Stock Price Trend Prediction using Evolutionary Learning

1.1.1 SUMMARY

An evolutionary learning approach was used to build a classifier to predict stock price trend changes. Genetic programming was used in model creation, parameter tuning, and for feature selection. Ten years of daily data for S&P 500 companies was used by the genetic algorithm to create a random forest classifier with the optimum parameters and features. Model performance was evaluated using 10 years of yearly return data for 23 companies across 11 sectors that were not part of the original training set.

The initial model underperformed the bowtie strategy because it was sensitive to short term trend changes inside of longer-term trends. This behavior led to false predictions inside of existing trends that negatively impacted the model performance. Signal smoothing was added to the model that weighted existing trends more heavily and only allowed signal changes when multiple successive signals occurred in the opposite direction. Adding signal smoothing improved model performance enough to statistically outperform the bowtie strategy across all market sectors.

An optimum portfolio was created using a genetic algorithm for the 23 leading companies in the different market sectors. Using the average returns and standard deviation for each company, a genetic algorithm was used to optimize the portfolio Sharpe Ratio. This resulted in an optimum portfolio that maximized expected returns for the lowest risk.

Future work could consider the impact of short positions on model performance since only long positions were considered for this project. The investigation could also be expanded to include other financial instruments such as commodities, futures, and options.

All code written for this project along with full experimental results and plots can be found at https://github.com/nosliwes/dsa5303

1.1.2 BACKGROUND

Trend following is an approach to investing that attempts to identify price trend changes and position investments to maximize return. The bow tie strategy is an example of a trend trading strategy that uses moving average crossovers to determine trend changes. Figure 1 illustrates the bowtie formed when the 10 period Simple Moving Average (SMA), 20 period Exponential Moving Average (EMA) and the 30 period EMA cross over.

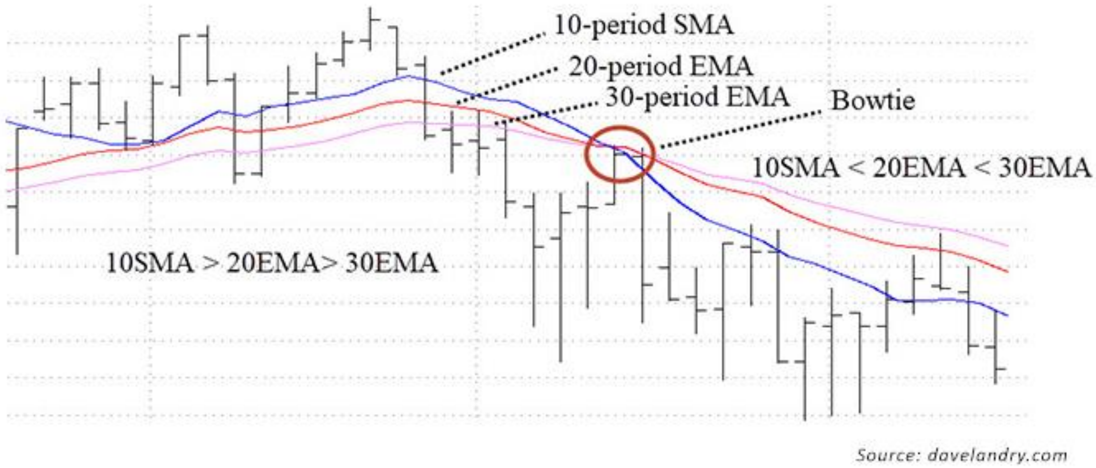


Figure 1. Example Bowtie formed using a 10 period SMA, 20 period EMA, and 30 period EMA.

One drawback of the bowtie strategy is that price changes more rapidly than moving averages. Additionally, as more traders use the moving averages for trading decisions, moving averages can provide support or resistance to price changes. The result is that false buy and sell signals can occur especially during periods when stock prices move sideways.

A second disadvantage is that moving averages are lagging indicators. This can decrease investment returns during periods of high volatility when price changes quickly without triggering buy or sell signals. This also prevents crossover strategies from identifying the best inflection points (minimum or maximum).

