Evaluating a News-Aware Quantitative Trader: The Effect of Momentum and Contrarian Stock Selection Strategies

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Abstract

We study the coupling of basic quantitative portfolio selection strategies with a financial news article prediction system, AZFinText. By varying the degrees of portfolio formation time, we found that a hybrid system using both quantitative strategy and a full set of financial news articles, performed the best. With a 1-week portfolio formation period we achieved a 20.79% trading return using a Momentum strategy and a 4.54% return using a Contrarian strategy over a five-week holding period. It was also found that trader overreaction to these events led AZFinText to capitalize on these short-term surges in price.

Keywords: Knowledge management, prediction from textual documents, quantitative funds

1. Introduction

Predicting activity in the stock market has always had a certain appeal to researchers. While numerous attempts have been made, the difficulty has always centered on the behaviors of human traders within this socially constructed system. With behavioral parameters not fully defined and constantly changing, making accurate predictions in this environment has been difficult. To further create confusion, there are two diametrically opposed philosophies of stock market research; fundamental and technical analysis techniques (Technical Analysis 2005). While fundamental analysis leverages the security's relative data, ratios and earnings, technical analysis utilizes charts and modeling techniques based on historical trading volume and pricing. The main issue between them becomes *Can the market be timed or not?*

Information technology and the desire for information are constantly changing the way brokerage houses and securities analysts are approaching securities trading (Baldwin and Rice 1997). With the advent of cheaper processing and knowledge acquisition techniques, the roles of computers in stock prediction has increased dramatically, where they have become mostly automated versions of existing fundamental and/or technical strategies. Their goal is to achieve better returns than their human counterparts by removing the elements of emotions and biases from trading (Jelveh 2006). The downside of these systems is that they lack intuition and context where they continue buying battered stocks even after unfavorable news events, such as losing a costly court battle. These systems instead rely on news events being translated to numeric data before appropriate decisions can be made. This problem introduces serious lag-time into decisions and in some cases, trades must be overridden by human analysts.

The motivation of this paper is the following. We plan to build and test a hybrid quantitative system that incorporates both traditional quantitative trading strategies and a financial news article prediction piece. We plan to test various quantitative strategies and couple them with a financial news article prediction engine to find an optimal trading system.

This paper is arranged as follows. Section 2 provides an overview of literature concerning Stock Market prediction, textual representations and quantitative portfolio building techniques. Sections 3 and 4 describe our proposed approaches and the AZFinText system respectively. Section 5 provides an overview of our experimental design. Section 6 details our experimental findings and discusses their impact on stock market prediction. Section 7 delivers our conclusions and a brief discourse on future research directions.

2. Literature Review

Within stock market research, there have been two theories that have had a significant impact on predicting security prices; Efficient Market Hypothesis (EMH) and Random Walk Theory. In Fama's EMH, the price of a security is a reflection of complete market information and whenever a change in financial outlook occurs, the market instantly adjusts the price of the security to reflect this new information (Fama 1964). Within EMH the amount of information can be varied to encompass three distinct levels; the weak form, the semi-strong and the strong form. In weak EMH, only historical data is embedded within the current price. The semi-strong form goes a bit farther by incorporating historical and current public information into its prices. The strong form includes historical, current public information and private information, such as Insider Trading. From this theory, it was believed that markets behaved efficiently and that instantaneous price corrections would make prediction models useless.

Random Walk Theory is similar to the Semi-Strong EMH model where it is assumed that all information is contained within the current price which makes it worthless for future prediction. This theory is slightly different in its approach by insisting that short-term price movements are indistinguishable from random activities (Malkiel 1973). This random activity produces unpredictable prices and makes it impossible to consistently outperform the market.

Studying the decisions of traders and the micro-effects of trading behavior on the scale of a market exchange is extremely difficult. However, to obviate this difficulty and test the impact of fundamental and technical trading strategies, LeBaron created an artificial stock market with simulated traders which can be dissected to inspect individual trading decisions (LeBaron, Arthur et al. 1999). He introduced new pieces of information into the market and adjusted the amount of time between when an individual trader would receive information and act upon it. It was found that traders with longer waiting times would form fundamental strategies (latching onto company performance data) while those that waited less time developed technical strategies (such as timing trades). This study had a more important contribution because it discovered a lag existed between the time that information was introduced to when the market would correct itself to equilibrium. This apparent delay in market behavior helped to dispel the instantaneous correction notions of EMH and lent support to the idea that the stock market could be forecast in short durations following the introduction of new information. Subsequent research into how long this short duration of time is, led to the discovery of a twenty minute window of opportunity before and after a financial news article is released (Gidofalvi 2001). Within this window, weak prediction of the direction of a stock price was found to be possible.

2.1 Financial News Articles

The introduction of new information into the market happens all the time. While rumors, eavesdropping and scandals can all move security prices, financial news articles are a more stable and generally a more trustworthy source, which has prompted some to declare news to be another form of commodity (Mowshowitz 1992) that can have differing values (Raban and

Rafaeli 2006). However, the exact relationship between financial news articles and stock price movement is complex. While the information contained in financial news articles can have a visible impact on a security's price (Wuthrich, Cho et al. 1998; Lavrenko, Schmill et al. 2000a; Gidofalvi 2001; Mittermayer 2004), sudden price movements can still occur from large unexpected trades (Camerer and Weigelt 1991).

