum of $3.00 a document. *Id.*

exploration expensive. A number of companies assemble documents filed in Chapter 11 cases, but their collections typically exclude some filings, particularly those in smaller Chapter 11 cases.[53] Obtaining large-scale data from these companies for research purposes is also difficult. Finally, extracting structured data from papers filed with the bankruptcy courts, although doable, is a daunting task, requiring significant expertise in natural-language processing systems.[54]

In 2017, the Federal Judicial Center, in conjunction with the Administrative Office of the U.S. Courts (AOUSC), made data available for almost ten years of bankruptcy case filings through its Integrated Database (IDB).[55] For each bankruptcy case, the Bankruptcy IDB provides 126 items of information plus a unique case key. A code book provides details about each item of information in the database.[56] Although the data does not contain debtor names, tax identification numbers, or other personally identifiable information, each record includes the docket number and district, allowing a researcher to look up a particular case on PACER.

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53. BUSINESSBANKRUPTCIES.COM, https://businessbankruptcies.com/ [https://perma.cc/B42H-M6FD] (last visited Feb. 22, 2019); *Frequently Asked Questions About Our Services and Database of Chapter 11 Bankruptcy Documents*, CHAPTER11LIBRARY.COM, http://www.chapter11library.com/Faq.aspx [https://perma.cc/FRK2-X3B9] (last visited Feb. 22, 2019); INFORUPTCY, https://www.inforuptcy.com/marketplace [https://perma.cc/XLV4-4Q32] (last visited Feb. 22, 2019); *Overview: Business Bankruptcy Research & Information from BrankruptcyData.com*, BANKRUPTCYDATA, http://www.bankruptcydata.com/p/bankruptcydata-overview [https://perma.cc/BJ85-ZS5F] (last visited Feb. 22, 2019) (providing examples of companies that collect and resell business bankruptcy information).

54. For an example of the techniques involved, see Gunnvant Saini, *How I used Natural Language Processing to extract context from news headlines*, TOWARDS DATA SCIENCE, (Apr. 12, 2018) https://towardsdatascience.com/how-i-used-natural-language-processing-to-extract-context-from-news-headlines-df2cf5181ca6 [https://perma.cc/XL4S-B53D]; *see also* Michael J. Bommarito II, Daniel Martin Katz, & Eric M. Detterman, *LexNLP: Natural language processing and information extraction for legal and regulatory texts*, AIRXIV.ORG (June 10, 2018), https://arxiv.org/abs/1806.03688 [https://perma.cc/Q4WD-Z3FM].

55. *Integrated Database (IDB)*, FED. JUD. CTR., https://www.fjc.gov/research/idb [https://perma.cc/T5RM-GDNP] (last visited Feb. 22, 2019) (retaining bankruptcy data on cases filed, terminated, and pending from FY 2008 to 2017).

56. *See generally* BANKRUPTCY PETITION NEWSTATS SNAPSHOTS DATABASE BPNS DATABASE CODEBOOK, FEDERAL JUDICIAL CENTER (Jan. 2018) [hereinafter IDB CODE BOOK]. The IDB Code Book is available for download at https://www.fjc.gov/sites/default/files/idb/codebooks/Bankruptcy%20Codebook%202008%20Forward%20%28Rev%20January%202018%29.pdf

The substantive information provided for each case is actually very limited. The IDB contains information about case opening and closure activity and final case disposition. For Chapter 11 cases, the IDB provides some summary financial information. However, information from the schedules and statement of financial affairs themselves and information about activity during the case is not available.

For this project, the authors extracted from the IDB information about every Chapter 11 case filed between fiscal year 2008 through fiscal year 2017.[57] When the authors excluded duplicate entries, a total data set of 118,725 cases remained. Some additional cases were removed from the analysis during the data review stage of the project. The authors removed 8,060 cases that were less than two years old that had not yet been disposed. The authors also removed 1,345 cases that were transferred to new districts, filed in error, or dismissed in error, as well as a minor number of additional cases with other data errors. The final data set used included 109,320 Chapter 11 cases. Although the authors removed cases that had been consolidated into a lead case for procedural purposes, cases identified as substantively consolidated cases were left in the dataset.[58]

Some of the information available in the IDB includes:

- The type of debtor;
- The nature of the business;
- Estimated assets, liabilities, and number of creditors, taken from the Chapter 11 petition;[59]

57. *Integrated Database (IDB)*, *supra* note 55. The federal court system runs on a fiscal year ending September 30th. *Id.* To create the IDB data, the AOUSC creates a snapshot of each case filed or open during the prior fiscal year. *Id.*

58. *Id.* About 1,077 substantively consolidated cases remained in the data set. *Id.* This excludes cases jointly administered at the start of the cases and later substantively consolidated. *Id.* One issue with removing substantively consolidated cases is that the Bankruptcy IDB does not directly identify the surviving case when two or more cases are substantively consolidated. *Integrated Database (IDB)*, *supra* note 55.

59. IDB CODE BOOK, *supra* note 56. The Chapter 11 petition requires the debtor to estimate the amount of assets, amount of debt, and number of creditors by selecting from a range of options. *Id.* Each "range" receives a different code in the IDB, and because the selections available change from time to

- Amounts of assets, real property, personal property, unsecured debt, secured debt, and priority debt, each taken from the summary of schedules filed with the debtor's schedules;
- Information about related and consolidated cases;
- Disposition codes, providing information about whether a case was converted or dismissed;
- Chapter 11 percentage dividend, where applicable;
- Chapter 11 future payments.

For the most part, all of the data was used for model development; however, a number of available fields were removed because they were either too sparse to provide usable information for a model[60] or because they were too closely related to matters at the end of the case (and thus inappropriate for use for a model designed to predict end results based on initial case information). In addition to using the filing date for each case, additional features were built based on the month in which the case was filed and the day of the week that the case was filed (for example, a Monday versus a Friday). One feature was the judicial district where a case was filed, and an additional feature included the specific office within a judicial district. Although the data set included the zip code for the debtors' principal places of business, this feature was removed from the dataset to reduce file sizes. However, the zip codes for the county in which the debtors were located were retained as a feature.

Before they could build a model, the authors needed a suitable label or dependent variable against which to train and test the model. The authors wanted to try to predict one of three case outcomes:

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time, some revisions to the data were needed to make the options uniform throughout the dataset. *Id.*

60. Sparse data refers to fields where a large percentage of the needed data is missing. Oscar Wärnling & Johan Bissmark, *The Sparse Data Problem Within Classification Algorithms*, (June 5, 2017) (unpublished Bachelor's thesis, Royal Institute of Technology, Stockholm, Sweden), DD142x, http://www.diva-portal.se/smash/get/diva2:1111045/FULLTEXT01.pdf [https://perma.cc/YGP8-PWSB]. The term is also sometimes used to refer to situations where almost all of the data points have the same value. ANDREW GELMAN & JENNIFER HILL, DATA ANALYSIS USING REGRESSION AND MULTILEVEL/HIERARCHICAL MODELS 529–44 (2006).

dismissal, conversion, or viability (defined as a case that either obtained confirmation of a Chapter 11 plan or lasted long enough for plan confirmation to be a viable outcome). A case received the "dismissed" label if one of the dismissal disposition codes was found and the case was still a Chapter 11 case when it closed. A case received the "converted" label if it was no longer a Chapter 11 case when it closed.[61] All other cases were treated as "viable" cases.[62] Of the total data set, 45.14% of the cases were classified as viable, 19.87% were converted to another case under the bankruptcy code,[63] and the rest of the cases were dismissed by the court.[64] Because of the difficulties in testing against three different labels, a second data set was built that combined the converted and dismissed cases into a single "non-viable" outcome, and the potential machine-learning systems were also evaluated using this two-outcome data set.[65]

As a result, the models that the authors built were being designed to test for different outcomes than the Gupta-Barzotto and LoPucki-Doherty models. Those models sought to predict whether a company would be able to continue, post-bankruptcy, as an independent, operating business. The authors' models sought to examine whether a debtor could obtain plan confirmation, either as a stand-alone operating business—as part of a sale or merger—or after a § 363 sale of substantially all of its assets. Prior models have been limited in terms of the amount of data available, as well as the scope of the cases available for examinations; these models were limited to the largest Chapter 11 cases. Although the authors' use of the IDB allows

