News-cycle based trading strategy based on Google Trends

COMP4971C - Independent Work

MANGLA, Aditya Vikram

Supervised by

Dr. David Rossiter

Dept of Computer Science and Engineering
The Hong Kong University of Science and Technology

Fall 2022

Abstract

This report investigates the formulation of a forex trading strategy based on Google Trends. Data from Google Trends is used to determine the interest of a particular country's financial news in another country. In this case, the United States' financial interest in China is used to trade the US Dollar and Chinese Yuan (Renminbi). After collecting three sets of relative Google Trends data varying in window size (day, week, and month) and devising a weighted algorithm; weighting calculations are done to calculate the optimal combination of weights as well as the efficacy of a particular algorithm.

The first algorithm devised has several issues that need to be iterated upon to lead to a more effective and robust second algorithm. Both of these two algorithms are tested on a dataset of 8 years of data, and the results will be compared to a baseline of a Buy & Hold strategy. The second algorithm will be found to be more effective than the first with a higher Compound Average Growth Rate (CAGR). This second algorithm will also be more malleable to minor modifications, however none of the modifications will yield a better result unfortunately.

While the project will be found to generate consistent profit with an incredible low Maximum Drawdown (MDD), the trading algorithm used in this report underperforms compared to the common Buy & Hold strategy. This report discusses the results and the implications of the results for future work. The results of the project are still found to be promising however, and the project will be found to be a good starting point for future work in this area; presenting an effective analysis on the results trading based on what is popular in the news as well as the shortcomings of the methods used in this report that can be improved upon with further testing.

Contents

List of Figures

List of Tables

1 Introduction

1.1 Context

Google Trends is a popular website for analyzing the trends of different countries and their various news cycles over time. For example, one can plot the popularity in news and Google searches (or 'trends') of the *Final Fantasy* franchise worldwide – showing that since 2004, interest in the game has been steadily declining with spikes during major game launches [1]. Google Trends includes some extra added functionality too, namely country-specific insights as well as the ability to compare and contrast interests in different topics on a single plot.

For example, one could plot the Global interest in the Super Bowl against the interest in the Harry Potter franchise, and even observe which countries sway which way. In Figure 1, we can observe that while generally Harry Potter is is around 10-20 times as popular as the Super Bowl, during the Super Bowl, Harry Potter is easily eclipsed by largely the United States' interest in the Super Bowl Alone.

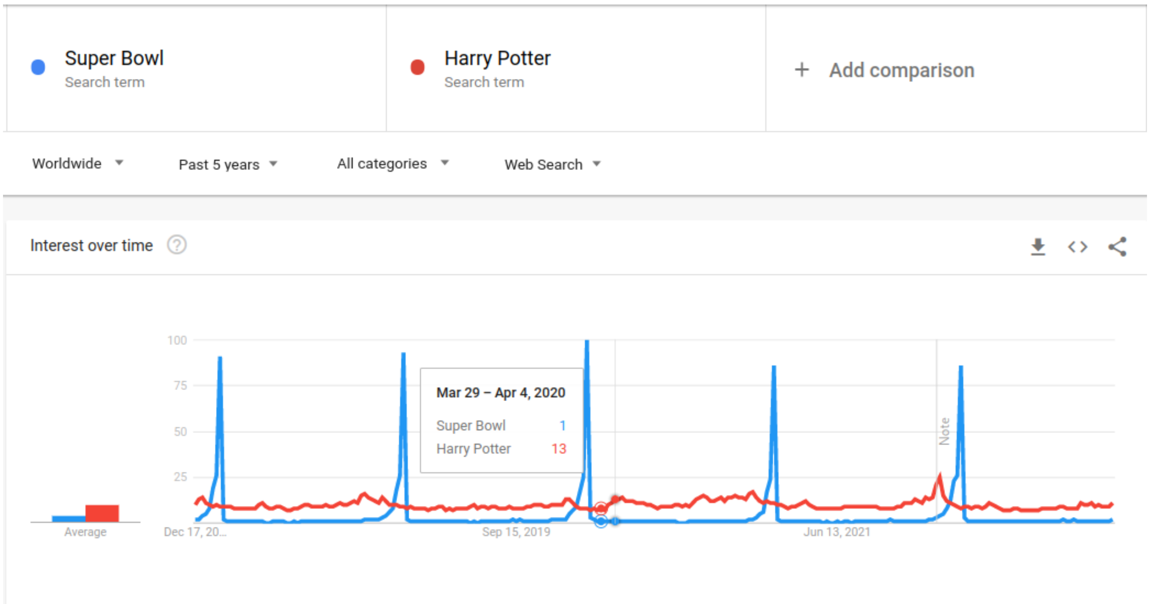

Figure 1: Google Trends plot of the Worldwide interest in the Super Bowl and Harry Potter