The first challenge of textual financial prediction is to process the large amounts of textual information that exist for securities. This material includes required reports such as periodic SEC filings, press releases and financial news articles reporting both unexpected events and routine news. These documents can be automatically parsed using Natural Language Processing (NLP) techniques and can identify the specific article terms most likely to cause dramatic share price changes. This method can take advantage of arbitrage opportunities faster than human counterparts by repeatedly forecasting price fluctuations and executing immediate trades.

Obtaining timely financial documents from Web sources is a critical step. Luckily there are a variety of financial news aggregation sites that provide such services. One of which is Comtex which offers real-time financial news in a subscription format. Another source is PRNewsWire which offers free real-time and subscription-based services. By contrast, Yahoo Finance is a compilation of 45 different news sources including the Associated Press, Financial Times and PRNewsWire among others. This source provides a variety of perspectives and timely news stories regarding financial markets.

2.2 Textual Representation

Once we have gathered the financial news articles, we must ultimately represent their important features in some machine-friendly form. This representation could take the form of article summarization (McKeown 1995), event detection (Li, Wang et al. 2005) or tokenization.

One such tokenization technique is to use a Bag of Words approach which has been extensively used in textual financial research (Lavrenko, Schmill et al. 2000a; Gidofalvi 2001). This process involves removing the meaningless stopwords such as conjunctions and declaratives from the text and using what remains as the textual representation. While this method has been popular, it suffers from noise issues associated with seldom-used terms as well as problems of scalability where immense computational power is required for large datasets. An improved representational system which addresses a majority of these shortcomings is Noun Phrases. This representation retains only the nouns and noun phrases within a document and has been found to adequately represent the important article concepts (Tolle and Chen 2000). As a consequence, this technique uses fewer terms and can handle article scaling better than Bag of Words. A third representational technique is Named Entities, which is an extension of Noun Phrases. It functions by selecting the proper nouns of an article that fall within well-defined categories. This process uses a semantic lexical hierarchy (Sekine and Nobata 2004) as well as a syntactic/semantic tagging process (McDonald, Chen et al. 2005) to assign candidate terms to categories. Selected categorical definitions are prescribed by the Message Understanding Conference (MUC-7) Information Retrieval task and they encompass the entities of date, location, money, organization, percentage, person and time. This method allows for better generalization of previously unseen terms. It also does not possess the scalability problems associated with a semantics-only approach. A fourth representational technique is Proper Nouns which functions as an intermediary between Noun Phrases and Named Entities. This representation is a subset of Noun Phrases which selects specific nouns and is also a superset of Named Entities, but without the constraint of pre-defined categories. This representation removes the ambiguity associated with those particular proper nouns that could be represented by more than one named entity category or fall outside one of the seven defined Named Entity categories. In a comparison study using these four representational techniques, it was found that Proper Noun representation was more effective in symbolizing financial news articles (Schumaker and Chen 2006).

Simply assigning one representational mechanism is not sufficient to address the scalability issues associated with large datasets. A common solution to this problem is to introduce a term frequency threshold (Joachims 1998). This method uses a term frequency cut-off to represent article terms that appear more frequently. This technique has the dual effect of eliminating noise from lesser used terms and reducing the number of features that need to be represented. Following this line of research, machine learning algorithms are unable to process raw article terms and require an additional layer of representation. A popular method is to represent the terms in binary where the term is either present or not in a given article (Joachims 1998). This solution leads to sparse matrices where the number of represented terms throughout the dataset will greatly outnumber the terms used in an individual article.

Once financial news articles are represented, computers can then begin the task of identifying patterns of predictable behavior. One accepted method, Support Vector Regression (SVR), is a regression equivalent of Support Vector Machines (SVM) but without the aspect of classification (Vapnik 1995). Like SVM, SVR attempts to minimize its fitting error while maximizing its goal function by fitting a regression estimate through a multi-dimensional hyperplane. This method is also well-suited to handling textual input as binary representations and has been used in similar financial news studies (Tay and Cao 2001; Schumaker and Chen 2006).

2.3 Quantitative Portfolio Building

There is a variety of investor considerations involved in building a stock portfolio. In Figure 1, we illustrate a taxonomy of the major portfolio-building considerations partially based on the works of Torre and Rudd (Torre and Rudd 2004).

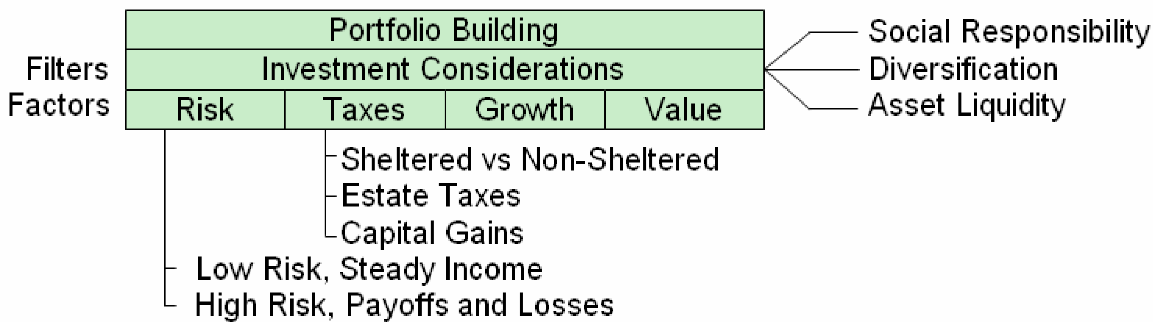

Figure 1. A Taxonomy of Quantitative Portfolio Building

From this taxonomy, there are several investment considerations that can be used to filter the number of stocks to choose from. These considerations could involve Social Responsibility, such as the energy consumption or environmental practices of companies, diversification issues where balancing portfolios in a mix of sectors may be a goal or asset liquidity where a high degree of liquidity in investments is needed to manage cash flow or seizing upon opportunities. Each of these filters can be particular to the goals of the investor.