61. *Integrated Database (IDB)*, *supra* note 55. The authors are aware that many Chapter 11 cases, especially smaller ones, involve a sale of substantially all assets under 11 U.S.C. § 363, after which the case is converted to Chapter 7 to allow a Chapter 7 trustee to complete the remaining tasks in the case, explore preference and fraudulent conveyance claims, and handle final distributions of funds. *Id.* Although these cases could be considered a success, the data in the IDB is not sufficient to identify these situations. *Id.*

62. *Id.* An analysis of the data demonstrated that the two Chapter 11 plan codes only applied to a subset of cases with confirmed Chapter 11 plans and also were apparently not consistently used by all judicial districts. *Id.* The IDB does not contain a specific code indicating whether a Chapter 11 plan was confirmed. *Id.*

63. *Integrated Database (IDB)*, *supra* note 55 (mostly Chapter 7 liquidation cases).

64. *Id.*

65. *Id.*

access to a much larger data set and the ability to examine cases of every size and type, it limits the scope of information available about each case. The IDB does not contain information sufficient to generate the success variable used in the Gupta-Barzotto and LoPucki-Doherty models, and it also does not contain the information needed to engineer the types of features used in those models. This particular project is limited to seeing what kinds of results can be obtained using the Bankruptcy IDB, without significant feature engineering. Better results could almost certainly be obtained by adding the kinds of financial and characteristic information available in the BRD and by engineering additional features.

III. Application of Standalone Algorithms

The authors' initial attempts to build a predictive system using the Bankruptcy IDB data were performed using standard machine-learning algorithms available through the SciKit-Learn library.[66] The three-label data set was used initially, followed by the two-label data set. Using three labels, the authors built models to predict whether particular cases would be dismissed, converted, or remain viable as a Chapter 11 case. Results were judged against a baseline of .45.[67] The use of a label with three categorical outcomes did limit the types of algorithms available. The data was examined using a K-nearest-neighbors (KNN) classifier and a decision-tree classifier. In each case, 20% of the data set was set aside for validating the models.[68]

66. *See* SCIKIT LEARN, https://scikit-learn.org/stable/ [https://perma.cc/HA7A-SRRQ] (last visited Jan. 30, 2019). SciKit Learn is a library of classes and functions available within the Python programming ecosystem, which allows the programmer to apply a broad variety of machine-learning algorithms to data. *Id.*

67. Baseline accuracy refers to the prediction accuracy that could be obtained without the use of the machine-learning model, and thus serves as a measure of whether the model is statistically useful. Rama Ramakrishnan, *Create a Common-Sense Baseline First*, TOWARDS DATA SCIENCE (Jan. 12, 2018), https://towardsdatascience.com/first-create-a-common-sense-baseline-e66dbf8a8a47 [https://perma.cc/UJ4K-VGRV]. In this case, if a person simply assumed that all cases were viable Chapter 11 cases, that person would be correct 45% of the time. *Id.*

68. The 20% is referred to as the test data, whereas the remaining 80% of the case data is referred to as the training data. The training data is used to build the machine-learning model, and then the model is

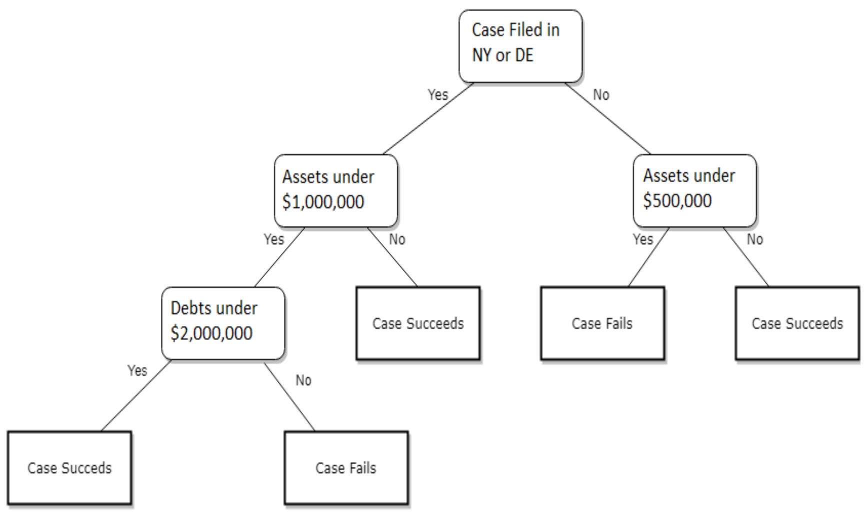
The KNN classifier predicts categories by comparing an unknown data record with similar instances for which the results are known. It operates by measuring similarities between two records based on their features, creating a "distance score" for each set of records within the data set. The algorithm makes a prediction about which class a particular record falls into by looking at the records with the smallest distance scores (its nearest neighbors) and assuming that the record falls into the same category as its neighbors. For example, if the algorithm is set to look at the five nearest neighbors for a particular Chapter 11 case, and three of the five most similar Chapter 11 cases converted to Chapter 7, the algorithm will predict that the Chapter 11 case being tested will also convert to Chapter 7.