We can confirm this by looking at the country-specific interest in Figure 2, where we can see that the United States is the only country where the Super Bowl is more popular than Harry Potter over the span of the last 5 years. We can also observe, unsurprisingly, that countries close to the United States such as Canada and Mexico still have a substantial Super Bowl interest compared to countries such as India or Japan. Google trends also allows us to compare interests within specific US states (for example, it can be found that of the US States, Utah is relatively the most interested in Harry Potter), however, this level of insight not be useful for our report.

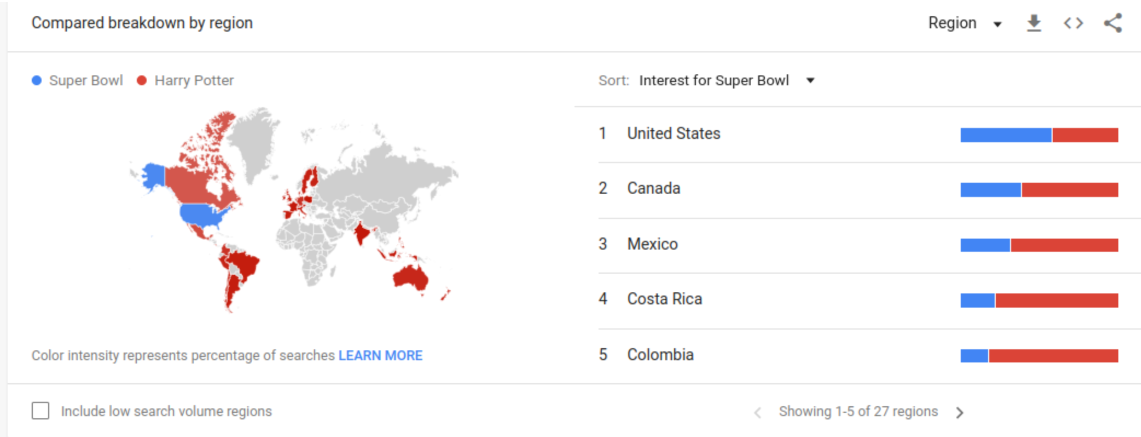

Figure 2: Google Trends table of the Country-specific interest in the Super Bowl and Harry Potter

As shown in Figure 3, these type of country specific insights can highlight numerous interesting trends about countries and their cultural relations, for example, almost the entire world favours the World of Warcraft franchise over it's Japanese competitor, Final Fantasy XIV – except for Japan, Singapore, Hong Kong, and Thailand. This can suggest that perhaps Hong Kong, Singamore, and Thailand are more closely (gaming) culturally intergrated with Japanese markets than American markets.

