Does past stock performance matter in investing?

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Abstract

In our project we investigate the impact of past stock data on future price movement. We consider two different approaches for predicting the future stock behavior: supervised learning based on feature vectors built from technical analysis indicators and sequence mining for discovering frequent patterns of stock price movements for a given stock.

1 Introduction

Stock market investors rely heavily on stock *technicals* to guide their investing, which are a wide range of formulas that seek to offer advice on a stock based on the stock's past performance. Technicals differ from stock *fundamentals* in that fundamentals are statistics about a company itself, its quarterly earnings, its debt ratio, etc, whereas technicals are derived solely from the trading of a company's stock.

Given the ubiquity of the use of technicals in investing, one might think that their predictive value is a given. The literature indicates that certain technicals do have a predictive value [1], but it is still not clear under what circumstances their predictive value holds, or whether certain combinations of technicals offer better prediction of stock price.

To this end, we have developed two data mining approaches to investigate the usefulness of technicals for an average investor, i.e. an investor that uses a middle to long term trading strategy over the period of weeks and months. We first use supervised learning to learn a classifier that can predict when a stock should be bought or sold based on stock technicals leading up to a day of trading. We then use frequent pattern mining to try to learn rules for trading that an average investor could use on a day to day basis.

2 Data

We gathered publicly available data from Yahoo! Finance[5] for different stocks in two sectors, basic materials and technology. The basic materials sector consists of companies involved with the discovery, development and processing of raw materials into consumer and industrial goods, such as food and chemical production. The technology sector contains stock data for companies in areas like software development, electronics manufacturing, and other businesses related to information technology. We screened the stocks in this sector based on two criteria, *i*) stocks must be a member of the S&P 500, a list of the top 500 companies in the NYSE and NASDAQ exchanges, and *ii*) stocks must have been listed in the stock market since January, 2005. We chose these criteria to match the investment strategies of average investors who prefer well-known, large companies that have been around for a number of years. Our data set consists of 42 stocks from the technology sector and 31 stocks from basic materials.

We chose these two sectors because they contain two different classes of companies: *non-cyclicals* and *cyclicals*. No single sector of stocks contains only one class of companies, however a number of companies in the basic materials sector are non-cyclicals, i.e. their stock price does not correlate strongly with the strength of the economy. Companies such as Kraft Foods (KFT), a maker of cereals and other consumer goods, and Altria Group (MO), a maker of cigarettes, tend to profit regardless of the state of the economy, as people continue to eat and smoke even during recessions.

Technology stocks, on the other hand, are often heavily dependent on the amount of disposable income consumers have, which varies with the economy. In recessionary periods, consumers do not buy as many electronics, and the price of technology stocks sag. The technology sector includes companies like Microsoft (MSFT), Apple (AAPL) and Dell (DELL), which are heavily involved in retail electronics.

2.1 Data preprocessing

In our case data preprocessing is a straightforward task since for each stock we are provided with a csv file consisting of the following data for each stock on each trading day: opening price, closing price, highest and lowest price and the volume, which measures how many times a stock as bought and sold, for the day. We directly use the numerical values in order to compute technical analysis indicators and to label days, respectively longer time periods, in a way describing in an informative manner the behavior of the stock for the considered time interval. Note that since our data contains no missing or inconsistent values no data cleaning is necessary.

2.2 Features

We used a number of well-known technicals indicators as features. For the description of the features, we use the following notation for stock data. Let c_i, l_i, h_i, and v_i be the closing price, daily low, daily high and volume of day i, respectively. Most of these features are calculated over a period n that starts on a day s.

Simple Moving Average (SMA) Let $SMA(n, s) = \frac{1}{n}\sum_{i=s}^{s+n} c_i$, where n is the period of the SMA and s is the start day of the period. We use a period of 200 days, which is a standard period for the SMA. In addition, we compute the change in the SMA over the past 20 days with $\frac{SMA(200,i)}{SMA(200,i-20)}$ in order to determine whether the stock has been increasing or decreasing in value.

