Improving Factor-Based Quantitative Investing by Forecasting Company Fundamentals

John Alberg
Euclidean Technologies
`john.alberg@euclidean.com`

Zachary C. Lipton
Amazon AI
Carnegie Mellon University
`zlipton@cmu.edu`

Abstract

On a periodic basis, publicly traded companies are required to report *fundamentals*: financial data such as revenue, operating income, debt, among others. These data points provide some insight into the financial health of a company. Academic research has identified some factors, i.e. computed features of the reported data, that are known through retrospective analysis to outperform the market average. Two popular factors are the book value normalized by market capitalization (book-to-market) and the operating income normalized by the enterprise value (EBIT/EV). In this paper, we first show through simulation that if we could (clairvoyantly) select stocks using factors calculated on *future* fundamentals (via oracle), then our portfolios would far outperform a standard factor approach. Motivated by this analysis, we train deep neural networks to forecast future fundamentals based on a trailing 5-years window. Quantitative analysis demonstrates a significant improvement in MSE over a naive strategy. Moreover, in retrospective analysis using an industry-grade stock portfolio simulator (backtester), we show an improvement in compounded annual return to 17.1% (MLP) vs 14.4% for a standard factor model.

1   Introduction

Public stock markets provide a venue for buying and selling shares, which represent fractional ownership of individual companies. Prices fluctuate frequently, but the myriad drivers of price movements occur on multiple time scales. In the short run, price movements might reflect the dynamics of order execution, and the behavior of high frequency traders. On the scale of days, price fluctuation might be driven by the news cycle. Individual stocks may rise or fall on rumors or reports of sales numbers, product launches, etc. In the long run, we expect a company's market value to reflect its financial performance, as captured in *fundamental data*, i.e., reported financial information such as income, revenue, assets, dividends, and debt. In other words, shares reflect ownership in a company thus share prices should ultimately move towards the company's *intrinsic value*, the cumulative discounted cash flows associated with that ownership. One popular strategy called *value investing* is predicated on the idea that long-run prices reflect this intrinsic value and that the best features for predicting *long-term* intrinsic value are the *currently* available fundamental data.

In a typical quantitative (systematic) investing strategy, we sort the set of available stocks according to some *factor* and construct investment portfolios comprised of those stocks which score highest. Many quantitative investors engineer *value factors* by taking fundamental data in a ratio to stock's price, such as EBIT/EV or book-to-market. Stocks with high value factor ratios are called *value* stocks and those with low ratios are called *growth* stocks. Academic researchers have demonstrated empirically that portfolios of stocks which overweight value stocks have significantly outperformed portfolios that overweight growth stocks over the long run [12, 7].

In this paper, we propose an investment strategy that constructs portfolios of stocks today based on *predicted future fundamentals*. Recall that value factors should identify companies that are inexpensively priced with respect to current company fundamentals such as earnings or book-value. We suggest that the long-term success of an investment should depend on the how well-priced the stock *currently is* with respect to its *future fundamentals*. We run simulations with a *clairvoyant model* that can access future financial reports (by oracle). In Figure 1, we demonstrate that for the 2000-2016 time period, a clairvoyant model applying the EBIT/EV factor with 12-month clairvoyant fundamentals, if possible, would achieve a 44% compound annualized return.
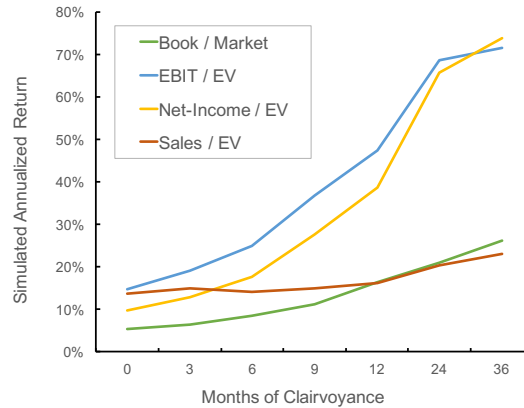

Figure 1: Annualized return for various factor models for different degrees of clairvoyance.

Motivated by the performance of factors applied to *clairvoyant* future data, we propose to *predict* future fundamental data based on trailing time series of 5 years of fundamental data. We denote these algorithms as Lookahead Factor Models (LFMs). Both multilayer perceptrons (MLPs) and recurrent neural networks (RNNs) can make informative predictions, achieving out-of-sample MSE of .47, vs .53 for linear regression and .62 for a naive predictor. Simulations demonstrate that investing with LFMs based on the predicted factors yields a compound annualized return (CAR) of 17.1%, vs 14.4% for a normal factor model and a Sharpe ratio .68 vs .55.

Related Work Deep neural networks models have proven powerful for tasks as diverse as language translations [14, 1], video captioning [11, 16], video recognition [6, 15], and time series modeling [9, 10, 3]. A number of recent papers consider deep learning approaches to predicting stock market performance. [2] evaluates MLPs for stock market prediction. [5] uses recursive tensor nets to extract events from CNN news reports and uses convolutional neural nets to predict future performance from a sequence of extracted events. Several preprinted drafts consider deep learning for stock market prediction [4, 17, 8] however, in all cases, the empirical studies are limited to few stocks and short time periods.