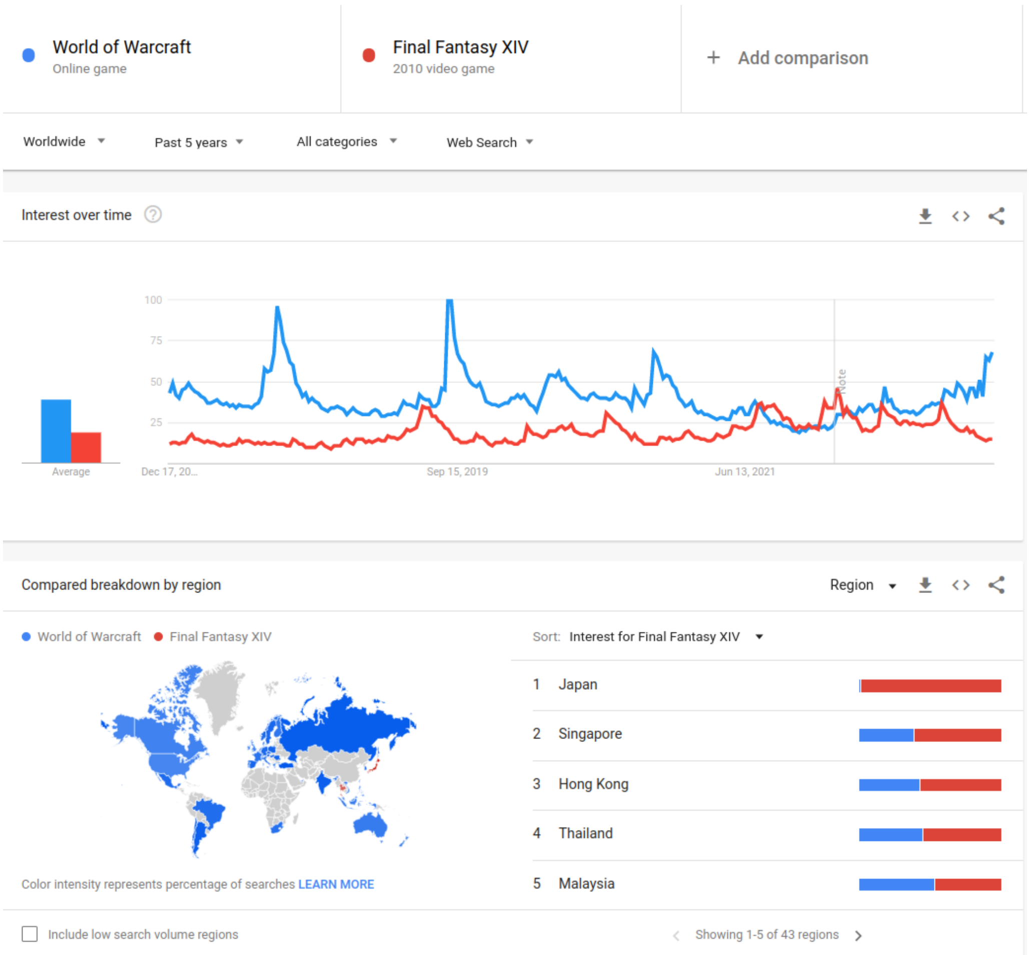

Figure 3: Google Trends Analysis of Worldwide interest in Final Fantasy XIV and World of Warcraft

Other interesting insights can be observed by observing the time graph, noticing that while World of Warcraft historically eclipsed Final Fantasy, the gap has recently been shrinking – even globally – and Final Fantasy temporarily overtook World of Warcraft from August 2021 to January 2022. By cross-referencing this observation with dated news reports, we can ascertain that this is likely due to the release of Final Fantasy XIV's Endwalker expansion in December 2021 [2], generating mass hype for the game, coinciding with World of Warcraft's undergoing a mass exodus and declining sales due to numerous sexual assault allegations levied against their publisher, Blizzard [3]. This type of cross cross-referencing will be employed in Section 2.3 to gain a deeper insight on the data being used in the report.

1.2 Hypothesis & Objective

It is a commonly touted fact that animals will flee a region with an incoming storm prior to humans getting any indication of an incoming storm. Following a similar principle, the objective with this project is under this analogy – with market spikes representing the storm and the news cycle representing the animals. The goal is to formulate an extensible trading strategy based on historical data from Google Trends to allow for predictive trading based on the popularity of certain topics in the news cycle.

While in this report the analysis will be applied to Forex (Foreign Exchange), in theory this analysis is possible on any stock, cryptocurrency, or topic.

The hypothesis is that Google Trends spikes should predict upcoming fluctuation within the market. By combining this foresight with an analysis of other factors – an advantageous trading strategy can be devised.

This report will apply this hypothesis to the currency exchange of USD-RMB. China was chosen as within the American news cycle, China and it's economy is frequently mentioned due to the US-China trade war – which has resulted in USD-RMB being the 6th most traded currency pair. This coupled with the relatively high volatility of the RMB caused by the trade war is why USD/RMB was chosen for this report [4].

2 Methodology

2.1 Data Collection

The greatest barrier to entry for historical analysis is harvesting the data. This is as simple as it is difficult. For collecting historical Google Trends data, all existing APIs are either paid or have significant limitations in their output that renders them effectively useless for an analysis of longer than a month or two at a time. Therefore, the most effective method is the most obvious yet time-consuming one. For data collection, Trends was manually sifted through from 2008 January 1st to 2015 December 31st three different sets of date frames.

Three set of collections was made as Trends presents data in varying degrees of accuracy based on the date range being examined, i.e. if looking over a multi-year frame, then the x-axis ticks are represented in months (Figure 4), whereas when looking over a 10-month frame, the data is represented in weeks (Figure 5), and while observing on a monthly frame, the data on the x-axis is presented in days (Figure 6).