Similarly, there are some factors worth considering in selecting a portfolio; investment risk, the effect of taxes, and growth and value stock selection approaches.

Risk is the dimension of investment that focuses on the risk tolerance of the Investor. This is usually a factor of age and/or investment goals, where low risk can provide a steady income and high risk can lead to high payoffs or losses. Taxes involve the tax consequences of investments and can sometimes play a role in asset selection. The choices between sheltered and non-sheltered investments and the effects of estate and capital gains taxes can all be a factor in stock selection.

While Risk level and Tax consequences are important factors in portfolio building, Growth and Value form two major criterion for stock selection (Fama and French 1998). Growth looks for above-average returns and a reasonable profit. Stocks under the Growth factor will generally have Earning Per Share (EPS) of greater than 20%. On the other hand, Value looks for out of favor stocks that are currently being ignored by the market. These stocks have low Price to Earnings (P/E), low price to book and sometimes high dividends to attract buyers.

Both Growth and Value have differing stock selection strategies. One of the more common approaches is the Securities Market Line (SML) approach which seeks to balance portfolio risk and return through a mathematical process of stock selection. A variety of techniques have used the SML approach and differ mainly in the exact mathematics used or external factors evaluated. These strategies include Modern Portfolio Theory (MPT), Capital Asset Pricing Model (CAPM) and Arbitrage Pricing Theory (APT).

In MPT, assets are priced by balancing the potential risk and return of adding one more stock to an existing portfolio (Markowitz 1952). CAPM prices assets by discounting future cash flows (Sharpe 1964) and APT prices assets by a function of risk and macro-economic factors (Ross 1976). APT further requires perfect competition which may not be an ideal choice for real-world application.

There are other selection strategies that do not use the SML approach. These include Growth at a Reasonable Price (GARP), Intrinsic Value and Momentum/Contrarian strategies. GARP balances Growth and Value by selecting securities based on good growth (e.g., EPS > 20%) and reasonable pricing (e.g., P/E < EPS growth rates). Intrinsic Value is a fundamental analysis of stocks to derive what the price of the security should be. Another selection strategy that does not use the SML approach is Momentum and Contrarian. In Momentum/Contrarian strategies, stocks are selected based upon recent returns, with the expectation that past winning stocks will continue to win and that past losers will continue to lose. This strategy is easy to implement, has been widely studied and is susceptible to movement from financial news articles.

In the Momentum/Contrarian strategies, there is a portfolio formation period of f where returns are analyzed and stocks are selected, and a holding period h where the stocks are generating their returns. The first step involves analyzing the stock returns within period f. Step two is a rank ordering of these returns. Then finally selecting the top fraction of stocks for period h is a Momentum strategy while selecting the bottom fraction of stocks is a Contrarian approach. From prior literature, it was found that past winning stocks will continue to outperform in intermediate-term horizons of 3-12 months (Jegadeesh and Titman 1993), while past losing stocks will turn-around and outperform in short-term horizons of weeks or months (Jegadeesh 1990; Lehmann 1990) and longer-term horizons of 3-5 years (De Bondt and Thaler 1985; De Bondt and Thaler 1987).

In order to implement these strategies, a determination of the length of the formation period and the exact threshold of stocks to use, must be determined. In selecting the period of f, there have been several implementations. One of which is to assign $f = h - 1$ (Gervais, Kaniel et al. 2001), or make period f and h equivalent (Conrad and Kaul 1998), or even assign f to be a series of values less than or equal to h (Kang, Liu et al. 2002), where the latter implementation provides a more robust model of strategies.

As for determining the top/bottom fractional cutoff for portfolio selection, there have also been several different instantiations. One is to assign the cutoff at 10% of stocks (Chan, Jegadeesh et al. 1996), or the more typically used 20% threshold (Lo and MacKinlay 1990; Jegadeesh and Titman 1993; Kang, Liu et al. 2002), and even 33% of stocks (Chan 2003).

While Momentum and Contrarian strategies are generally linked to price, there are several approaches other than price. The first of which is earnings, where the momentum of earnings surprises can have an effect on current estimates (Chan, Jegadeesh et al. 1996). Second, in using a dividend contrarian strategy, Asness found a strong relation between dividend yield and the contrarian returns (Asness 1997). Rouwenhorst studied the effects of market capitalization and found that larger companies were more prone to Momentum because of their market exposure (Rouwenhorst 1998). In terms of Volume, Gervais et. al., found that stocks with unusually high or low trading volumes outperform those with normal trading volumes (Gervais, Kaniel et al. 2001). However, using price returns is the most common usage of these strategies.

The reason behind the success of Momentum and Contrarian strategies is mainly because of investor's under or overreaction to news events. Investors tend to overweight recent information (overreaction) and underweight past information (underreaction) (De Bondt and Thaler 1985). This overreaction was found to be a result of price shocks which cause excess trading volume and volatility (Chan and Franklin 2003). Underreaction is when investors do not react quickly enough to a news event (Forner and Marhuenda 2003). However, the reaction times are generally measured in terms of weeks, months and years following a news event in which price drift is evident and not in terms of minutes following a news release.

