Computing trading strategies based on financial sentiment data using evolutionary optimization

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Abstract

In this paper we apply evolutionary optimization techniques to compute optimal rule-based trading strategies based on financial sentiment data. The sentiment data was extracted from the social media service StockTwits to accommodate the level of bullishness or bearishness of the online trading community towards certain stocks. Numerical results for all stocks from the Dow Jones Industrial Average (DJIA) index are presented and a comparison to classical risk-return portfolio selection is provided.

Keywords: Evolutionary optimization, sentiment analysis, technical trading, portfolio optimization

1 Introduction

In this paper we apply evolutionary optimization techniques to compute optimal rule-based trading strategies based on financial sentiment data. The number of application areas in the field of sentiment analysis is huge, see especially [11] for a comprehensive overview. The field of Finance attracted research on how to use specific financial sentiment data to find or optimize investment opportunities and strategies, see e.g. [2], [17], and [20].

This paper is organized as follows. Section 2 describes the financial sentiment data used for the evolutionary approach to optimize trading strategies and portfolios. Section 3 presents an evolutionary optimization algorithm to create optimal trading strategies using financial sentiment data and how to build a portfolio using single-asset trading strategies. Section 4 contains numerical results obtained with the presented algorithm and a comparison to classical risk-return portfolio optimization strategies as proposed by [14] using stock market data from all stocks in the Dow Jones Industrial Average (DJIA) index. Section 5 concludes the paper.

2 Financial Sentiments

We apply financial sentiment data created by PsychSignal[1]. The PsychSignal technology utilizes the wisdom of crowds in order to extract meaningful analysis, which is not achievable through the study of single individuals, see [12] for a general introduction to measurement of psychological states through verbal behavior. Let a group of individuals together be a crowd. Not all crowds are wise, however four elements have been identified, which are required to form a wise crowd: diversity of opinion, independence, decentralization and aggregation as proposed by [21]. These
four elements are sometimes present in some forms of social media platforms, e.g. in the financial community StockTwits, from which the crowd wisdom used for the evolutionary approach described in this paper is derived.

Emotions are regarded as being unique to individual persons and occurring over brief moments in time. Let a mood be a set of emotions together. In order to quantify the collective mood of a crowd, distinct emotions of individual members within the crowd must be quantified. Subsequently, individual emotions can be aggregated to form a collective crowd mood. PsychSignals’ Natural Language Processing Engine is tuned to the social media language of individual traders and investors based on the general findings of e.g. [9] and of [22] for the financial domain. The engine further targets and extracts emotions and attitudes in that distinct language and categorizes as well as quantifies these emotions from text. The methodology is based on the linguistic inquiry and word count (LIWC) project, which is available publicly.

The main idea is to assign a degree of bullishness or bearishness on stocks depending on the messages, which are sent through StockTwits, which utilizes Twitter’s application programming interface (API) to integrate StockTwits as a social media platform of market news, sentiment and stock-picking tools. StockTwits utilized so called cashtags with the stock ticker symbol, similar to the Twitter hashtag, as a way of indexing people’s thoughts and ideas about companies and their respective stocks. The available sentiment data format is described in Tab. 1. The data was obtained through Quandl, where PsychSignal’s sentiment data for stocks can be accessed easily.

Both intensities $I_{bull}$ and $I_{bear}$ are measured on a real-valued scale from 0 to 4, where 0 means no bullish/bearish sentiment and 4 the strongest bullish/bearish sentiment. We normalize these values to 1 by diving the respective value by 4 and obtain the variables $i_{bull}$ and $i_{bear}$. Furthermore, we create two relative variables for the number of bullish and bearish messages, i.e. $r_{bull} = n_{bull}/n_{total}$ as well as $r_{bear} = n_{bear}/n_{total}$, such that we end up in the final data format we are going to use for subsequent analysis. See Tab. 2 for an example of the stock with the ticker symbol BA (The Boeing Company).