Researchers have investigated predictive models to identify trend changes in the past. The usual approach involves selecting a specific type of classification model or regression model to investigate (i.e. support vector machines, neural networks) followed by parameter optimization.

The initial goal of this work was to investigate if an evolutionary learning process could find an optimum trend classifier to identify stock price trends more accurately and reliably than the bowtie moving average crossover strategy.

Following this, a second goal was to generalize the model across multiple market sectors using a portfolio of leading companies in each sector.

Finally, the last goal was to use a genetic algorithm to solve a portfolio optimization using model returns from the portfolio companies.

1.1.3 Experimental Method

The experimental method involved model construction followed by back testing model performance on a portfolio of companies. The portfolio included 23 leading companies from 11 market sectors and are listed in the appendix.

Data Collection

The data collection effort involved data mining to build a representative stock list that was used to train a genetic classification model. The representative stock list included a collection of historical stock prices in the S&P 500. The model was trained using a subset of historical prices from 200 companies in the S&P 500.

Data Labeling

Each data point was labeled as uptrend or down trend. Labeling was accomplished by starting at each of the moving average crossover points and finding the maximum and minimum daily prices between the crossovers. Daily data was then labeled as uptrend from minimum to maximum points and down trend from maximum to minimum points.

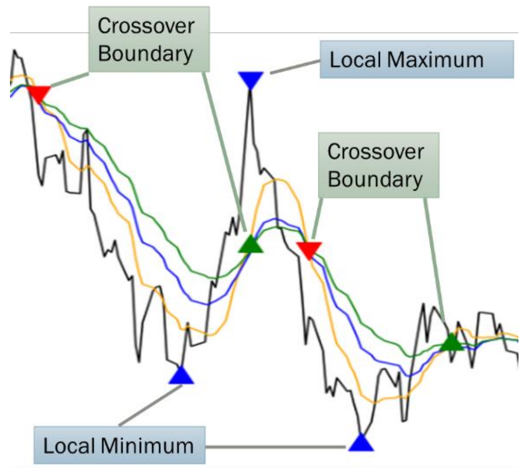


Figure 2. Labeling method for up and down trends

Model Selection

The python programming language was used for data collection, preparation and to build the genetic algorithm models. Although a custom genetic algorithm was implemented for feature selection in this work, various other supporting python libraries were used to expedite data collection and preparation (i.e. pandas, numpy, scikit-learn, etc.). In addition, the genetic algorithm in the TPOT learning library was used to identify the best classification model for trend identification.

The features available for model training were obtained from historical daily price data and included open price, close price, high price, low price, and volume. Calculated Features were added from technical indicators to capture the time series nature of the data. The calculated features included simple moving averages, exponential moving averages, relative strength, and moving average crossovers. Final feature selection was accomplished using the genetic algorithm.

Evaluation

The bowtie strategy and the model were each back tested using 10 years of annual return data for the portfolio companies. The following assumptions were used in the back-testing calculations.

1. Buying and selling occurred at the closing price of each day.
2. Only long positions were included in the testing, i.e. short selling was not allowed.
3. Transactions were based on buying and selling 100 shares.
4. Returns were calculated based on the initial cash required for 100 shares at the daily close.
5. All positions were sold on the last day of the year.
6. Positions were opened on the first day of the year when a sell signal was the first signal a that year.

The annual gain/loss between the model return and the bowtie strategy return was calculated for each stock and used in hypothesis testing.

1.1.4 Model Selection

Automated machine learning with TPOT was used for the model selection, parameter tuning and feature selection steps. TPOT is an open source python library developed at the University of Pennsylvania. TPOT automates the machine learning process using genetic programming and evaluates multiple models simultaneously to determine the best combination of model type, model parameters and features. The final output from TPOT was a random forest classifier that was further developed during the next phase of model training and validation.

1.1.5 Model Training and Validation

For model training, an 80-20 train test split and group shuffle split cross validation was used. The best accuracy that was achieved from training was 0.77. The results show a slight bias toward up trend prediction over down trend most likely since the market in general has an uptrend bias over time. As a result, the model is weakest when predicting uptrends during longer term downtrends. This resulted in false buy signals during downtrends and reduced model performance when the market was in a downtrend. To overcome this issue, a signal smoothing factor was applied to the model.