Exponential Moving Average (EMA) Let $EMA(n, s) = \alpha c_i + (1 - \alpha)(EMA(n - 1, s + 1))$, where $\alpha = \frac{2}{n+1}$. We use a standard period of 50 days along with the direction of the EMA using $\frac{EMA(50,i)}{EMA(50,i-20)}$.

Relative Strength Index (RSI) Let $RSI(n, s) = \frac{EMA(U(n,s),14)}{EMA(D(n,s),14)}$, where $U = \{c_i - c_{i-1} | (c_i - c_{i-1}) > 0, s < i \leq s + n\}$ and $D = \{|c_i - c_{i-1}| \mid (c_i - c_{i-1}) < 0, \forall s < i \leq s + n\}$. Note that in a slight abuse of notation, we indicate that the EMA is to be taken over the sets U and D with a period of 14 days. The sets U and D represent periods of increasing stock price and decreasing stock price respectively.

Williams Percent R (W%R) Let $W\%R(n, s) = \frac{h^* - c_s}{h^* - l^*}$, where $l^* = argmax_{l_i}\{l_i, s \leq i \leq s + n\}$ and $h^* = argmax_{h_i}\{h_i, s \leq i \leq s + n\}$. The values h^* and l^* represent the highest high and the lowest low during the period. We use a period of 60 and 10 days for our features.

Stochastic Oscillator (SOSC) Let $SOSC(n, s) = \frac{c_s - l^*}{h^* - l^*}$, where h^* and l^* are defined as in Williams Percent R. The stochastic oscillator is very similar to Williams Percent R, but provides a slightly different view of the same data. We use a stochastic oscillator with period 20 days, along with $\frac{SOSC(20,i)}{SOSC(20,i-20)}$ to determine the movement of the SOSC over time.

Commodity Channel Index (CCI) Let $CCI(n, s) = \frac{t_i - SMA(t_i,n,s)}{\sigma(t_i)}$, where $t_i = \frac{h_i + l_i + c_i}{3}$ is the "typical price". The CCI is normally multiplied by $\frac{1}{0.015}$, but since it is constant, we have removed it.

Volume Moving Average (VMA) Let $VMA(n, s) = \frac{1}{n}\sum_{i=s}^{s+n} v_i$, which is a measure of the average volume of a stock. We use a standard period of 200 days, and include a feature $\frac{VMA(200,i)}{VMA(200,i-20)}$ that measures the change of the VMA over the past 20 days.

3 Supervised learning

We perform supervised learning by splitting the data from a stock into a three year training set beginning on January 3, 2005 and ending on January 2, 2008, and a two year testing set beginning on January 2, 2009 and ending on January 3, 2011. We separate the training set from the testing set to ensure that none of the features computed for the testing set overlap any days in the training set and, thus, taint the testing set with information that was used to build our classifier.

Our training set is labeled with five different labels: Strong Buy, Buy, Hold, Sell, Strong Sell. We use these five labels in order to allow a trader using this data mining code to exercise discretion over when to perform a trade. The labels provide guidance outside of just the confidence of the classifier. In order to label days, we calculate the average profit or loss of buying a stock on a particular day and selling it any of the following 2 years of trading. We then take the average profit or loss calculated for each day, and label each day according to where it falls in the distribution of profits and losses. We label the bottom 5% of days with the label "Strong Sell", the next 20% of days with "Sell", the next 50% with "Hold", the following 20% with "Buy" and the top 5% with "Strong Buy". Note that due to the volatility of stocks, there are always some periods that are more desirable than others, even with a stock that is constantly moving upwards. We use this labeling strategy because it attempts to find days for buying a stock that are relatively robust. That is, the days following a buy or strong buy label are likely to provide a profit, and days following a sell label are likely to result in a loss.

We compared several different supervised learning algorithms to see which could provide the largest monetary gain on our dataset. The algorithms we show are Naive Bayes, a Multilayer Perceptron and a Support Vector Machine (SVM) with a polynomial kernel. using the WEKA library [2]. We used default parameters and performed no tuning, as the WEKA algorithms are well tuned for a wide range of applications.