## 3 Evolutionary Investment Strategy Generation

We aim at creating an evolutionary optimization approach to generate optimal trading strategies for single stocks based on the sentiment analysis data described above. Evolutionary and Genetic Programming techniques have been applied to various financial problems successfully. See
Table 2: Sentiment values for stock BA starting at the first trading days in 2011.

| Date       | bull | bear | bull | bear | total |
|------------|------|------|------|------|-------|
| 2011-01-03 | 0.59 | 0    | 0.50 | 0    | 4     |
| 2011-01-04 | 0    | 0    | 0    | 0    | 1     |
| 2011-01-05 | 0    | 0.11 | 0    | 1    | 1     |
| 2011-01-06 | 0.61 | 0    | 0.25 | 0    | 4     |
| 2011-01-07 | 0.52 | 0    | 0.17 | 0    | 6     |
| 2011-01-11 | 0.67 | 0    | 1    | 0    | 2     |

especially the series of books on Natural Computing in Finance for more examples, i.e. [3], [4], and [7]. Generating automatic trading rules has been a core topic in this domain, see especially [8], [5], [6], [13], and the references therein.

One main technique in the field of meta-heuristics and technical trading is to let the optimizer generate optimal investment rules given a set of technical indicators. However, instead of using a variety of technical indicators for generating an optimal trading rule, we use the above described financial sentiment data to create investment rules. Thereby we start by using a simplified rule-set approach, whereby the rules are generated by a special genotype encoding. Furthermore, as we are considering to create a portfolio allocation out of the single asset strategies and additionally focus on stocks only, we do not allow for shorting assets, i.e. the decision is whether to enter or exit a long position on a daily basis. The rule is based on the respective sentiment values, such that this basic rule-set can be defined as shown in Eq. (1).

\[
\begin{align*}
&\text{IF} (i_{\text{bull}} \geq \nu_1)_{b_1} \text{ AND } (i_{\text{bear}} \geq \nu_3)_{b_3} \text{ IF} (r_{\text{bull}} \geq \nu_2)_{b_2} \text{ THEN long position.} \\
&\text{IF} (i_{\text{bear}} \geq \nu_3)_{b_3} \text{ AND } (r_{\text{bear}} \geq \nu_4)_{b_4} \text{ THEN exit position.}
\end{align*}
\]

Each chromosome within the evolutionary optimization process consists of the values 

\[(b_1, b_2, b_3, b_4, \nu_1, \nu_2, \nu_3, \nu_4), \]

where the \( b \) values are binary encoded (0, 1) and the \( \nu \) values are real values between 0 and 1. The \( b \) values indicate whether the respective part of the rule notated in square brackets is included (1) or not (0), while the \( \nu \) values represent the concrete values within the conditions. Consider the following example: the (randomly chosen) chromosome \((0,1,1,0.4,0.3,0.5,0.2)\) results in the rule-set shown in Eq. (2).

\[
\begin{align*}
&\text{IF} (r_{\text{bull}} \geq 0.3) \text{ THEN long position.} \\
&\text{IF} (i_{\text{bear}} \geq 0.5) \text{ AND IF} (r_{\text{bear}} \geq 0.2) \text{ THEN exit position.}
\end{align*}
\]

In this special case, the sum of \( b_1 \) and \( b_2 \) as well as \( b_3 \) and \( b_4 \) must be greater or equal to 1, to have at least one condition for entering and leaving the long position. We end up with nine different possible assignments for \( b \). A repair operator has to be applied after each evolutionary operation, which may distort this structure.