2 Deep Learning for Forecasting Fundamentals

Data In this research, we consider all stocks that were publicly traded on the NYSE, NASDAQ or AMEX exchanges for at least 12 consecutive months between between January, 1970 and September, 2017. From this list, we exclude non-US-based companies, financial sector companies, and any company with an inflation-adjusted market capitalization value below 100 million dollars. The final list contains $11,815$ stocks. Our features consist of reported financial information as archived by the *Compustat North America* and *Compustat Snapshot* databases. Because reported information arrive intermittently throughout a financial period, we discretize the raw data to a monthly time step. Because we are interested in long-term predictions and to smooth out seasonality in the data, at every month, we feed in inputs with a 1-year lag between time frames and predict the fundamentals 12 months into the future.

For each stock and at each time step t, we consider a total of 20 input features. We engineer 16 features from the fundamentals as inputs to our models. Income statement features are cumulative *trailing twelve months*, denoted TTM, and balance sheet features are most recent quarter, denoted MRQ. First we consider These items include *revenue* (TTM); cost of goods sold (TTM); selling, general & and admin expense (TTM); earnings before interest and taxes or EBIT (TTM); net income (TTM); cash and cash equivalents (MRQ); receivables (MRQ); inventories (MRQ); other current assets (MRQ); property plant and equipment (MRQ); other assets (MRQ); debt in current liabilities (MRQ); accounts payable (MRQ); taxes payable (MRQ); other current liabilities (MRQ); total liabilities (MRQ). For all features, we deal with missing values by filling forward previously observed values, following the methods of [9]. Additionally we incorporate 4 *momentum features*, which

indicate the price movement of the stock over the previous 1, 3, 6, and 9 months respectively. So that our model picks up on relative changes and doesn't focus overly on trends in specific time periods, we use the percentile among all stocks as a feature (vs absolute numbers).

Preprocessing   Each of the fundamental features exhibits a wide dynamic range over the universe of considered stocks. For example, Apple's 52-week revenue as of September 2016 was $215 billion (USD). By contrast, National Presto, which manufactures pressure cookers, had a revenue $340 million. Intuitively, these statistics are more meaningful when scaled by some measure of a company's size. In preprocessing, we scale all fundamental features in given time series by the market capitalization in the last input time-step of the series. We scale all time steps by the same value so that the neural network can assess the relative change in fundamental values between time steps. While other notions of size are used, such as enterprise value and book equity, we choose to avoid these measure because they can, although rarely, take negative values. We then further scale the features so that they each individually have zero mean and unit standard deviation.

Modeling   In our experiments, we divide the timeline in to an *in-sample* and *out-of-sample* period. Then, even within the in-sample period, we need to partition some of the data as a validation set. In forecasting problems, we face distinct challenges in guarding against overfitting. First, we're concerned with the traditional form of overfitting. Within the in-sample period, we do not want to over-fit to the finite observed training sample. To protect against and quantify this form of overfitting, we randomly hold out a validation set consisting of 30% of all stocks. On this *in-sample* validation set, we determine all hyperparameters, such as learning rate, model architecture, objective function weighting. We also use the in-sample validation set to determine early stopping criteria. When training, we record the validation set accuracy after each training epoch, saving the model for each best score achieved. When 25 epochs have passed without improving on the best validation set performance, we halt training and selecting the model with the best validation performance. In addition to generalizing well to the in-sample holdout set, we evaluate whether the model can predict the future *out-of-sample* stock performance. Since this research is focused on long-term investing, we chose large in-sample and out-of-sample periods of the years 1970-1999 and 2000-2016, respectively.

In previous experiments, we tried predicting relative returns directly with RNNs and while the RNN outperformed other approaches on the in-sample period, it failed to meaningfully out-perform a linear model (See results in Table 2a). Given only returns data as targets, RNN's easily overfit the training data while failing to improve performance on in-sample validation. **One key benefit of our approach** is that by doing *multi-task learning*, predicting all 16 future fundamentals, we provide the model with considerable training signal and may thus be less susceptible to overfitting.

The price movement of stocks is extremely noisy [13] and so, suspecting that the relationships among fundamental data may have a larger signal to noise ratio than the relationship between fundamentals and price, we set up the problem thusly: For MLPs, at each month t, given features for 5 months spaced 1 year apart ($t - 48$, $t - 36$, $t - 24$, $t - 12$), predict the fundamental data at time $t + 12$. For RNNs, the setup is identical but with the small modification that for each input in the sequence, we predict the corresponding 12 month lookahead data.