From this study of prior research, we identified several gaps which we plan to investigate. While Momentum and Contrarian strategies are well-understood in horizons of weeks or longer, short-term linkage to news event releases has not been studied. Will investors overreact to news events within the minutes following the release of a news article? We can indirectly measure this by applying basic quantitative strategies to an existing financial news prediction system and predict where the stock should be according to the news article terms.

3. Research Questions

From these gaps, we have formulated several research questions. The first of which is:

- What is the predictive effect of combining Quantitative strategies with a financial news article prediction system?

While we know from the literature that both Quantitative and financial news article systems provide superior price predictions, combining the two may provide a better predictive mechanism.

As a follow-up to this question, we also ask:

- Should a combined system use all financial news articles or only the articles of companies selected by the Quantitative strategy?

4. System Design

In order to properly evaluate our research questions, we adapted the AZFinText system (Schumaker and Chen 2007) to make predictions from a predetermined quantitative portfolio. Figure 2 illustrates the AZFinText system design.

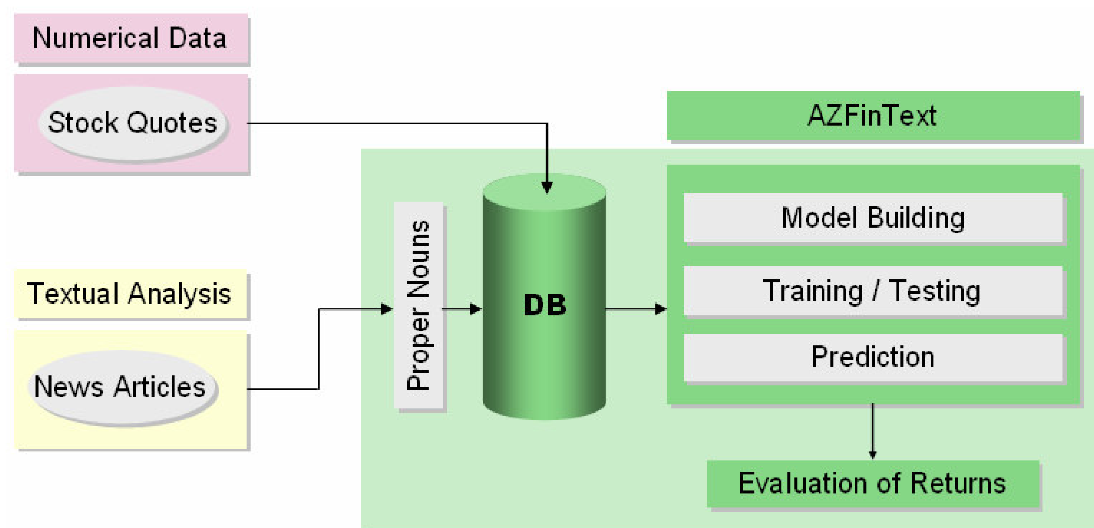

Figure 2. AZFinText system design

From the AZFinText system design in Figure 2, there are several major components to describe in detail. The first component is Numerical Data which gathers stock price data in one minute increments from a commercially available stock price database. The second component is Textual Analysis. This component gathers financial news articles from Yahoo Finance and represents them by their proper nouns. This module further limits extracted features to three or more occurrences in any document, which cuts down the noise from rarely used terms (Joachims 1998).

For the textual analysis portion of AZFinText, we modified the Arizona Text Extractor (AzTeK) system to extract the proper nouns from financial news articles (McDonald, Chen et al. 2005). Although the AzTeK system was selected due to availability, it was found to perform adequately for proper noun extraction. There are many other such systems as reported in the Message Understanding Conference (McDonald, Chen et al. 2005), that can be adopted for this type of analysis.

Once this data has been gathered, AZFinText makes its predictions on each financial news article. From prior empirical testing, we found that including the proper noun representations and the stock price at the time the news article was released, provided AZFinText with superior predictive performance compared to other textual representations and different pieces of price information (Schumaker and Chen 2006).

Within the Model Building stage of AZFinText, we partitioned the data gathered in order to best answer our research questions. In the cases of the Quantitative strategies, this involved buying or shorting those stocks within the quantitative portfolio; Momentum and Contrarian.

For the machine learning algorithm we chose to implement the SVR Sequential Minimal Optimization (Platt 1999) function through Weka (Witten and Eibe 2005). This function allows for discrete numeric prediction instead of classification. In keeping with prior research, we selected as parameters a linear kernel and ten-fold cross validation in our SVR algorithm

(Schumaker and Chen 2007). A similar prediction method was employed in the forecasting of futures contracts (Tay and Cao 2001).

AZFinText is then trained on the data and issues price predictions for each financial news article encountered. Evaluations are then made regarding the effect of stock returns in terms of the quantitative models generated.

5. Experimental Design

For our experiment, we selected a consecutive period of time to serve as our experimental baseline. We selected a five-week research period of Oct. 26, 2005 to Nov. 28, 2005, which incorporates twenty-three trading days. The five-week period of study was selected because it gathered a comparable number of articles in comparison to prior studies: 6,602 for Mittermayer (Mittermayer 2004) and 5,500 for Gidofalvi (Gidofalvi 2001). We also observe that the five-week period chosen did not have unusual market conditions (e.g., sudden market or industry-wide price fluctuations) which would be a good testbed for our evaluation and be generalizable to other market periods. In order to identify companies with more financial news, we further limited the scope of activity to focus on companies listed in the S&P 500 as of Oct. 3, 2005. Articles gathered during this period were restricted to occur between the hours of 10:30am and 3:40pm. While trading starts at 9:30am, we felt it important to reduce the impact of overnight news on stock prices and selected a period of one-hour to allow prices to adjust. The 3:40pm cut-off for news articles was selected to disallow any +20 minute stock predictions to occur after market hours. A further constraint was introduced to reduce the effects of confounding variables, where two articles on the same company cannot exist within twenty minutes of each other or both will be discarded. The above processes had filtered the 9,211 candidate news articles gathered during this period to 2,809, where the majority of discarded articles occurred outside of market hours. Similarly, 10,259,042 per-minute stock quotations, 302 analyst recommendations and 3,937 insider transactions were gathered during this period. This large testbed of time-tagged articles and fine-grain stock quotations allow us to perform our evaluation systematically.

