Predicting M&A Outcomes with Deep Learning

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1 Introduction

Mergers and Acquisitions (M&A) involve the purchase of a target company by an acquiring entity. They occur frequently with important market implications, particularly when the target company is publicly owned. These deals are announced to the public once the companies come to an agreement. Once announced, however, deals can still be withdrawn for a variety of reasons including antitrust, tough economic climate, either party getting cold feet, or competing offers. Because of this, the fair value of a stock after deal announcement prices in the probability that the deal will fail. As a result, the price of the stock in the time between when the deal is announced and the deal is completed is usually below the final deal price.

Merger Arbitrage is a trading strategy that takes advantage of this risk associated with M&A transactions falling through by buying shares of the target company after announcement and capturing the spread between the current and final price if the deal is completed. **Figure 1** provides an example of a successful deal, where the price initially jumped from around $48 to $93.80, and converged to the final deal price set at $95. An important caveat to this is that the acquiring company typically pays a relatively high premium (~30-40% above market value) for the target company. If the deal is withdrawn, the price of the stock will usually fall back to the pre-announcement price, which could lead to significant losses if you bought shares in hopes of performing merger arbitrage. **Figure 2** shows an example of a withdrawn merger. The motivation behind this paper is to try and use Deep Learning to predict the outcome of these M&A

transactions in order to have a sense of when deals might fail, which would allow for a more profitable merger arbitrage strategy.

To perform this analysis, SDC Platinum M&A transaction data is merged with VIX volatility data. After subsetting for deals with a public target that occurred between 1990 and 2021, and dropping entries that are missing important features, the final dataset contains roughly 15,000 deals with 32 predictive features. Of these deals, roughly 87% are "Completed", meaning that they are successful transactions. Section 2 focuses on the results of different modeling techniques, and section 3 discusses the outcomes and future of this problem.

2 Results

As a baseline model, logistic regression is used to predict M&A outcomes before moving into a deep learning. Given the relatively high dimensionality of this data, it is likely that logistic regression will not perform as well as deep learning. In both cases, the final model is trained on the 10,000 data points and tested on remaining deals. These points were randomly shuffled to prevent any time trends M&A success from potentially affecting the testing set. The R data cleaning file used for this project as well as the SDC data files and full models can be found at the github link in the Appendix.

A Logistic Regression

The training and test accuracy as well as the loss curve for the logistic regression is shown in **Figure 3**. After some tuning of the learning rate and number of iterations, the test accuracy remained at around 85% at its highest. This accuracy is actually worse than the accuracy attained by randomly guessing that the merger would succeed each time. The logistic regression model would likely perform better than always assuming the deal will be successful, however, since it correctly predicted some of the failed deals. **Figure 4** gives the confusion matrix for the logistic regression, which shows that it performs poorly when it comes to predicting failed deals, but does manage to get 39/643 or about 6%. Since it is much more profitable to predict these failed deals, it might be an improvement to the typical merger arbitrage strategy.

B Deep Learning Model

Initially, the deep learning model wanted to characterize every single deal as completed. It was clearly getting stuck in a bad local minima (or saddle point), and did not want to diverge from it. I found that it took several hundred epochs of training to get the model to begin to learn the training data, but it became apparent that it was overfitting. While the true model is a black box, I assume that it was partially just memorizing what some of the deals looked like in order to improve accuracy rather than actually learning features of the data. As a result, the validation error got worse while the training error improved.

Table 1 gives the current model structure. Previous iterations included convolutional layers which actually performed slightly better than the standard DNN, but these layers were removed due to the fact that there is no true reason why convolutional layers should work better for this data. **Figure 5** shows the final validation error for the data, which is roughly 84% compared to the training error of roughly 90%. The overfitting was much worse than this in previous iterations, and so a dropout layer and some regularization was added. Too much regularization, however, made it even more difficult to escape the bad local minima. **Figure 6** gives the confusion matrix for the deep learning model. It is apparent that there is some improvement in the prediction of withdrawn mergers over the logistic regression. Still, the model needs further improvement to be market-ready.