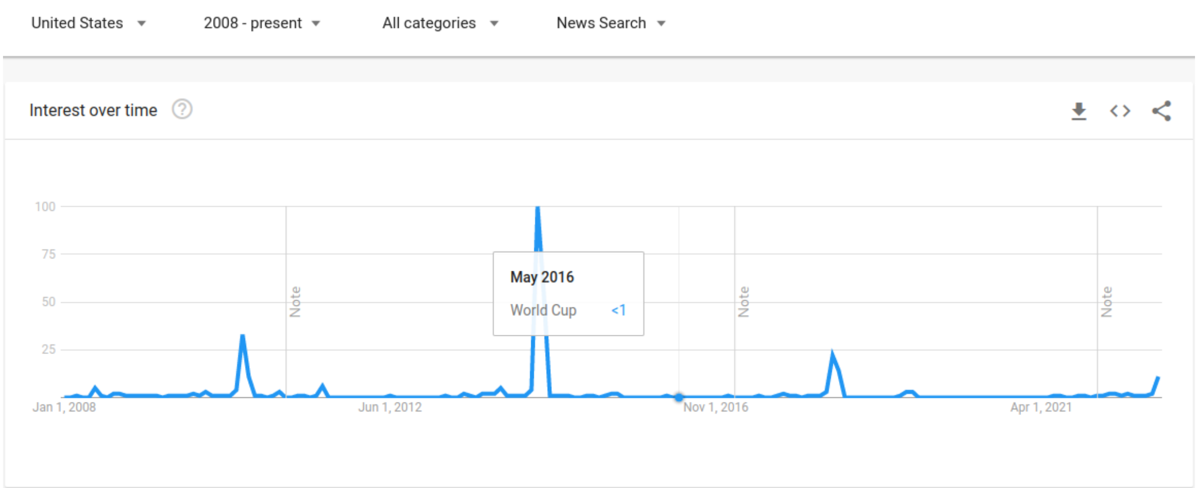

Figure 4: United States news cycle on the Football World Cup over a multi-year window showing daily x-axis ticks [1]

Figure 5: United States news cycle on the Football World Cup over a 10-month window showing weekly x-axis ticks [1]

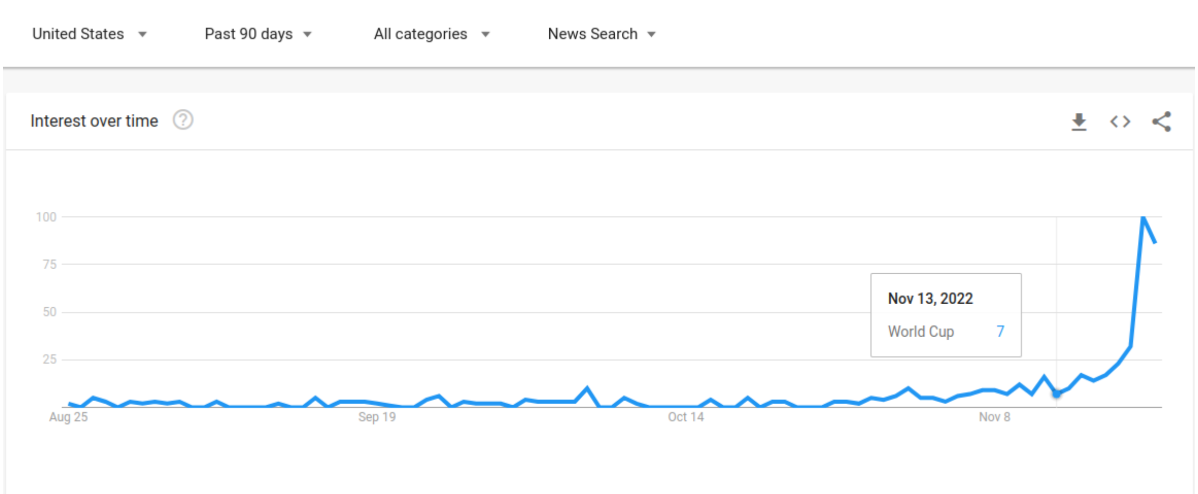

Figure 6: United States news cycle on the Football World Cup over a 90-day window showing daily x-axis ticks [1]

With this in mind, for the purposes of this analysis, the data was collected thrice such that weightings could be applied to the day, week, and month and an ideal formula can be devised; an example segment of the data can be seen in Appendix A

Continuing, the forex data between 2008 and 2015 was also scraped through *investing.com*. This data consisted of the date, price, open, high, low, and change %. From the forex data, primarily the price and change % values were used, with date used as an index.