For our quantitative portfolio, we followed the work of Kang et. al., and used our study period of Oct. 26 to Nov. 28 as our holding period *h* (Kang, Liu et al. 2002). Immediately preceding this period is the portfolio formation period *f*, where stock price returns are rank ordered and the top quintile of stocks becomes the Momentum portfolio while the bottom quintile of stocks becomes the Contrarian portfolio. The length of *f* is varied in 1 week increments up to 5 weeks in order to increase the model's robustness.

To answer our first research question on finding the most profitable strategy in terms of quantitative portfolios and financial news prediction, we created four models to test, as shown in Figure 3.

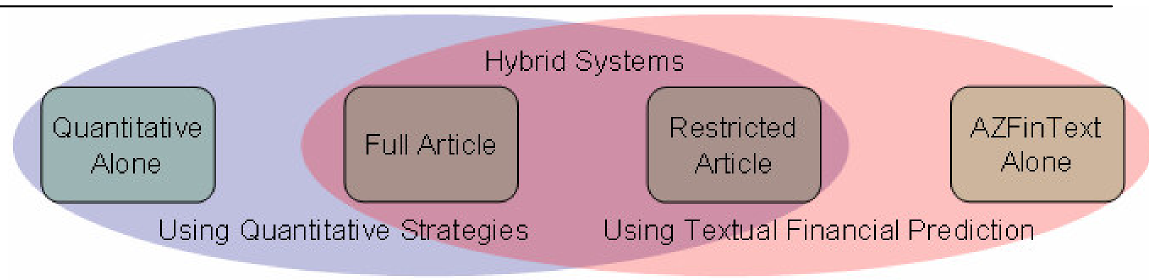

Figure 3. Four models to analyze

From this figure, the first model utilizes quantitative strategies by themselves, by measuring the returns of Momentum and Contrarian portfolios during the holding period under differing formation periods. In this model, trading returns are simply the percentage difference between the stock at the beginning and end of period *h*.

Our second and third models are hybrid systems incorporating both quantitative strategy and financial news prediction. In these models, AZFinText is limited to performing trades on only those companies within the Momentum or Contrarian portfolios. These models differ from one another on the scope of financial news articles available for system training. Model two, or 'Full Article,' uses all financial news articles regardless of whether they are in the quantitative portfolio. Model three, or 'Restricted Article,' limits AZFinText to only those financial news articles within the portfolio. This differentiation can help determine the value of using financial news articles from peer organizations as a prediction tool.

The fourth model is the financial news prediction system, AZFinText, by itself. This model is free to trade on all of the S&P500 stocks and uses all financial news articles at its disposal.

Prior research has also shown that grouping companies based on their industry sectors leads to better results. One such grouping classification system is the Global Industrial Classification System (GICS) which was developed by Morgan Stanley. This classification system was found to be superior to other systems (Bhojraj, Lee et al. 2003) and is also best able to describe analysts' areas of expertise (Boni and Womack 2004). This method will be repeated on our models using AZFinText, where articles are trained within each GICS Sector and then aggregated together to determine trading returns.

While computing the trading returns of a quantitative-only strategy is straight-forward, for the models incorporating AZFinText we utilize a modified version of Lavrenko's Trading Engine (Lavrenko, Schmill et al. 2000a) that examines the percentage return of the stock. When a stock demonstrates an expected movement exceeding 1%, then $1,000 worth of that stock is then either bought or shorted and then disposed of after twenty minutes. This modified version differs from Lavrenko's original design in regards to the dollar amount of stock bought. We further assume zero transaction costs, consistent with Lavrenko.

An example of our system's operation is shown in Figure 4.