The smoothing factor weighted the current trend more heavily and only changed trends when multiple successive signals occurred in the opposite direction. The effect of the smoothing factor increased average model returns by 13.4%.

Accuracy 0.77

	Predicted Down	Predicted Up
Actual Down	89906	47470
Actual Up	30905	176941

	precision	recall	f1-score
0	0.74	0.66	0.69
1	0.79	0.84	0.81

Figure 3. Model performance metrics

1.1.6 Experimental Results

Back testing was performed for both the model and bowtie strategies to determine annual returns using each approach. The value for δ was calculated using the equation below where R_M was the annual return using the model and R_B was the annual return using the Bowtie method.

$$\delta = R_M - R_B$$

A few of the results are shown in the following table for the portfolio stocks in the Energy sector. Experiments were repeated for all symbols in the portfolio from 2009-2019 and these results were used in hypothesis testing. The experiments showed that the model returns were greater than the Bowtie method returns 204 out of 241 samples, or 84.6% more frequently.

Table 1. Sample of experimental results for energy sector

Sample	Sector	Symbol	Year	Bowtie	Model	δ
0	Energy	XOM	2009	-11.72	7.49	19.22
1	Energy	XOM	2010	9.56	19.73	10.18
2	Energy	XOM	2011	-16.53	-1.90	14.63
3	Energy	XOM	2012	-4.12	7.31	11.43
4	Energy	XOM	2013	6.63	22.47	15.84
5	Energy	XOM	2014	-4.91	6.03	10.94
6	Energy	XOM	2015	-5.34	-3.13	2.22
7	Energy	XOM	2016	5.81	9.38	3.57
8	Energy	XOM	2017	-4.26	-1.10	3.16
9	Energy	XOM	2018	4.79	7.43	2.64
10	Energy	XOM	2019	-12.57	3.11	15.68
11	Energy	CVX	2009	-9.38	4.92	14.30
12	Energy	CVX	2010	17.73	30.88	13.15
13	Energy	CVX	2011	-4.04	13.88	17.92
14	Energy	CVX	2012	4.00	16.15	12.16
15	Energy	CVX	2013	-7.91	8.84	16.75
16	Energy	CVX	2014	4.01	15.42	11.41
17	Energy	CVX	2015	-9.23	15.43	24.66
18	Energy	CVX	2016	30.78	30.43	-0.35
19	Energy	CVX	2017	6.62	17.82	11.20
20	Energy	CVX	2018	-7.27	1.56	8.84
21	Energy	CVX	2019	-10.69	3.67	14.36

Signal results were also plotted against price for all portfolio symbols and years for both the bowtie method and the model. These plots were useful to qualitatively show that the model consistently predicted price changes earlier than the bowtie method. An example of this improvement is shown in the figure below.