2.2 Libraries Used

The data processing was completed using Python in VSCode/Vim running Jupyter notebooks. In order to make this easier, numerous libraries were employed:

Table 1: Libraries used in the analysis

Library	Usage
Pandas	Used for its powerful *DataFrame* object for data processing and manipulation
Numpy	Used for its expanded numerical capabilities for data manipulation and analysis
Matplotlib	Used for data visualization and analysis
Scikit-learn	Used to calculate the slope of a line of best fit for data processing
Tensorflow	Used to generate simple LSTM models for confluence trading analysis
Seaborn	Used for data visualization for 2D heatmaps

2.3 Initial Data Exploration

Before any analysis can be performed, the data must be processed. Later on for the algorithm, all possible weighting combinations will be tested. However, for the initial data exploration, the data was processed through a simple product of the three obtained values with equal weightings.

By plotting the Trends data and scrolling through the timeline, some interesting patterns can be observed. For plotting these graphs, the red line is used to represent the volatility (or the absolute value of the Change %) of the USD/RMB exchange rate and the blue line (or Relative Trends Interest) represents the Trends data, where a higher number represents a higher relative interest during that time period. While observing these however, it is important to note that selection bias comes heavily into play, and these graphs serve better to give an idea of how the data should be analysed than actually traded upon. For example, the most promising results can be seen in Figure 7, where a blue spike clearly precedes volatility. By checking the news during this time, the second round of the 'US-China Strategic and Economic Dialogue' was held, thus justifying this data [5].

On the other hand however, looking at Figure 8, the opposite trend is seen where a large currency volatility is followed by instead of preceded by Trends volatility. This could be due to two reasons: one is that the US dollar changed respective to every currency, not just the RMB – and thus the Trends spike is unrelated to the change; or second, that the Trends spike is a spike in news outlets reporting the change after the fact – and not before.

In this case, we can observe it to be a mixture of both. Where China was locally broadcasting news that may have made financial ripples without triggering the US news cycle through announcements on their 5 year plan that eased investor worries [6][7]. The US market had also been performing particularly well in of itself [7], and it can be seen as a trend that when the US news cycle is reporting on itself, it can become rather self-centered and neglect overseas news. A takeaway from this is that some currency volatility will be missed by Trends purely based on the nature of the news cycle, and thus delayed reporting may cause issues.

And of course as is expected, there are cases where both spike nearly simultaneously as seen in Figure 9, although in this unfortunately the Trends spike is just a few days after the currency volatility, and thus not directly useful to trade upon. In this case, the currency volatility was due to two explosions at a Chinese port, causing local economic disruptions [8].

