Using Machine Learning to Detect Accounting Fraud

Jason Choi and Kyle Cummings of "The Data Smurfs"

Abstract

Accounting fraud inflicts widespread harm across society when it occurs and therefore has been a rich topic of interest for regulators and researchers alike. Indeed, not only do investors in the fraudulent company's financial securities suffer an immediate, acute loss, but even more insidious is the chronic widening of risk premiums borne by all market participants. We seek to reexamine this problem, drawing and building upon previous researchers' findings and utilizing the most contemporaneous data available. Specifically, we will train a neural network (NN) model to predict fraud in publicly traded U.S. firms using publicly available financial statement data. Building, tuning, and refining such a predictive model is of great importance to U.S. regulators and auditors, who must carefully budget limited resources, as well as investors, who may hedge their exposure to or speculatively profit, via short sales, from suspect firms.

Project Description

Unfortunately, accounting fraud continues to be a worldwide problem. Congruent with prior literature studying this topic, we seek to model detected material accounting misstatements as disclosed in the Security and Exchange Commission's Accounting and Auditing Enforcement Releases (AAERs), as our variable of interest. We emphasize that this fraud sample is comprised of *detected* occurrences of fraud; However, given the clandestine, illegal nature of fraud, it is the best, observable feature available. By tuning and validating prior predictive models with cotemporaneous data, we seek to increase their predictive accuracy *out of sample* and thereby increase the perceived costs and risks to managers contemplating fraud. Hence, our desired future-state is a decrease in *occurrences* of fraud and a commensurate diminished risk premium such fraud entails. Both state variables are latent.

Because our objective is accurate predictive modeling out of sample, without regard to causal inference within sample, our study will fall outside the primary canon of extant social science research. Such predictive tasks are extremely well-suited for neural networks, especially when interpreting the marginal effects of individual features is not important. Several studies have used predictive NN models, including Choi and Green (1997), Cogger and Fanning (1998), Feroz et al. (2000), Lin et al. (2003), Kaminski et al. (2004), Kirkos et al. (2007), Ravisankar et al. (2011), and Song et al. (2014). However, these studies are either relatively dated or in the case of Ravisankar et al. (2011), and Song et al. (2014), examine Chinese-listed firms only. We are thus curious to re-visit this predictive problem using a feed-forward NN model, incorporating the past several decades of observations for U.S.-listed firms.

Methods

We will obtain our dependent variable data – the SEC's AERs -- from the University of California-Berkeley Center for Financial Reporting and Management (CFRM). Our explanatory variables will consist of publicly available financial statement data from S&P Global Market Intelligence ("Compustat") as available through the Wharton Research Data Services (WRDS). Extensive prior literature has identified those financial statement items and ratios that have the greatest explanatory power for detecting accounting fraud (e.g., Cecchini et al. [2010] and Dechow et al. [2011]), and we intend to follow this literature in identifying our data matrix. Of note, Bao et al. (2019) specifically tried a "kitchen sink" approach to their Ensemble model, i.e., they included virtually the entire Compustat database in their model, but found it performed worse than the more tightly-specified model in Cecchini et al. (2010) which relies on 28 raw financial statement items. While such a finding demonstrates simply including additional raw data columns, without additional supplemental theory, yields poor results, we also retain the option to experiment with adding different financial statement items to satiate our curiosity and build upon prior literature.

In accordance with prior predictive model literature, we intend to split our sample into a training and testing partition, run the data matrix through a feed-forward neural network, and gauge model performance with the Area Under the Curve (AUC) metric. Our second predictive metric is Normalized Discounted Cumulative Gain at the position k (NDCG@k).

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