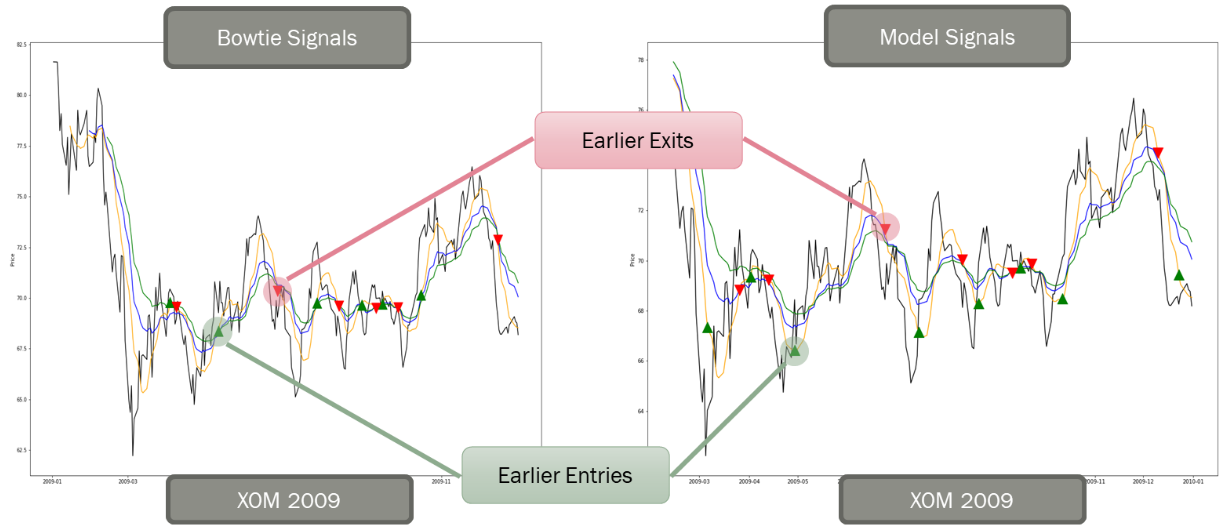


Figure 4. Plot showing earlier entries and exits for model compared to bowtie method

The following hypotheses were considered when evaluating model performance.

<u>Hypothesis 1:</u> A predictive model exists that can identify trend changes earlier and more accurately than trend trading strategies using the bowtie moving average crossover.

Null	Hypothesis
$H_0: \delta \leq 0$	$H_1: \delta > 0$

$$where\ \delta = R_M - R_B$$

$$R_M = Return\ from\ predictive\ model$$

$$R_B = Return\ from\ bowtie\ method$$

<u>Hypothesis 2:</u> The predictive model generalizes across different sectors of the market.

Null	Hypothesis
$H_0: \delta_S \leq 0$	$H_1: \delta_S > 0$

$$where\ \delta_S = R_M - R_B$$

$$R_M = Return\ from\ predictive\ model\ for\ the\ sector$$

$$R_B = Return\ from\ bowtie\ method\ for\ the\ sector$$

The results showed that the model statistically outperformed the bowtie crossover strategy for the overall market as well as each individual sector. The model performed the worst on the communication services sector but was still two standard deviations above the mean.

Table 2 Hypothesis testing results for portfolio symbols by industry sector

Sector	n	$\bar{\delta}$	σ	Z score	P value	Test Result
All	241	11.69	15.99	11.33	0.000	$Reject\ H_0$
Energy	22	11.54	6.08	8.90	0.000	$Reject\ H_0$
Utilities	33	8.70	5.15	9.70	0.000	$Reject\ H_0$
Materials	22	16.64	36.54	2.14	0.016	$Reject\ H_0$
Industrials	22	17.59	17.94	4.60	0.000	$Reject\ H_0$
Consumer Discretionary	22	10.09	14.26	3.32	0.000	$Reject\ H_0$
Consumer Staples	22	8.81	7.50	5.51	0.000	$Reject\ H_0$
Healthcare	22	13.37	14.13	4.44	0.000	$Reject\ H_0$
Financials	22	10.45	13.38	3.66	0.000	$Reject\ H_0$
Information Technology	22	12.94	10.65	5.70	0.000	$Reject\ H_0$
Communication Services	16	7.10	14.19	2.00	0.023	$Reject\ H_0$
Real Estate	16	11.59	9.31	4.98	0.000	$Reject\ H_0$

1.1.7 Portfolio Optimization

The approach used for portfolio optimization was an Array-Based Genetic Algorithm. The structural components of the genetic algorithm are listed below.

Table 3. Genetic algorithm structural components

Array-Based Genetic Algorithm	
Chromosome Structure	One dimensional array of real numbers
Evolutionary Operators	Linear mutation and arithmetic crossover
Selection Method	Tournament selection
Fitness Evaluator	Sharpe ratio

The chromosome structure used was a one-dimensional array of real numbers between 0 and 1. The real numbers represented the weights of each stock held in the portfolio. To ensure that the Markowitz Model constraint is satisfied, $\sum w_i = 1$, each real valued weight was normalized using the formula:

$$w_i = \frac{w_i}{\sum_{j=1}^{n} w_j}$$

Linear mutation was used since the genetic algorithm searches for real valued solutions instead of typical used binary values (0,1). Linear mutation is a variant of the bit-flip mutation. In linear mutation, each element ci ∈ c has a chance to be replaced by a random value between the minimum of ci and the maximum of ci. The actual value was chosen using the uniform probability distribution.