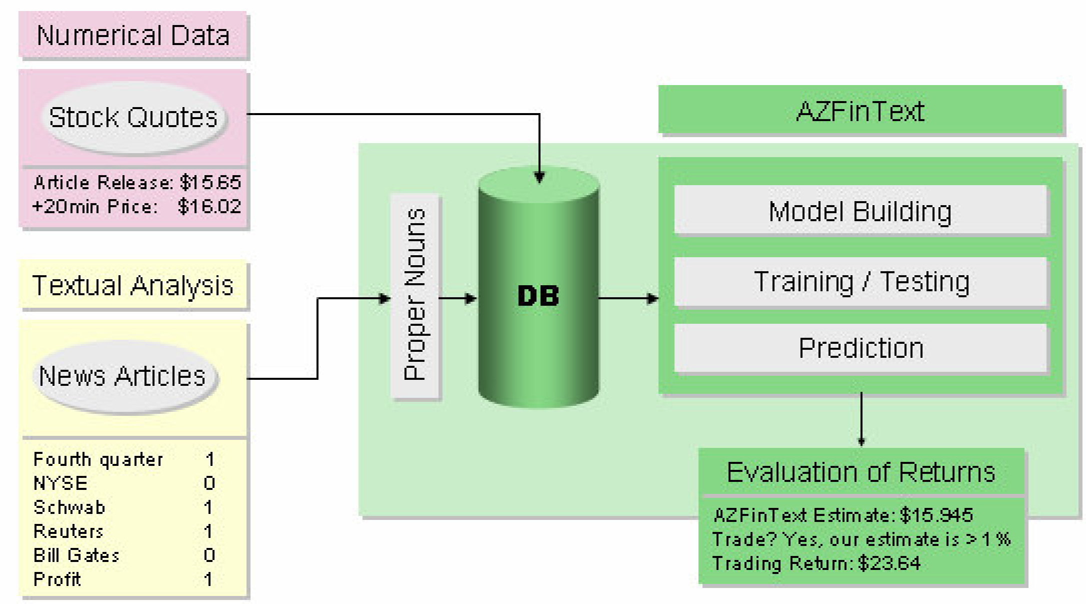

Figure 4. Example of AZFinText Processing

The first part of operation is to extract financial news articles. The entire corpus of news articles are represented by its Proper Nouns in binary as to whether or not that particular Proper Noun feature is present in the article and then stored within the database. Concurrently, stock quotations gathered on a per minute basis and are similarly stored. Analyst Recommendations and Insider Transactions are also captured and stored. To build a model, we first pair together the representational Proper Nouns and stock quotation at the time the article was released, for each financial news article. Then, depending upon the particular model that is tested, data is aggregated and passed to our machine learning component for training and testing. Stock price predictions are then made for each financial news article and passed along to the evaluation instruments.

In the example above, AZFinText derived a prediction price of $15.945 which is greater than 1% of the stock price at the time the article was released, $15.65. Our trading engine makes a trade and disposes of it in twenty minutes time, for a trade return of $23.64 or 2.36%.

6. Experimental Results

To answer our first research question of *What is the effect of combining Quantitative strategies with a financial news article prediction system*, we tested four models of varying levels of quantitative and financial news prediction as well as different portfolio formation periods. The results of the Momentum strategies are presented in Table 1 and Contrarian is in Table 2.

	Trading Returns							
					Full Article Training		Restricted Article	
	Strategy Alone		AZFinText Alone		AZFinText		AZFinText	
Momentum Strategies	n	Return	n	Return	n	Return	n	Return
1 week formation	92	-5.54%	1998	8.50%	513	**20.79%**	513	0.33%
2 week formation	92	-3.93%			534	**14.53%**	534	-2.36%
3 week formation	92	-3.19%			648	**12.00%**	648	-0.23%
4 week formation	92	-2.69%			541	**7.40%**	541	1.08%
5 week formation	92	-2.49%			588	**6.80%**	588	-0.19%

Table 1. Trading Returns for Momentum Strategies

In Table 1, we are measuring the trading returns of each strategy. As a note to readers, the n's for each strategy reflect the number of trading returns, which in the case of 'Strategy Alone' is also the number of companies in the portfolio. For the remaining three models, n-values are still a measure of the number of trading returns performed, but on a news article-basis. Since we are ultimately evaluating the number of trading returns, whether they are company or article-based, we feel that these values are comparable and can be evaluated.

The first thing to notice is that the 'Full Article' AZFinText hybrid outperformed the Momentum strategy alone in all five portfolio formation periods (20.79% to -5.54%, etc.), with p-values < 0.05. While the Momentum strategies by themselves are successful in the 3-12 month horizon, they are not successful by themselves in the short-term, five week period of our study, as evidenced by the negative trading returns for each of the five portfolio formation periods.

The second item of interest, is that 'Full Article' AZFinText outperformed 'Restricted Article' AZFinText for all five portfolio formation periods (20.79% to 0.33%, etc.), p-values < 0.05. It would appear that AZFinText needs a breadth of articles from peer companies not in its portfolio, to make better predictions.

Third, 'Full Article' AZFinText steadily loses returns with additional portfolio formation time (20.79% to 14.53%, etc.), p-values < 0.05. This result most likely capitalizes on short-term investor overreaction to news articles while the company is still in the headlines and consequently in our portfolio. These results were not totally unexpected as Schiereck et. al. found similar decreasing returns with increasing portfolio formation time (Schiereck, DeBondt et al. 1999).

Fourth, in comparing 'Full Article' AZFinText to 'AZFinText Alone,' the hybrid system had better returns for portfolio formation periods of three weeks or less (20.79% to 8.50%, etc), p-values < 0.05. It seems that the incorporation of a Momentum strategy into AZFinText helped it to achieve higher returns than would be ordinarily possible.

We present the results of the Contrarian strategy in Table 2.

	Trading Returns							
					Full Article Training		Restricted Article	
	Strategy Alone		AZFinText alone		AZFinText		AZFinText	
Contrarian Strategies	n	Return	n	Return	n	Return	n	Return
1 week formation	92	3.36%	1998	8.50%	505	**4.54%**	505	0.37%
2 week formation	92	1.86%			541	**13.18%**	541	0.60%
3 week formation	92	1.40%			432	**4.87%**	432	1.44%
4 week formation	92	0.87%			497	**11.65%**	497	1.91%
5 week formation	92	0.29%			490	**11.94%**	490	-0.08%

Table 2. Trading Returns for Contrarian Strategies

From this table, the first thing to note is that Contrarian 'Strategy Alone' outperformed Momentum 'Strategy Alone' for all five portfolio formation periods. Prior studies noted that Contrarian strategies by themselves are successful in the short-term (weekly, monthly) and long-term (3-5 year) horizons. However, Contrarian's best success of a 3.36% return was overshadowed by an overall market return of 5.62%.