The evaluation of the chromosomes is such that the respective trading strategy is tested on the in-sample testing set of length \( T \), i.e. we obtain a series of returns \( r_1, \ldots, r_T \) for each chromosome, which can be evaluated with different financial metrics. The following strategy performance characteristics are considered:

- The cumulative return \( r \), and the standard deviation \( \sigma \).
Table 3: Statistical summary of sentiment values for stock BA 2010-2014.

|       | Minimum | First Quantile | Median | Mean   | Third Quantile | Maximum |
|-------|---------|----------------|--------|--------|----------------|---------|
| bull  | 0       | 0              | 0.3821 | 0.2987 | 0.5050         | 0.8250  |
| bear  | 0       | 0              | 0      | 0.1763 | 0.3887         | 0.86    |

- The maximum drawdown $d$, and the Value-at-Risk $v_\alpha$ ($\alpha = 0.05$), as well as
- the ratio $s$ of expected return divided by the standard deviation, which is based on the Sharpe-ratio proposed by [19].

We use simple mutation operators for new populations because the chromosome encoding of the investment rule described above is short, i.e. contains only eight genes. The following mutation operators are applied:

- $b$ binary flip: One randomly selected gene of the binary $b$ part is $0 \rightarrow 1$ flipped. The resulting chromosome needs to be repaired with the repair operator, which itself determines randomly, which of the two possibilities is set to 1 if necessary.
- $v$ random mutation: One randomly selected gene of the binary $v$ part is replaced by a uniform random variable between 0 and 1.
- $v$ mutation divided in half: One randomly selected gene of the binary $v$ part is divided in half. The rationale of this operation is that the intensities of bullishness and bearishness are often small, see e.g. Tab. 3 for the statistics of the sentiment values for a selected stock.

Besides these operators, elitist selection is applied as well as a number of random additions will be added to each new population. The structure of the algorithm is a general genetic algorithm, see e.g. [1] for a description of this class of meta-heuristics.

The analysis above is based on single assets. To compose a portfolio out of the single investment strategies, the resulting portfolio will be created as an equally weighted representation of all assets, which are currently selected to be in a long position by its respective trading strategy for each day.

4 Numerical Results

In this section we begin with a description of the data used to compute numerical results in Section 4.1. Section 4.2 summarizes the in-sample and out-of-sample results of the evolutionary sentiment trading strategy. A short overview of classical risk-return portfolio optimization is given in Section 4.3 and finally a performance comparison is presented in Section 4.4. Everything was implemented using the statistical computing language R [18].

4.1 Data

We use data from all stocks from the Dow Jones Industrial Average (DJIA) index using the composition of September 20, 2013, i.e. using the stocks with the ticker symbols AXP, BA, CAT, CSCO, CVX, DD, DIS, GE, GS, HD, IBM, INTC, JNJ, JPM, KO, MCD, MMM, MRK, MSFT, NKE, PFE, PG, T, TRV, UNH, UTX, V, VZ, WMT, XOM.

Training data is taken from the beginning of 2010 until the end of 2013. The out-of-sample tests are applied to data from the year 2014.
4.2 Results of the Evolutionary Optimization

For each stock, the optimal strategy was computed. The evolutionary parameters were set to be as follows:

- The initial population size has been set to 100, and each new population
- contains the 10 best chromosomes of the previous population (elitist selection), as well as
- 20 of each of the three mutation operators described above, and
- 10 random chromosomes, such that the population size is 80.

For evaluation purposes, the parameter $s$ will be maximized. Of course, the system is flexible to use any other risk metric or a combination of metrics. See Tab. 4 for the in-sample performance results comparing a long-only buy-and-hold strategy of each asset compared to the trading strategy of the best respective strategy, e.g. the best strategy for AXP is $(1, 0.44, 0.41, 0.17)$ and for BA $(1, 0, 1, 0, 0.41, 0.37, 0.5, 0.41)$, while for CAT it is $(0, 1, 1, 1, 0.195, 0.34, 0.02, 0.24)$ to give an impression of single strategy results. The cumulative return performance $r$ is raised (sometimes significantly) for almost all assets except for MCD, UTX, V. However, in those three cases the decrease in profit is low. The standard deviation $\sigma$ is lower (i.e. better) in all cases, which was expected as the algorithm leaves the long-position for a certain time, such that the standard deviation clearly has to decrease. The Sharpe-ratio like metric $s$ is better for all assets but DIS, JNJ, UTX, XOM. Again, the loss in all four cases is low compared to the gain of the other positions. In summary, the in-sample results show that the fitting of the algorithm works very well.