The Sharpe ratio was used as the fitness evaluator in the genetic algorithm. The Sharpe ratio was calculated using the following equation where R_P is the expected portfolio return, R_f is the risk-free rate, and σ_P is the portfolio standard deviation.

$$S_r = \frac{R_P - R_f}{\sigma_P}$$

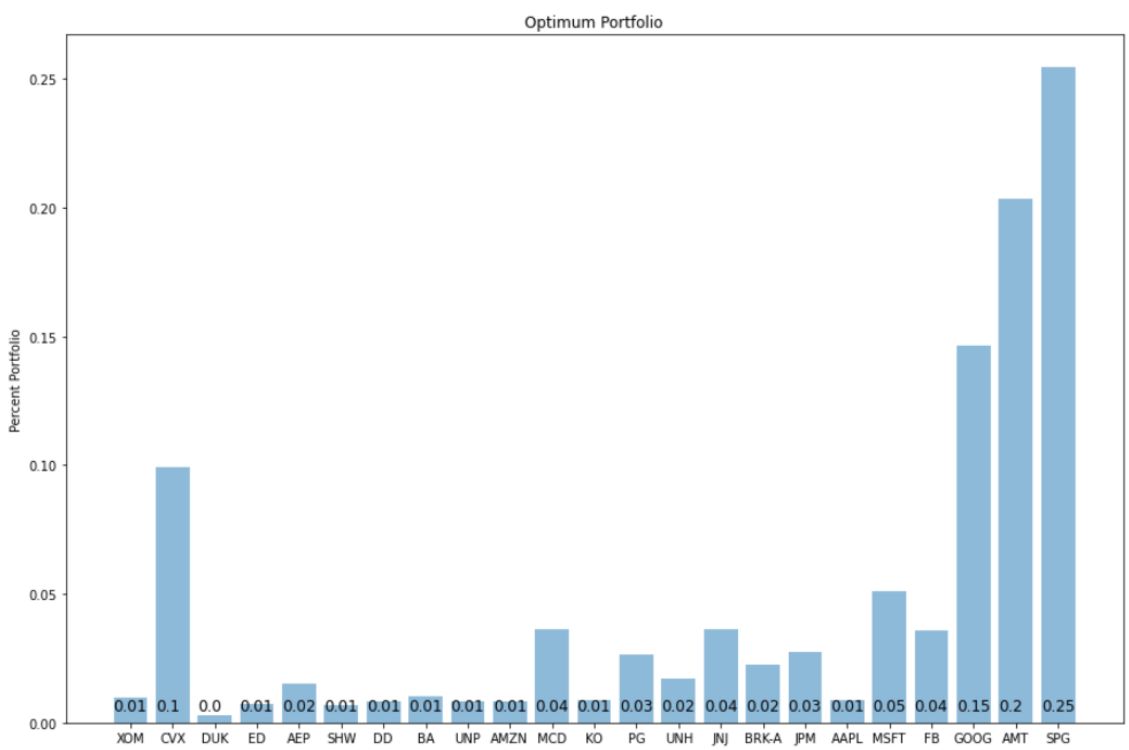
The portfolio return, R_P was given by the following equation for portfolio return where R_i is the expected return of the individual asset and w_i is the weight of the asset in the portfolio.