An initial model was built using the SciKit-Learn KNeighborsClassifier (a form of KNN classifier) and was set to look at the 100 nearest case filings while weighting those 100 nearest cases based on their distance from the case being tested—in other words, the most similar cases were treated as more relevant. The results on the training set were impressive; the model was able to discern outcomes with 99.9% accuracy. However, the model generated did not do as well on the test set that had been set aside. Accuracy on the test set was only 47%, only slightly above the baseline metric. In short, the algorithm was able to do a good job describing the data used to build a model, but that model failed to generalize to new data.

An alternative model was built that used fewer neighbors but did not use distance weighting. This methodology avoided the extreme overfitting demonstrated by the weighted model while showing similar accuracy on the test data. It had a 57% accuracy on the training data and a 48% accuracy on the test data. However, despite the model's ability to perform better than random guessing, its ability to sort cases into the three categories of converted, dismissed, and viable was not much above the baseline.

applied to the test data to determine how well it performs.

Better results were obtained with a decision-tree algorithm. A decision tree is a branched structure where the branches are controlled by choices made about the features in our data set.[69] The ends of the branches—called leaves—represent the potential outcomes—called class labels.[70] The branches themselves represent conjunctions of features that lead to those class labels.[71] A very simple decision tree might look like this:



At each branch, we examine a different feature variable and make a choice about it—sorting some cases down one branch and the other cases down the other branch. Each data set representing a separate bankruptcy case ends up located in a particular leaf at the end of the decision tree and is assigned a prediction based on the actual results for the majority of the cases that ended up in that leaf. Decision-tree algorithms use statistical measures of accuracy to design the tree to generate the best results. The algorithm determines which data

69. KEVIN D. ASHLEY, ARTIFICIAL INTELLIGENCE AND LEGAL ANALYTICS 110–11 (Cambridge Univ. Press, 2017).
70. *Id.*
71. *Id.*

feature to examine at each branch and the rule that sends a case down one branch as opposed to another.

For this project, the authors built a decision-tree model using the SciKit-Learn DecisionTreeClassifier. Decision trees can easily overfit, and the initial model built was no exception, achieving accuracy of 99.93% on the training data. Efforts were made to generalize the model by reducing the number of splits used by the decision-tree algorithm and preventing splits when the number of samples in a node became too small. The best results were obtained by limiting the number of splits in the tree to twenty levels and requiring a node to have at least 110 cases in it to split further. This produced models with training accuracy of about 70% and accuracy of about 65% on the test data.[72] Although above baseline numbers, this decision-tree model did not obtain high-accuracy results.

Better prediction results were obtained when the system attempted to predict between two outcomes instead of three. To build a two-outcome model, converted and dismissed cases were combined into a single category called non-viable. The models were then trained to predict whether a particular case was viable or non-viable—that is, either dismissed or converted as opposed to the viable category. A decision-tree-classifier algorithm was able to predict between two outcomes with 80% accuracy on the training data and 76% accuracy on the test data.[73] Compared with a baseline of 54.86%, this model showed both better performance over the baseline than the three-outcome model and better overall accuracy.[74]

72. The decision-tree model was tuned using a grid search adjusting both the number of branch splits and number of minimum data points required for a split in order to find the optimum combination of parameters.

73. This model used a maximum of twenty-five layers and required 170 data points in order to split further at a particular point. The model, when trying to predict viability, had on the test data a precision of .75, a recall of .69, and an F-score of .72.