The Naive Bayes algorithm trains a simple classifier based on Baye's theorem, which predicts the probability of the value of a random value given some independent evidence[1]. A class label is assigned to a feature vector by computing the maximum likelihood estimations of the probabilities for each class.

Multilayer Perceptrons work by creating a network of perceptrons in which an input layer accepts a feature vector, a hidden layer processes data from the input layer, and then passes data on to an output layer which predicts a class label. The Multilayer Perceptron in WEKA uses backpropagation to attempt to adjust each perceptron's weight to maximize the likelihood of a correct label prediction by the network.

SVMs [4] are a classification method that maps features from their original space into a higher dimensional space in which a separation hyperplane can be found between two class labels. SVMs utilize the *kernel trick* to perform the mapping.

3.1 Results

We evaluated the performance of each classifier with a simulation of stock trading based on the output of the classifier. We start the testing period with $10,000 and receive a label for each day from the classifier. If the label is "Strong Buy", we purchase as many shares as we have money for. Conversely, if the label is "Strong Sell" we sell all the shares currently owned. If the label is "Buy" we attempt to buy $2,500 worth of shares. If the label is "Sell", we attempt to sell $2,500 worth of shares.

Table 1 show the results of our experiments. The buy & hold strategy involves purchasing a stock at the beginning of the testing period and not selling it until the end. Buy & Hold outperforms all of our classifiers, earning on average $21,900 from $10,000 in the technology sector and $13,300 in the basic materials sector. The simple buy & hold strategy is able to outperform even our best classifier $6,600 in the technology sector and by $1,100 in the basic materials sector. This gives a strong indication that

[1]In spite of the independence assumption, Naive Bayes can be used on problems where the features contain dependencies.

	Technology				Basic Materials			
	Avg.	Stdev	Min	Max	Avg.	Stdev	Min	Max
Naive Bayes	14.6	8.3	7.6	57.9	10.7	2.5	4.6	19.3
Multi. Perceptron	14.8	7.0	6.8	38.9	11.7	3.5	4.7	21.9
SVM	15.3	7.7	6.8	41.4	12.2	3.5	4.7	19.8
Buy & Hold	21.9	10.7	7.3	58.8	13.3	4.0	4.6	24.6

Table 1: A comparison of different data mining algorithms to a Buy & Hold strategy. All values are in thousands, with the Avg. column showing the average amount of money at the end of the testing period after starting with $10,000 and using a disciplined trading strategy. The min and max columns show the minimum and maximum amount of money left over all stocks in the sector.

stock technicals do not influence price in ways that are easy to capture using data mining methods, and that perhaps watching stock fundamentals and the news would be a better way to increase gains.

The largest gain of the Buy & Hold strategy, which earned $58,800 from the original money, came from F5 Networks (FFIV), which saw large gains over the testing period. On that particular stock, the best classifier was Naive Bayes, which managed to earn $57,900, indicating that in some situations the classification algorithms can compete with a buy & hold strategy. On the same stock the SVM earned $41,400 and the Multilayer perceptron $38,900.

Overall, the SVM performed the best out of our classifiers. This is not all that surprising given the large amount of dependencies present in the features. More surprising is that naive bayes was able to perform well at all, since all of the features are ultimately based on the same few pieces of data.

4 Frequent pattern mining

4.1 Motivation

Our goal is to find frequently occurring patterns of price movements. Unlike in the previous section we do not acquire any information from stock technicals. The intuition is to try to detect price movement dependencies in a more direct way by simply considering the past stock performance. The intuition is that sometimes technicals might give too much information which dilutes the picture we want to analyze, namely how does the price curve look.

Consider for example the graph of the curve for the stock price movement of Adobe in Figure 1. We see there are certain reoccurring patterns, for example a sharp fall is followed by a sharp rise of the price in three different situations as indicated by the shaded regions.