4.3 Classical Portfolio Optimization

To compare the performance of the portfolio created with single asset investment strategies based on financial sentiments with a standard approach to portfolio optimization, we construct a portfolio using classical risk-return portfolio selection techniques. [14] pioneered the idea of risk-return optimal portfolios using the standard deviation of the portfolios profit and loss function as risk measure. In this case, the optimal portfolio $x$ is computed by solving the quadratic optimization problem shown in Eq. 3. The investor needs to estimate a vector of expected returns $r$ of the assets under consideration as well as the covariance matrix $C$. Finally the minimum return target $\mu$ has to be defined. Any standard quadratic programming solver can be used to solve this problem numerically.

\[
\begin{align*}
\text{minimize} & \quad x^T C x \\
\text{subject to} & \quad r^T x \geq \mu \\
& \quad \sum x = 1
\end{align*}
\]  

(3)

In addition, we also compare the performance to the 1-over-N portfolio, which equally weights every asset under consideration. It has been shown that there are cases, where this simple strategy outperforms clever optimization strategies, see e.g. [10].

4.4 Performance Comparison

The asset composition of the optimal Markowitz portfolio is shown in Tab. 5 - only eight out of the 30 assets are selected. The underlying covariance matrix was estimated from daily returns of the training data, i.e. using historical returns from the beginning of 2010 until the end of
Table 4: Single stock in-sample results of the evolutionary optimization.

|       | Long-only stock | Trading strategy |
|-------|-----------------|------------------|
|       | \( r \) | \( \sigma \) | \( s \) | \( r \) | \( \sigma \) | \( s \) |
| AXP   | 1.223 | 0.016 | 0.057 | 1.574 | 0.013 | 0.068 |
| BA    | 1.450 | 0.016 | 0.063 | 1.771 | 0.013 | 0.070 |
| CAT   | 0.575 | 0.018 | 0.034 | 0.978 | 0.014 | 0.043 |
| CSCO  | -0.070 | 0.019 | 0.006 | 1.246 | 0.011 | 0.061 |
| CVX   | 0.597 | 0.013 | 0.042 | 0.723 | 0.012 | 0.044 |
| DD    | 0.912 | 0.015 | 0.051 | 1.177 | 0.011 | 0.070 |
| DIS   | 1.351 | 0.015 | 0.065 | 1.522 | 0.013 | 0.065 |
| GE    | 0.842 | 0.015 | 0.048 | 1.054 | 0.013 | 0.050 |
| GS    | 0.042 | 0.019 | 0.012 | 0.662 | 0.010 | 0.041 |
| HD    | 1.825 | 0.014 | 0.082 | 2.209 | 0.012 | 0.087 |
| IBM   | 0.430 | 0.012 | 0.036 | 0.711 | 0.005 | 0.083 |
| INTC  | 0.249 | 0.015 | 0.022 | 0.600 | 0.009 | 0.043 |
| JNJ   | 0.415 | 0.008 | 0.045 | 0.415 | 0.008 | 0.041 |
| JPM   | 0.399 | 0.019 | 0.027 | 0.873 | 0.016 | 0.037 |
| KO    | -0.277 | 0.019 | -0.004 | 0.363 | 0.006 | 0.042 |
| MCD   | 0.549 | 0.009 | 0.052 | 0.515 | 0.006 | 0.060 |
| MMM   | 0.688 | 0.013 | 0.048 | 0.795 | 0.012 | 0.051 |
| MRK   | 0.359 | 0.012 | 0.032 | 0.516 | 0.010 | 0.041 |
| MSFT  | 0.222 | 0.014 | 0.021 | 0.509 | 0.012 | 0.031 |
| NKE   | 0.190 | 0.022 | 0.022 | 0.511 | 0.019 | 0.030 |
| PFE   | 0.677 | 0.012 | 0.048 | 0.805 | 0.011 | 0.049 |
| PG    | 0.332 | 0.009 | 0.036 | 0.406 | 0.007 | 0.046 |
| T     | 0.238 | 0.010 | 0.026 | 0.397 | 0.007 | 0.040 |
| TRV   | 0.805 | 0.012 | 0.053 | 0.946 | 0.011 | 0.064 |
| UNH   | 1.400 | 0.016 | 0.063 | 2.443 | 0.013 | 0.091 |
| UTX   | 0.621 | 0.013 | 0.042 | 0.563 | 0.011 | 0.042 |
| V     | 1.530 | 0.017 | 0.062 | 1.494 | 0.010 | 0.072 |
| VZ    | 0.471 | 0.011 | 0.041 | 0.572 | 0.009 | 0.045 |
| WMT   | 0.464 | 0.009 | 0.045 | 0.654 | 0.007 | 0.058 |
| XOM   | 0.473 | 0.012 | 0.039 | 0.506 | 0.010 | 0.036 |
Table 5: Optimal Markowitz portfolio using daily return data from 2010-2013.