74. A random forest decision-tree algorithm was also applied to the two-outcome data. A random forest decision-tree model reduces overfitting problems by generating a number of decision trees and combining them into a generalized model. Slight improvements were obtained over the standard decision-tree model. A random forest decision-tree model was able to predict between two outcomes with 80.4% accuracy on the training data and 77.3% accuracy on the test data.

IV. The Decision Options Ensemble System and Results

Evaluating potential algorithms to generate appropriate models can be a slow process, and similar or superior results can often be obtained using ensemble systems. When using the techniques discussed above, each type of algorithm has to be evaluated separately. This means building an additional code block to run and test the algorithm and manually adjusting the parameters for each algorithm to identify the combination of parameters that produce the best results. Sometimes changes need to be made to the data set itself to accommodate a particular algorithm. Ensemble systems, which test a number of different algorithms automatically, help avoid this extra work. They also allow the application of multiple algorithms to a particular problem, which can produce superior results.

To test the ensemble methods, the authors deployed a combination of statistical modeling and neural networks to create a model that is able to predict if a bankruptcy case is going to be viable or not. Thus, this model is making a binary prediction.

The authors used an AI platform, Decision Options Technology (DoT),[75] that incorporates over 100 statistical-modeling algorithms and neural-network optimizers. It is able to consume raw data and transform the data to be amenable to modeling in the pre-processing stage. Once the data is cleaned and organized, the platform can conduct feature engineering—that is, select the attributes that are most valid for the problem being solved. In large datasets, it also does sampling with an objective of no information loss. These steps reduce the amount of data that needs to be fed into the modeling process and allows the system to quickly evaluate a large number of possible algorithms. We then optimize these engines by fine-tuning parameters that control the algorithms. For example, the neural net could have many different layers, and the number of neurons in each layer can vary. Additionally, convergence of the modeling process depends on the initial conditions specified as well as the optimizer

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75. *See generally* DECISION OPTIONS, http://www.decisionoptions.com/ [https://perma.cc/RGC6-MTCH] (last visited Feb. 22, 2019) (DoT is a product of Decision Options).

used. Thus, for the selected mathematical techniques, we create hundreds of models that differ in their configurations, each producing a different level of confidence and robustness. The technology works from the cloud and uses heavy, parallel processing to create usable models within the allocated time.

During the modeling phase, the authors ran statistical algorithms and neural nets and selected those showing the highest robustness. In making the selection of the best approaches, the authors used what is called a "[ten-fold] cross-validation."[76] One issue with ensemble modeling is that it is easy to overfit the data—that is, the system can make models with very high confidence using the data presented but fail when used on new data. These models will not be useful in practice. To avoid this, we take the entire dataset and divide it into ten different pieces. We take extreme care not to have duplicates in these ten, mutually exclusive bundles of data. Then we create a model taking nine of the data bundles described to make the model and then test the model on the remaining tenth bundle. The confidence of this model is indicative of robustness as we are testing on unseen data. We repeat this process ten times, each time making a different bundle to be the test bundle and the remaining nine used in training the model. We then average the confidence levels across the ten models to get an estimate of expected confidence of the mathematical approach if used on unseen data.

Once the authors selected the best mathematical technique by comparing hundreds of techniques using the cross-validation process described above, they generated models using these techniques, each able to make predictions at different confidence levels. In the problem described in this paper, the authors ended up with eighteen different techniques; some statistical and others neural net based. The authors created an ensemble model by wrapping these models using a weighted-voting mechanism.[77] That is to say, the ultimate predictions

76. ASHLEY, *supra* note 69, at 113.

77. *See generally* D. Optiz & R. Maclin, *Popular Ensemble Methods: An Empirical Study*, 11 J. ARTIFICIAL INTELLIGENCE RES. 169 (1999).

made by the ensemble model is a sort of weighted consensus of the eighteen models that passed the robustness test. This allows us to further enhance the usefulness and validity of the modeling process.

The ensemble model described shows about 75% confidence in correctly predicting for both classes. We see approximately the same confidence level in random split hold-out data. Because the confidence level is produced by cross-validation, we expect this to be the case if the model is applied on newly arriving data. This means that if it were to predict if a case is viable at inception using the characteristics of the case (when the outcome was not known), we would be correct three-fourths of the time. Because the model will make a probabilistic prediction for a new case—that is, it will give a probability that the case will be viable—the results can be further interpreted in practice.