4.2 General setting

We consider the price movement of a given stock over a certain time period. We divide the period in small subintervals of at least one day which we consider data points in a sequence. We label the data points such that the label indicates the stock price movement. We use three distinct labels F, H and R indicating whether a given price will decrease its value over a given period (F), will retain approximately the same value (H), or will increase its price (R). They are obtained depending on the opening and closing price for the period.

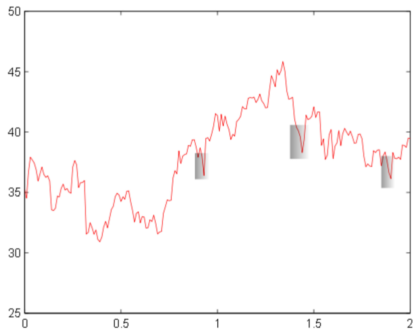

Figure 1: Price movement for Adobe from 1994-07-13 to 1995-04-27.

4.3 A modified Apriori approach

Formally, we are given a sequence $\mathbb{S}$ of symbols $s \in \mathcal{A}$ over some alphabet $\mathbb{A}$. Let the support of a subsequence $S \subseteq \mathbb{S}$ be $\sup(S) = \frac{\#S}{|\mathbb{S}|-|S|}$ where $\#S$ is the number of occurrences of the subsequence S in $\mathbb{S}$ and $|\mathbb{S}|$ and $|S|$ are the lengths of $\mathbb{S}$ and S, respectively. That is, the support of a given sequence S is the number of its occurrences divided by the number of all subsequences in $\mathbb{S}$ of length $|S|$. For a given support threshold σ and a confidence threshold τ we want to find all subsequences $S \subset \mathbb{S}$ such that $\sup(S) \geq \sigma$ and $\text{conf}(S) \geq \tau$. The confidence $\text{conf}(S)$ of a rule derived from S is defined as $\frac{\sup(S)}{\sup(S \backslash \ell)}$ where ℓ is the last symbol in S.

The above definitions are similar to the itemset and transaction setting in the classic frequent pattern mining context. However, an important difference is that one can build only linearly many subsequences of a given sequence, thus the following algorithm avoids the combinatorial explosion caused by Apriori for lower support thresholds and is thus much more efficient [3].