Second, 'Full Article' AZFinText outperformed the Contrarian 'Strategy Alone' for all five formation periods (4.54% to 3.36%, etc.), p-values < 0.05. This result was similarly observed in Momentum strategies and would imply that the addition of financial news article prediction has helped the system achieve better returns.

Third, 'Full Article' again performed better than 'Restricted Article' for all five portfolio formation periods (4.54% to 0.37%, etc.), p-values < 0.05. Again it would appear that AZFinText needs a breadth of articles from companies not in its portfolio to make better predictions.

The Contrarian 'Full Article' AZFinText did not perform as well against 'AZFinText Alone' (4.54% to 8.50%), p-value < 0.05. While the 2, 4 and 5 week portfolio formation returns of 13.18%, 11.65% and 11.94% performed better than the 8.50% of 'AZFinText Alone,' there was no consistency in trading returns as a function of portfolio formation periods, as was observed in Momentum.

In both Momentum and Contrarian, 'Full Article' AZFinText performed the best. However, in comparing the two against one another, Momentum appeared stronger with sizably larger returns. This may be from capitalizing on investor overreaction to news on companies that have had recent success. Investors bid the stock price higher than it should be and AZFinText makes a profit on it.

7. Conclusions

From our investigations we found several valuable results. The first of which is that using a Momentum strategy coupled with ‘Full Article’ training of AZFinText led to the best trading returns. While the ‘Contrarian Alone’ strategy outperformed the ‘Momentum Alone’ strategy in all five portfolio formation periods, coupling the financial news prediction system of AZFinText to Momentum led to better overall performance on our five-week dataset. Furthermore, the one-week portfolio formation time led to the best trading returns of 20.79% and most likely capitalizes on the short-term overreaction to news articles while the company is still in the headlines.

While more research on this phenomenon is definitely worth pursuing, we feel that our system is taking advantage of current arbitrage opportunities that exists between the release of a financial news article and the human analysts trading decisions. Extending our automation process in a wide-spread fashion would limit these opportunities.

We would also suggest several future directions for this stream of research. The first of which is to investigate the linguistic weighting of trained article terms. Within the machine learning algorithm, certain article terms will be weighted higher than others, indicating their prominence in predicting future prices. Investigating the impact of the most important terms will provide insights into future tuning activities.

Second, an investigation into the type of financial news article being used would be essential. Perhaps certain classes of news articles such as acquisitions, changes in directorships, etc. may lead to trader sensitivity and further overreaction. Some article types may not provide additional predictive capacity and may be omitted from prediction activity.

Third, the roles of market exchanges and market capitalization on the predictive abilities of a financial news system is not known. Perhaps traders are more likely to pursue large-cap stocks on particular exchanges and open profit-taking opportunities on the lesser traded stocks. Analyzing these features may lead to better predictability and a better understanding of how a financial news article system beats the market.

References

1. Asness, C., (1997), The Interaction of Value and Momentum Strategies. *Financial Analysts Journal* 53(2), 29-37.

2. Baldwin, N. and R. Rice, (1997), Information-seeking Behavior of Securities Analysts: Individuals and Institutional Influences, Information Sources and Channels, and Outcomes. *Journal of the American Society for Information Science* 48(8), 674-693.

3. Bhojraj, S., C. M. C. Lee, et al., (2003), What's My Line? A Comparison of Industry Classification Schemes for Capital Market Research. *Journal of Accounting Research* 41(5), 745-774.

4. Boni, L. and K. L. Womack, (2004), Industries, Analysts, and Price Momentum. *Tuck School of Business Working Paper No. 03-12,* Dartmouth College.

5. Camerer, C. and K. Weigelt, (1991), Information Mirages in Experimental Asset Markets. *Journal of Business* 64(4), 463-493.

6. Chan, L., N. Jegadeesh, et al., (1996), Momentum Strategies. *The Journal of Finance* 51(5), 1681-1713.

7. Chan, S. W. K. and J. Franklin, (2003), Dynamic Context Generation for Natural Language Understanding: A Multifaceted Knowledge Approach. *IEEE Transactions on Systems, Man and Cybernetics, Part A* 33(1), 23-41.

8. Chan, W., (2003), Stock Price Reaction to News and No-News: Drift and Reversal After Headlines. *Journal of Financial Economics* 70(2), 223-260.

9. Conrad, J. and G. Kaul, (1998), An Anatomy of Trading Strategies. *The Review of Financial Studies* 11(3), 489-519.

10. De Bondt, W. and R. H. Thaler, (1985), Does the Stock Market Overreact? *The Journal of Finance* 40(3), 793-805.

11. De Bondt, W. and R. H. Thaler, (1987), Further Evidence on Investor Overreaction and Stock Market Seasonality. *The Journal of Finance* 42(3), 557-581.

12. Fama, E., (1964), The Behavior of Stock Market Prices. *The Journal of Business* 38(1), 34-106.

13. Fama, E. and K. French, (1998), Value versus Growth: The International Evidence. *The Journal of Finance* 53(6), 1975-1999.

14. Forner, C. and J. Marhuenda, (2003), Contrarian and Momentum Strategies in the Spanish Stock Market. *European Financial Management* 9(1), 67-88.

15. Gervais, S., R. Kaniel, et al., (2001), The High-Volume Return Premium. *The Journal of Finance* 56(3), 877-919.

16. Gidofalvi, G., (2001), Using News Articles to Predict Stock Price Movements. *Department of Computer Science and Engineering,* University of California, San Diego.