| Ticker symbol | HD  | JNJ | MCD | PG  | UNH | V   | VZ  | WMT |
|---------------|-----|-----|-----|-----|-----|-----|-----|-----|
| Portfolio weight [%] | 10.26 | 16.69 | 22.67 | 11.92 | 6.41 | 4.22 | 7.56 | 20.27 |

Table 6: Selected risk metrics for the different out-of-sample tests.

|                        | Markowitz | 1-over-N | Evolutionary |
|------------------------|-----------|----------|--------------|
| Semi Deviation         | 0.0042    | 0.0048   | 0.0038       |
| Downside Deviation (Rf=0%) | 0.0040    | 0.0047   | 0.0037       |
| Maximum Drawdown       | 0.0631    | 0.0687   | 0.0549       |
| Historical VaR (95%)   | -0.0092   | -0.0105  | -0.0081      |
| Historical ES (95%)    | -0.0125   | -0.0157  | -0.0124      |

2013. This portfolio is used as a buy-and-hold portfolio over the year 2014. This out-of-sample performance is shown in Fig. 1. While the performance of the 1-over-N portfolio is not shown graphically, Fig. 2 depicts the performance of a portfolio, which is created by equally weighting all single asset trading strategies computed by the evolutionary optimization algorithm based on financial sentiment data into one portfolio. To get a better impression of the differences see Tab. 6, where some important risk metrics are summarized for all three strategies. The evolutionary trading portfolio exhibits better risk properties than both other portfolios in all five metrics. Especially important is the reduction of the maximum drawdown, which is of importance to asset managers nowadays, because investors are increasingly looking to this metric if they are searching for secure portfolios.

5 Conclusion

In this paper an evolutionary optimization approach to compute optimal rule-based trading strategies based on financial sentiment data has been developed. It can be shown that a portfolio composed out of the single trading strategies outperforms classical risk-return portfolio optimization approaches in this setting. The next step is to include transaction costs to see how this active evolutionary strategy loses performance when transaction costs are considered. Future extensions include extensive numerical studies on other indices as well as using and comparing different evaluation risk metrics or a combination of metrics. One may also consider to create a more flexible rule-generating algorithm e.g. by using genetic programming. Finally, to achieve an even better out-of-sample performance the recalibrating of the trading strategy can be done using a rolling horizon approach every month.

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5Performance graphs are generated using the PerformanceAnalytics R package [12].
Figure 1: Out-of-sample performance of a buy-and-hold Markowitz portfolio in 2014.
Figure 2: Out-of-sample performance of an equally weighted portfolio out of the evolutionary sentiment trading strategies in 2014.
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