Algorithm 1 *Frequent sequence mining*

```
1. Find frequent symbols, set $k = 2$.
2. Join frequent subsequences of length $k - 1$ if the last $k - 2$ symbols of the first subsequence are
   identical to the first $k - 2$ symbols of the second subsequence
3. build a set of candidates of length $k$ and filter out infrequent subsequences.
4. repeat steps 2–3 until no new frequent subsequences can be obtained.
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Lemma 1 *The algorithm correctly identifies all frequent subsequences of a given sequence.*

Proof. For a subsequence S to be frequent the Apriori property that all proper subsequences S' of S are frequent must hold. Thus, assuming we have identified all frequent subsequences of length $k - 1$, steps 2 and 3 return a superset of the frequent subsequences of length k. Correctness follows by a simple inductive argument. □

Example: Let us consider a simple concrete example: the sequence $\mathcal{S} = abcbcaababcaabccbaabbabcbcacba$ contains 30 symbols. We are interested in all k-subsequences with frequency at least 0.15, i.e. occurring in at least 10% of all subsequences of length k. The 1-subsequences are the symbols themselves and we find that all of them are frequent since they appear more than 4.5 times ($4.5 = 0.15 \cdot 30$). Then we build candidate subsequences as $aa, ab, ac, ba, bb, bc, ca, cb, cc$ since they all satisfy the joining condition: the last 0 symbols of the first subsequence agree with the first 0 symbols of the second one. From these symbols we find that the subsequence aa appears only once, ab – five times, ac – one time, ba – 4 times, *bb* – one time, *bc*– 6 times, *ca* – three times, *cb*– three times and *cc* – one time. The total number of 2-subsequences is 29, thus threshold is now $0.15 \cdot 29 = 4.35$. Thus, the frequent 2-subsequences are *ab*, *ba* and *bc*. From these we build the following candidate 3-subsequences: *aba*, from *ab* and *ba*, *bab*, from *ba* and *ab*, and *abc*, from *ab* and *bc*. Note that *ba* and *bc* can not be combined since they don't satisfy the joining condition. Now *aba* appears only once, *bab* twice, and *abc* – four times. Thus, no 3-subsequence is frequent, i.e. occur more than $4.2 = 0.15 \cdot 28$ times, and the algorithm terminates.

In the very same way as in Apriori one computes the confidence of each rule.

4.4 Results

4.4.1 Labeling

We experimented with several values for the number of labels. It turns out that the more labels we have the more difficult it becomes to detect any frequent subsequences for a reasonable support threshold. Thus, we choose to present results when only three labels are used.

As already mentioned, the three different labels F, H and R indicate whether the price will fall, remain relatively the same, or raise in the considered time period t, respectively. The labels are obtained in a natural way: given some threshold τ, we compute the value $f := \frac{c-o}{c}$ where c is the closing price for the considered period t, and o is the opening price. Note that we divide by c in order to achieve normalization not depending on the absolute values of the stock price. Then we label t as H if $-\tau \leq f \leq \tau$, as F if $f < -\tau$, and as R otherwise.

It is in general a difficult problem to choose an optimal threshold τ, since choosing a small value will lead to labeling periods as either F or R even for non-significant changes of the stock price. On the other hand, big values of τ result in too many periods labeled as H and this makes it difficult to mine rules with consequent different from H. We observed that values of about 0.1 give a balanced distribution among labels for most stocks for short time periods and allow the mining of reasonable amount of rules.

We also experimented with labeling different time periods: it seems that for longer periods valuable information for price movements within the period is lost, while for some stocks for short periods like one day it is difficult to capture the effect of, say, more slowly price movement.

4.4.2 Choosing the best rule

In certain situations we might be able to apply more than one rule. For example, the labels for the last three time periods are HHF and we have the rules $HF \rightarrow F$ and $HHF \rightarrow H$. The most natural choice is the rule with the best confidence. However, a rule with a longer antecedent might give us better information since it takes into account more information. We implemented both strategies. It is difficult to say which one performs better, since apparently different stocks behave differently.

4.4.3 Average correctness