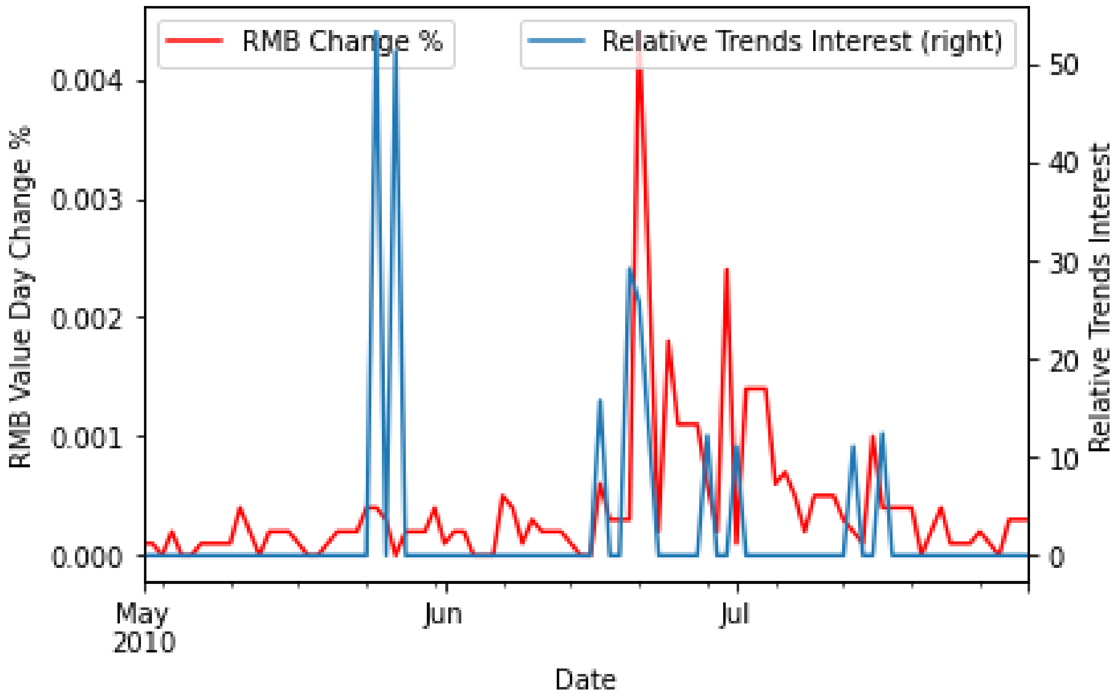

Figure 7: Promising results showing Trends volatility preceding currency volatility

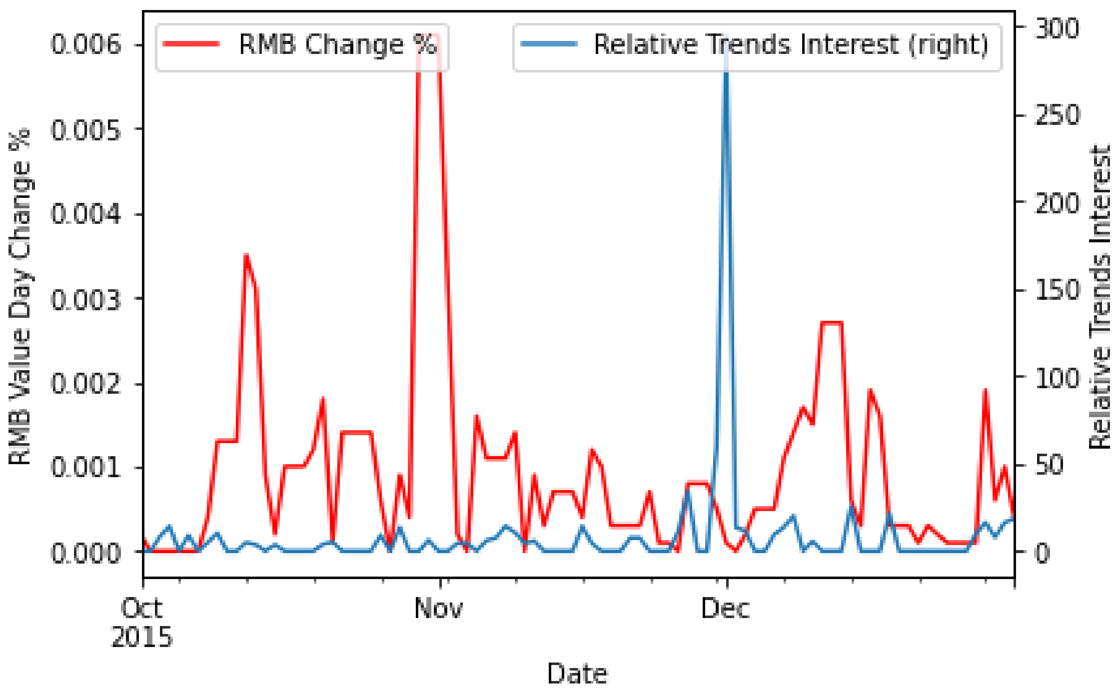

Figure 8: Unpromising results showing currency volatility preceding Trends volatility