$$R_P = \sum_{i=0}^{N} R_i w_i$$

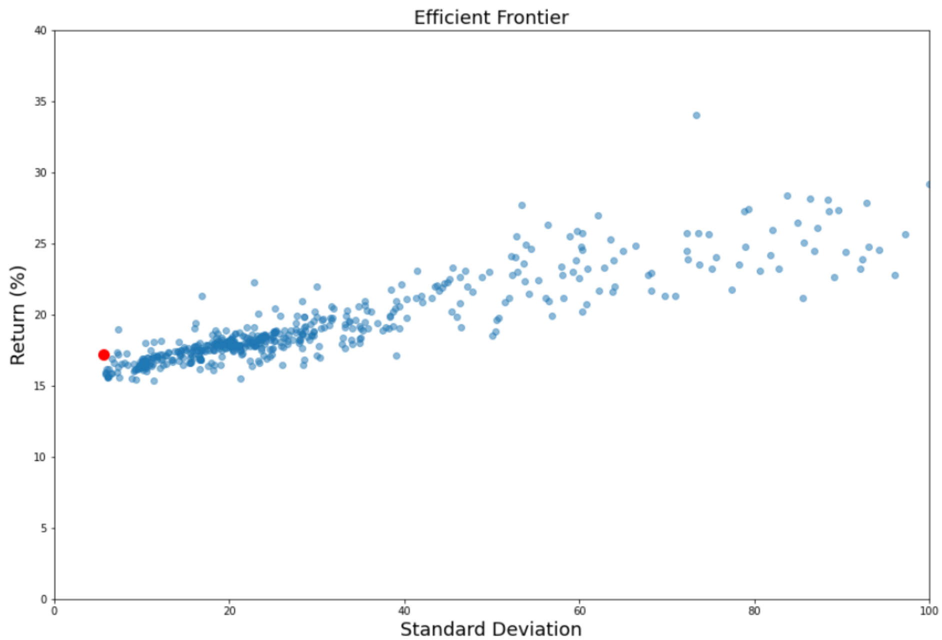
Finally, the portfolio standard deviation was calculated from the following equation where σ_{ij} is the covariance and w_i is the weight of asset i and w_j is the weight of asset j.

$$\sigma_P = \sum_{i=0}^{N} \sum_{j=0}^{N} \sigma_{ij} w_i w_j$$

The genetic algorithm was run with a population size of 50 over 10 generations with 0.8 crossover rate, 0.2 mutation rate and no elitism. The resulting optimum portfolio is shown in the figure below. There were a few practical issues with the optimum portfolio that are easy to see in figure. The most obvious is that there is no minimum limit set for a position leading to very small allocations for some stocks. This would need to be corrected for an actual implementation but overall, the genetic algorithm was effective at building an optimum portfolio.



Finally, all of the portfolio returns and standard deviations that were evaluated by the genetic algorithm were plotted to show the efficient frontier. The red symbol on the chart is the optimum portfolio that yields the highest return for the lowest standard deviation.



1.1.8 Conclusions

In conclusion, an evolutionary learning approach was effective at building a classifier to predict stock price trend changes. Genetic programming with TPOT successfully selected a model, tuned parameters and selected features. The initial model underperformed the bowtie strategy because it was sensitive to short term trend changes inside of longer-term trends. However, the addition of signal smoothing improved model performance enough to statistically outperform the bowtie strategy across all market sectors.

An optimum portfolio was also created using a genetic algorithm for the portfolio companies in the different market sectors. Using the average returns and standard deviation for each company along with the Sharpe ratio fitness function, a genetic algorithm successfully found an optimized portfolio.

Future work could consider the impact of short positions on model performance since only long positions were considered for this project. The investigation could also be expanded to include other financial instruments such as commodities, futures, and options.

1.1.9 References

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1.1.10 Appendix

Table 4. Portfolio of companies used for experimentation and portfolio optimization

Sector	*Symbol*	*Company Name*
Energy	XOM	Exxon Mobil
Energy	CVX	Chevron
Utilties	DUK	Duke Energy
Utilties	ED	Consolidated Edison
Utilties	AEP	American Electric Power
Materials	SHW	Sherwin-Williams
Materials	DD	DuPont
Industrials	BA	Boeing
Industrials	UNP	Union Pacific
Consumer Discretionary	AMZN	Amazon
Consumer Discretionary	MCD	McDonald's
Consumer Staples	KO	Coca-Cola

Consumer Staples	PG	Proctor & Gamble
Healthcare	UNH	UnitedHealth Group
Healthcare	JNJ	Johnson & Johnson
Financials	BRK-A	Berkshire Hathaway
Financials	JPM	JPMorgan Chase
Information Technology	AAPL	Apple
Information Technology	MSFT	Microsoft
Communication Services	FB	Facebook
Communication Services	GOOG	Google
Real Estate	AMT	American Tower
Real Estate	SPG	Simon Property Group