After labeling the data for a given stock over a certain time period, say 3 days, we perform frequent sequence mining over the sequence. We use the first 2/3 of the sequence for frequent pattern mining, and the last 1/3 for applying our rules and correctness testing of our predictions. For all considered stocks we mined the sequences for the whole price history.

The following table shows the label distribution and the percentage of correct predictions we obtain for certain stocks from the technology sector for threshold $\tau = 0.012$ and label period $t = 2$. A more comprehensive list can be found in the appendix.

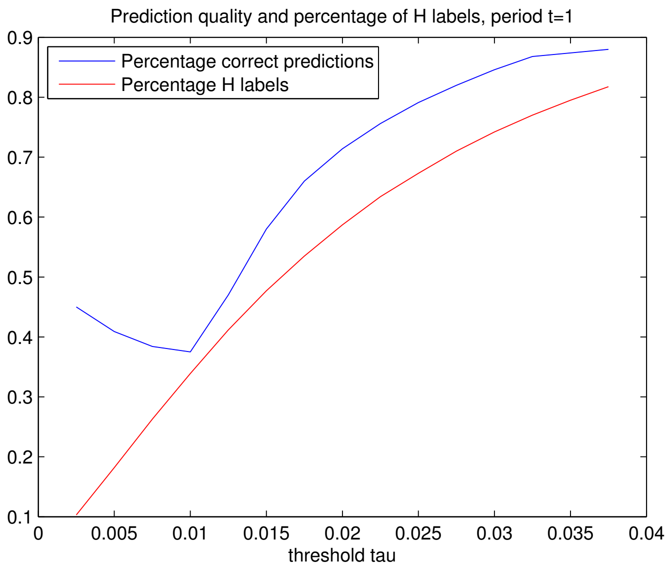
Stock	average F	average R	average H	correct predictions
AAPL	0.3490	0.2935	0.3574	0.3888
ADBE	0.3476	0.2828	0.3695	0.3805
DELL	0.32164	0.3154	0.3628	0.3823
HPQ	0.2973	0.3819	0.3207	0.3333
MSFT	0.2839	0.4013	0.3146	0.5702
WFR	0.3988	0.2172	0.3839	0.4628

A similar table for the basic materials sector with $\tau = 0.009$ and $t = 2$:

Stock	average F	average R	average H	% correct predictions
ADM	0.38	0.248	0.3716	0.4006
AVP	0.3516	0.2838	0.3644	0.3841
MKC	0.2774	0.4095	0.3129	0.3435
NWL	0.3618	0.2701	0.3680	0.4640
RAI	0.2638	0.4146	0.3214	0.3846
TAP	0.3192	0.3412	0.3394	0.3946

Different stocks behave differently and for example Microsoft turns out to be much more predictive than Hewlett-Packard. Nevertheless, for all stocks the percentage of correct predictions is significantly better than guessing at random based solely on the labels distribution. We observe that the higher threshold τ we choose, i.e. we are more conservative in labeling a price movement as F or R, the better predictions we get. See Figure 2. This has two explanations: First, most rules should have consequent H, thus simply predicting H for each next day should also give a good estimate. On the other hand, as one clearly sees from the graphic the percentage of correct predictions is growing faster than the percentage of H labels. The intuitive explanation is that the price movement becomes less sensitive to small oscillations.

Figure 2: Correctness



4.5 Can we become rich?

One obvious question that arises is how to use the discovered knowledge to make some profit. First of all, we would like to distinguish between *knowledge discovery* and *use of the discovered knowledge*. An experienced investor can use the mined rules in a much cleverer way and the primary goal of this project is applying data mining techniques for discovering knowledge, not a real world application of the discovered knowledge. Nevertheless, out of curiosity, we implemented the following simple strategy: If our rule for the next day predicts R we buy 10 stocks in the morning and sell them in the evening, thus our revenue is $10 \cdot (close\_price - open\_price)$. Note that since we are buying and selling stocks in the same day, the effect inflation has on the stock price movement is minimized. The revenues we obtained for different stocks are shown below.

Stock	Prediction	Revenue	Stock	Prediction	Revenue
AAPL	0.3765	207.3	ADI	0.3624	23.6
ADSK	0.2866	13.6	ALTR	0.3921	0
AMD	0.3702	-39.6	BMC	0.5142	55.19
DELL	0.4773	0.0	EMC	0.3916	-8.1
FFIV	0.3609	157.2	FLSR	0.29	-306.1
NVDA	0.3315	33.5	MSFT	0.6155	0.0

We wanted to check whether a more conservative labeling strategy would yield better revenue. The Figure 3 table summarizes the average revenue over all 42 stocks in the technology sector. Despite some fluctuations, the average revenue drops for higher values of τ, i.e. more labels H.

5 Conclusions

We have shown two methods for guiding the average investor using data mining. Using supervised learning, we saw that using a simple buy & hold strategy outperformed a classifier approach, indicating that average investors should take a simple approach to investing and not try to overanalyze the situation with technicals.

Our frequent pattern mining clearly shows that certain rules can be mined and for most of the stocks they turn out to be to some degree accurate. However, much deeper research is required in order to analyze which requirements should a stock satisfy in order to obtain a reliable labeling. Apparently, simply dividing stocks into sectors is not enough and more subtle subdivision needs to be performed. It is in general questionable whether approaches based on "purely" frequent pattern mining techniques can be successful since they only take into account the price movement. A more promising direction would be to use frequent pattern mining in combination with other techniques in order to support the prediction based on other methods. But such a study is beyond the scope of a course project.

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