3 Discussion

The main takeaway from this deep learning application is that this dataset is quite difficult to predict. Deep learning is incredibly powerful for many applications, but it is possible that this data might not be one of them. Given that many of the reasons as to why M&A deals fair are event-driven, it is hard to predict them. Still, it is possible that this model is missing something, or that a different type of machine learning model could perform better.

Additionally, the model may have some use in merger arbitrage after all. Of the deals that the model predicted a value of .99 or greater, roughly 93% of them were completed deals. This is far better than assuming that most deals which correctly categorizes 87% of deals. Additionally, of the deals where the model predicted 10% chance of completion or lower, roughly 26% of these deals were correctly classified as withdrawn. This is about twice as good as randomly guessing that mergers will fail, which would net a 13% probability. The model also showed improvement over the logistic regression, which is promising for the potential of using deep learning for this problem. Overall, the model can definitely be used in tandem with fundamental techniques for M&A outcome prediction, and provides some interesting information that can likely be useful for merger arbitrage. Hopefully with some improvements, a model can be tested on the live market some day.

4 Appendix

Figure 1

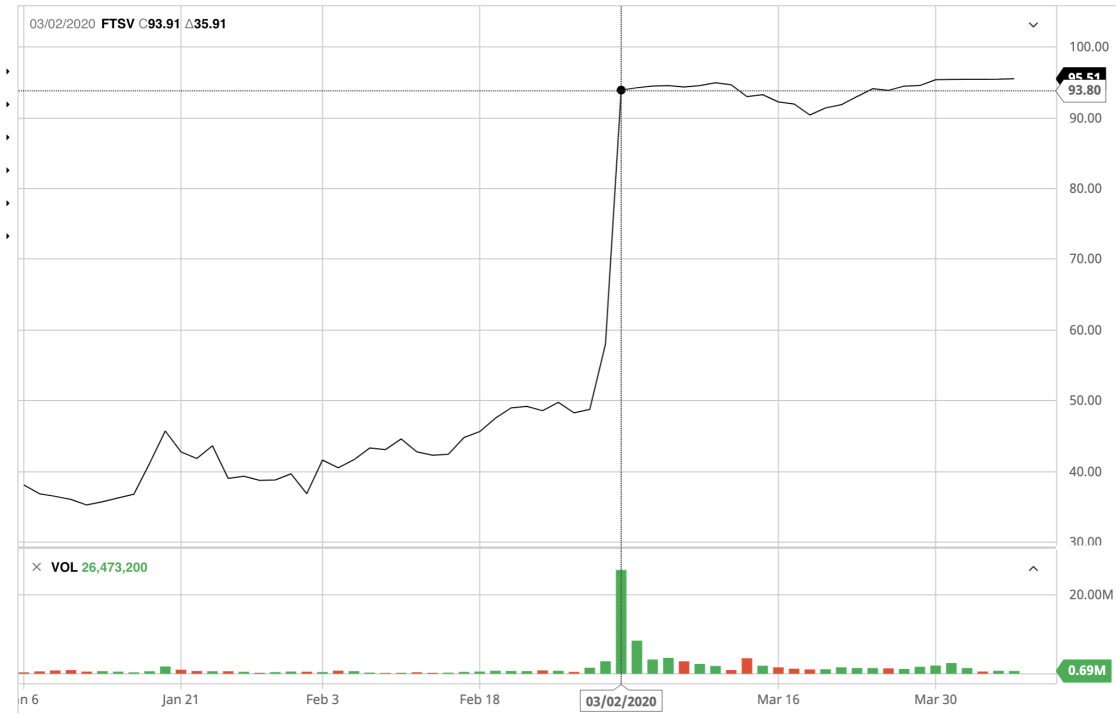

Figure 2

Figure 3

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Misclassification rate on training data = 16.09 %
Misclassification rate on testing data = 15.869521713027817 %
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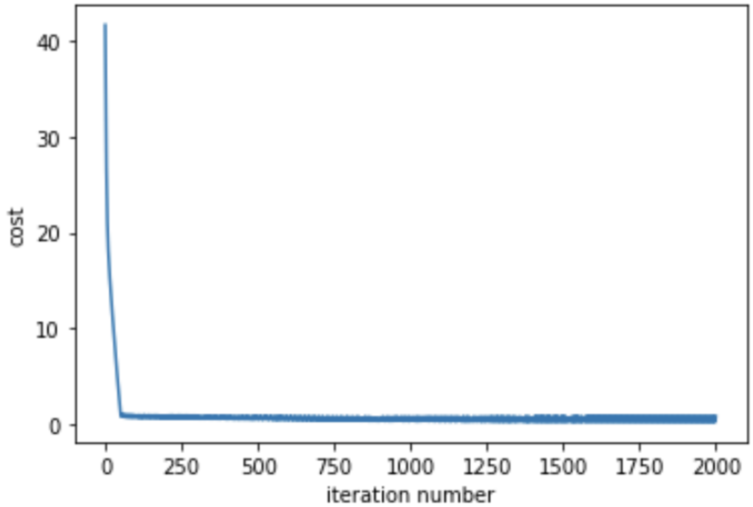

Figure 4

	C (predicted)	W (predicted)
C	4165	189
W	604	39

Table 1

Layer (type)	Output Shape	Param #
dense_197 (Dense)	(None, 1, 30)	960
dense_198 (Dense)	(None, 1, 50)	1550
dense_199 (Dense)	(None, 1, 50)	2550
dense_200 (Dense)	(None, 1, 50)	2550
dense_201 (Dense)	(None, 1, 50)	2550
dense_202 (Dense)	(None, 1, 50)	2550
dropout_24 (Dropout)	(None, 1, 50)	0
dense_203 (Dense)	(None, 1, 50)	2550
dense_204 (Dense)	(None, 1, 30)	1530
dense_205 (Dense)	(None, 1, 1)	31

Total params: 16,821
Trainable params: 16,821
Non-trainable params: 0

Figure 5

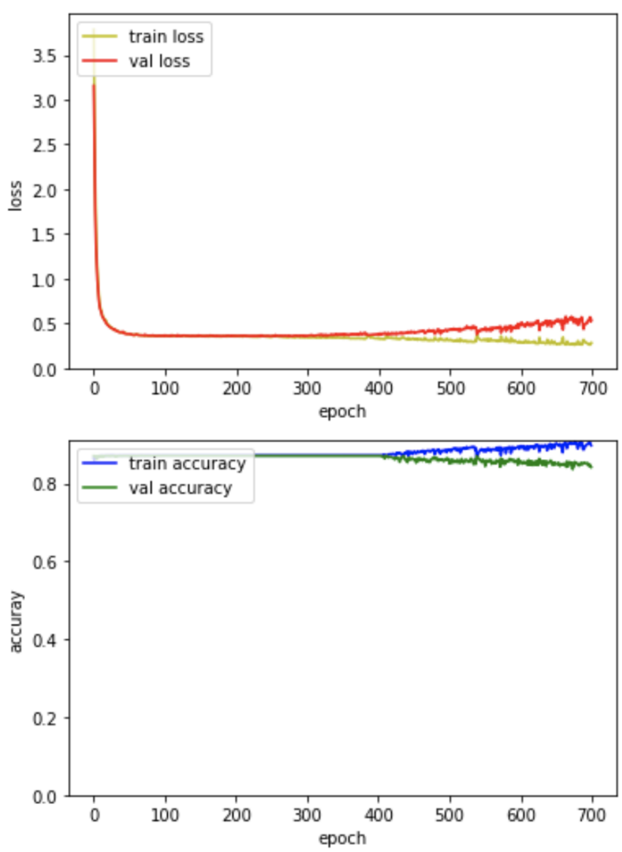

Figure 6

	C (predicted)	W (predicted)
C	4150	204
W	586	57

Models, Data Cleaning, and Data at https://github.com/bengluckow/M-A