17. Jegadeesh, N., (1990), Evidence of Predictable Behavior of Security Returns. *The Journal of Finance* 45(3), 881-898.

18. Jegadeesh, N. and S. Titman, (1993), Returns to Buying Winners and Selling Losers: Implications for Stock Market Efficiency. *The Journal of Finance* 48(1), 65-91.

19. Jelveh, Z., (2006), How a Computer Knows What Many Managers Don't. *The New York Times*, July 9.

20. Joachims, T., (1998). Text Categorization with Support Vector Machines: Learning with Many Relevant Features. *European Conference on Machine Learning*, Chemnitz, Germany.

21. Kang, J., M.-H. Liu, et al., (2002), Contrarian and Momentum Strategies in the China Stock Market: 1993-2000. *Pacific-Basin Finance Journal* 10(3), 243-265.

22. Lavrenko, V., M. Schmill, et al., (2000a). Language Models for Financial News Recommendation. *International Conference on Information and Knowledge Management*, Washington, DC.

23. LeBaron, B., W. B. Arthur, et al., (1999), Time Series Properties of an Artificial Stock Market. *Journal of Economic Dynamics and Control* 23(9-10), 1487-1516.

24. Lehmann, B., (1990), Fads, Martingales, and Market Efficiency. *Quarterly Journal of Economics* 105(1), 1-28.

25. Li, Z., B. Wang, et al., (2005). A Probabilistic Model for Retrospective News Event Detection. *28th Annual International ACM SIGIR Conference on Research and Development in Information Retrieval*, Salvador, Brazil.

26. Lo, A. and C. MacKinlay, (1990), When are Contrarian Profits Due to Stock Market Overreaction? *The Review of Financial Studies* 3(2), 175-205.

27. Malkiel, B. G., (1973), <u>A Random Walk Down Wall Street</u>. New York, W.W. Norton & Company Ltd.

28. Markowitz, H., (1952), Portfolio Selection. *The Journal of Finance* 7(1), 77-91.

29. McDonald, D. M., H. Chen, et al., (2005). Transforming Open-Source Documents to Terror Networks: The Arizona TerrorNet. *American Association for Artificial Intelligence Conference Spring Symposia*, Stanford, CA.

30. McKeown, K., (1995). Generating Summaries of Multiple News Articles. *18th Annual International ACM SIGIR Conference on Research and Development in Information Retrieval*, Seattle, WA.

31. Mittermayer, M., (2004). Forecasting Intraday Stock Price Trends with Text Mining Techniques. *Hawaii International Conference on System Sciences*, Kailua-Kona, HI.

32. Mowshowitz, A., (1992), On the Market Value of Information Commodities. The Nature of Information and Information Commodities. *Journal of the American Society for Information Science* 43(3), 225-232.

33. Platt, J. C., (1999), Fast Training of Support Vector Machines using Sequential Minimal Optimization. Advances in Kernel Methods: Support Vector Learning. B. Scholkopf, C. Burges and A. Smola. Cambridge, MA, MIT Press: 185-208.

34. Raban, D. and S. Rafaeli, (2006), The Effect of Source Nature and Status on the Subjective Value of Information. *Journal of the American Society for Information Science and Technology* 57(3), 321-329.

35. Ross, S., (1976), The Arbitrage Theory of Capital Asset Pricing. *Journal of Economic Theory* 13(3), 341-360.

36. Rouwenhorst, K., (1998), International Momentum Strategies. *The Journal of Finance* 53(1), 267-284.

37. Schiereck, D., W. DeBondt, et al., (1999), Contrarian and Momentum Strategies in Germany. *Financial Analysts Journal* 55(6), 104-116.

38. Schumaker, R. P. and H. Chen, (2006). Textual Analysis of Stock Market Prediction Using Financial News Articles. *Americas Conference on Information Systems*, Acapulco, Mexico.

39. Schumaker, R. P. and H. Chen, (2007), Textual Analysis of Stock Market Prediction Using Breaking Financial News: The AZFinText System. *ACM Transactions on Information Systems* Under Review.

40. Sekine, S. and C. Nobata, (2004). Definition, Dictionaries and Tagger for Extended Named Entity Hierarchy. *Language Resources and Evaluation Conference*, Lisbon, Portugal.

41. Sharpe, W., (1964), Capital Asset Prices: A Theory of Market Equilibrium Under Conditions of Risk. *The Journal of Finance* 19(3), 425-442.

42. Tay, F. and L. Cao, (2001), Application of Support Vector Machines in Financial Time Series Forecasting. *Omega* 29, 309-317.

43. Technical Analysis, The Trader's Glossary of Technical Terms and Topics. Retrieved on Mar. 15, 2005, from http://www.traders.com

44. Tolle, K. M. and H. Chen, (2000), Comparing Noun Phrasing Techniques for Use with Medical Digital Library Tools. *JASIS* 51(4), 352-370.

45. Torre, N. and A. Rudd, (2004), The Portfolio Management Problem of Individual Investors: A Quantitative Perspective. *The Journal of Wealth Management* 7(1), 56-64.

46. Vapnik, V., (1995), The Nature of Statistical Learning Theory. New York, Springer.

47. Witten, I. H. and F. Eibe, (2005), Data Mining: Practical Machine Learning Tools and Techniques. San Francisco, Morgan Kaufmann.

48. Wuthrich, B., V. Cho, et al., (1998). Daily Stock Market Forecast from Textual Web Data. *IEEE International Conference on Systems, Man, and Cybernetics*, San Diego, CA.