We evaluated two classes of deep neural networks: MLPs and RNNs. For each of these, we tune hyperparameters on the in-sample period. We then evaluated the resulting model on the out-of-sample period. For both MLPs and RNNs, we consider architectures evaluated with 1, 2, and 4 layers with 64, 128, 256, 512 or 1024 nodes. We also evaluate the use of dropout both on the inputs and between hidden layers. For MLPs we use ReLU activations and apply batch normalization between layers. For RNNs we test both GRU and LSTM cells with layer normalization. We also searched over various optimizers (SGD, AdaGrad, AdaDelta), settling on AdaDelta. We also applied L2-norm clipping on RNNs to prevent exploding gradients. Our optimization objective is to minimize square loss.

To account for the fact that we care more about our prediction of EBIT over the other fundamental values, we up-weight it in the loss (introducing a hyperparameter α_1). For RNNs, because we care primarily about the accuracy of the prediction at the final time step (of 5), we upweight the loss at the final time step by hyperparameter α_2 (as in [9]). Some results from our hyperparameter search on in-sample data are displayed in Table 1. These hyperparameters resulted in MSE on in-sample validation data of 0.6141 for and 0.6109 for the MLP and RNN, respectively.

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Strategy	MSE	CAR	Sharpe Ratio
S&P 500	n/a	4.5%	0.19
Market Avg.	n/a	7.7%	0.29
Price-LSTM	n/a	11.3%	0.60
QFM	0.62	14.4%	0.55
LFM-Linear	0.53	15.9%	0.63
LFM-MLP	0.47	17.1%	0.68
LFM-LSTM	0.47	16.7%	0.67

(a) Out-of-sample performance for the 2000-2016 time period. All factor models use EBIT/EV. QFM uses current EBIT while our proposed LFMs use predicted EBIT. Price-LSTM is trained to predict relative return.
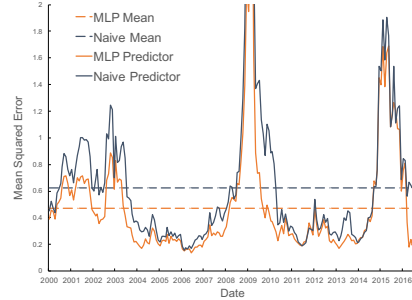
(b) MSE over out-of-sample period for MLP (orange) and naive predictor (black).

Figure 2: Quantitative results

Evaluation As a first step in evaluating the forecast produced by the neural networks, we compare the MSE of the predicted fundamental on out-of-sample data with a naive prediction where predicted fundamentals at time t is assumed to be the same as the fundamentals at $t - 12$. To compare the practical utility of traditional factor models vs lookahead factor models we employ an industry grade investment simulator. The simulator evaluates hypothetical stock portfolios constructed on out-of-sample data. Simulated investment returns reflect how an investor might have performed had they invested in the past according to given strategy.

Hyperparameter	MLP	RNN
Hidden Units	1024	64
Hidden Layers	2	2
Input Dropout Keep Prob.	1.0	1.0
Hidden Dropout Keep Prob.	0.5	1.0
Recurrent Dropout Keep Prob.	n/a	0.7
Max Gradient Norm	1.0	1.0
α_1	0.75	0.5
α_2	n/a	0.7

Table 1: Final hyperparameters for MLP and RNN

The simulation results reflect assets-under-management at the start of each month that, when adjusted by the S&P 500 Index Price to January 2010, are equal to $100 million. We construct portfolios by ranking all stocks according to the factor EBIT/EV in each month and investing equal amounts of capital into the top 50 stocks holding each stock for one-year. When a stock falls out of the top 50 after one year, it is sold with proceeds reinvested in another highly ranked stock that is not currently in the simulated portfolio. We limit the number of shares of a security bought or sold in a month to no more than 10% of the monthly volume for a security. Simulated prices for stock purchases and sales are based on the volume-weighted daily closing price of the security during the first 10 trading days of each month. If a stock paid a dividend during the period it was held, the dividend was credited to the simulated fund in proportion to the shares held. Transaction costs are factored in as $0.01 per share, plus an additional slippage factor that increases as a square of the simulation's volume participation in a security. Specifically, if participating at the maximum 10% of monthly volume, the simulation buys at 1% more than the average market price and sells at 1% less than the average market price. Slippage accounts for transaction friction, such as bid/ask spreads, that exists in real life trading.

Our results demonstrate a clear advantage for the lookahead factor model. In nearly all months, however turbulent the market, neural networks outperform the naive predictor (that fundamentals remains unchanged) (Figure 2b). Simulated portfolios lookahead factor strategies with MLP and RNN perform similarly, both beating traditional factor models (Table 2a).

3 Discussion

In this paper we demonstrate a new approach for automated stock market prediction based on time series analysis. Rather than predicting price directly, predict future fundamental data from a trailing window of values. Retrospective analysis with an oracle motivates the approach, demonstrating the superiority of LFM over standard factor approaches. In future work we will thoroughly investigate the relative advantages of LFMs vs directly predicting price. We also plan to investigate the effects of the sampling window, input length, and lookahead distance.

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