ANALYSIS

The results from this project provide a number of insights to guide future activity in building prediction systems for Chapter 11 cases. Both the manual decision-tree model and the ensemble model generated similar accuracy results, showing a demonstrated ability to correctly identify whether a particular Chapter 11 case is viable about 75% of the time. This result is significantly better than the baseline of 55%, which someone may achieve by simply assuming that all cases fail or by guessing randomly. On the other hand, model accuracy is substantially below that claimed for the Gupta-Barzotto model discussed earlier. This is possibly because accuracy numbers for that model were only reported for the training information or possibly because of the richer information available in the BRD compared with the Bankruptcy IDB.[78] On the other hand, the models described here can be applied to all bankruptcy cases, not just the large capital cases tracked by the BRD.[79] The larger dataset used also allows for

78. Gupta & Barzotto, *supra* note 15, at 31.
79. *A Window on the World of Big-Case Bankruptcy*, *supra* note 47.

more statistically relevant results in addition to allowing researchers to employ methods, such as neural networks, that cannot generate reliable models with small datasets.

Another question worth considering is how the models described in this paper may compare with or supplement current practices. In many Chapter 11 cases, attorneys and courts make decisions about potential viability by reviewing the relevant information available in the case and qualitatively evaluating the case's prospects. Sometimes these decisions are easy ones. For example, assume that the debtor operates a retail store, the lease was terminated pre-petition, and the landlord is asking the court for permission to evict. Here, predicting a conversion or dismissal is easy. In many other cases, however, deciding whether a case will succeed is very difficult using qualitative methods. Quantitative financial analysis is often employed to ascertain potential outcomes, but the courts themselves are limited to the analysis provided to them by the parties, and—especially in smaller Chapter 11 cases—the parties lack access to financial professionals capable of doing an adequate job using quantitative methods. In any case, financial professionals of case parties are often tasked with providing a quantitative basis to support a particular outcome; these analyses are valuable but not statistically relevant. Statistical models can certainly supplement other techniques, as well as provide a mechanism for decision making using smaller information sets.

Ideally, the techniques discussed in this paper could be applied to richer information than what is currently available through the IDB. This could include financial information from publicly available sources or historical company financial statements, information extracted from the petition, schedules, and first-day pleadings (possibly using natural language processing techniques) and docket information. However, building useful models requires collecting relevant information for a large set of prior cases, not just the case being examined. The BRD does this currently for a relatively small number of cases.[80] However, expanding this information collection to the complete corpus of Chapter 11 cases presents practical issues, mostly how to avoid the economic cost of obtaining court documents through PACER.[81]

Even so, models like the ones described in this paper will provide tactical and strategic advantages for the stakeholders that employ them, as well as improve decision-making. The techniques described can also be used to predict other aspects of the bankruptcy process such as short-term outcomes, professional fees, and distribution results. They can also be applied to other Chapters of the Bankruptcy Code.[82]

Decision models like these are not static. Typically, these models are built as learning models and are able to self-learn and retune as new data with known outcomes become available. If systematically deployed in a decision process, these models can enhance human judgment and intuition. Further, model behavior over time will indicate changes that may be driven by regulations, behaviors, and other structural changes, or even changes in decision-making behavior driven by the model's use. Building usable models requires access to large datasets as well as a combination of domain knowledge and data science expertise not yet widely available in the legal industry. However, AI and machine-learning-based models can provide dynamic and statistically accurate results to support decision-making in ways not currently available.

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80. *Id.*

81. The Electronic Court Records Reform Act of 2018, introduced September 6th, 2018, would eliminate PACER access costs, greatly reducing the cost of assembling court information for modeling use. Jason Tashea, *Proposed Legislation Would Eliminate PACER Fees*, ABA J. (Sept. 18, 2018), http://www.abajournal.com/news/article/new_bill_wants_to_end_pacer_fees [https://perma.cc/2P7W-RRJM]. However, it does not appear to be making progress in the House of Representatives. *Id.*

82. *See generally* Warren Agin, *Using Machine Learning to Predict Success or Failure in Chapter 13 Bankruptcy Cases*, 2018 ANN. SURV. OF BANKR. L. 13 (2018).