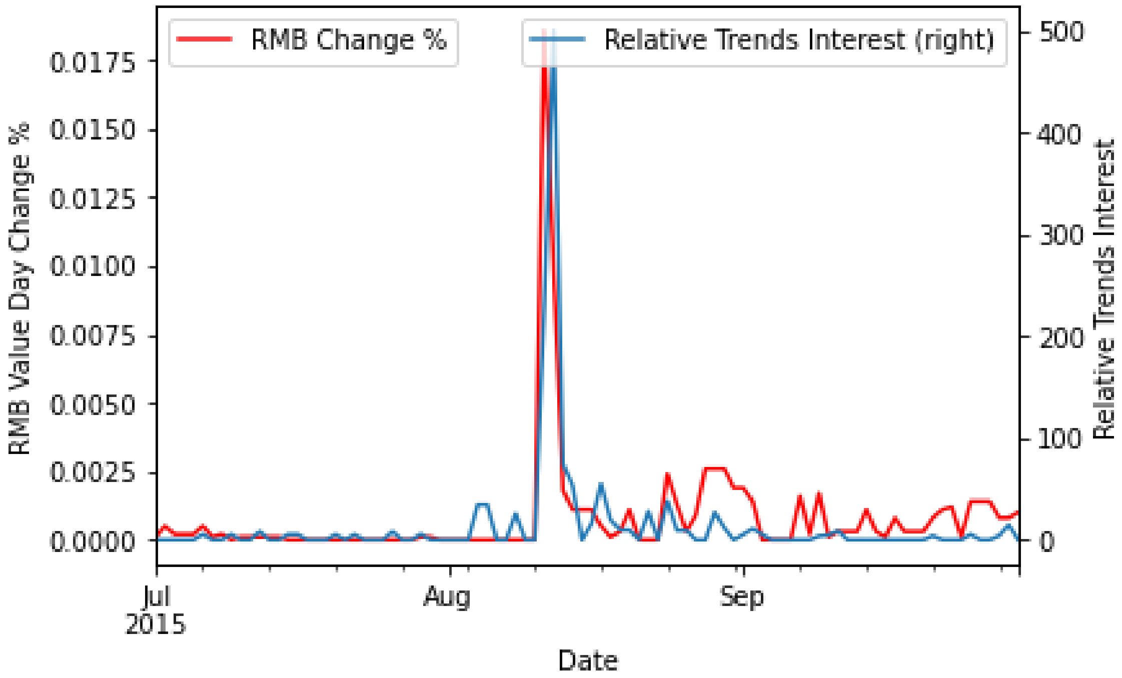

Figure 9: A point where both the Trends data and the Change % of RMB spike at nearly the same time however still unpromising with the currency volatility preceding Trends volatility

2.4 Weighting Calculations

While the forex data was collected in a single collection, the Google Trends data was collected in three separate collections. To analyze what level of granularity should be prioritized in the collection of Trends data, ideal weightings had to be calculated (e.g. should you weigh the Trends of this week compared to the past few weeks more than that of today compared to the same duration in days).

Once a trading algorithm using Trends data is formulated, automated backtesting can be applied on all possible weighting combinations (see Table 2) to determine the best one.

Table 2: Weighting example set

Day Weighting	Week Weighting	Month Weighting
0.98	0.01	0.01
0.97	0.02	0.01
0.96	0.03	0.01
...	...	...

A limitation of this method is that the computer used was unable to handle running more than 250 iterations at a time, and thus the over 4800 different possible iterations had to be manually run in steps of 250.

2.5 Back-testing

To analyze the effectiveness of the rends data in predicting forex price movements, a simple trading algorithm was devised. Based on the performance of the algorithm, it was later iterated upon – this will be explored in Section 3.3. This algorithm was the following:

Trade signal:

$$
\begin{aligned}
\alpha &= \text{Total Number of Values Observed in Dataset (so far)} \\
\beta &= x \text{ Size of window being observed in days} \\
\vartheta &= \text{Dataset being passed in (i.e. days, weeks, or months)} \\
p_x &= \text{Value at Position x in Dataset} \\
SMA_{\vartheta}(\beta) &= \frac{1}{\beta} \sum_{i=\alpha-\beta+1}^{\alpha} p_i \\
f(x) &= (SMA_{day}(x) * Weight_{day}) \\
&* \ (SMA_{week}(x) * Weight_{week}) \\
&* \ (SMA_{month}(x) * Weight_{month}) \\
\textbf{TRADE IF: } & f(3) > f(30)
\end{aligned}
\tag{1}
$$

Once a trade signal is received, the algorithm simply trades based on a 5-day linear regression line, trading following the trend.

2.6 Evaluation Method

Once weighting analysis is completed and has determined an ideal set of weights to trade upon, the quality of trading based on Google Trends will be compared to Buy & Hold.

3 Original Algorithm Data Analysis

3.1 Backtesting Results

Based on running backtesting on on the full 2008-2015 dataset on all the possible weightings with an initial capital of 1000 USD and 10 RMB, flaws with the algorithm were discovered. Specifically, it was discovered that not only would the algorithm perform poorly in general, but the algorithm performed identically based on the combination of weightings, and the specific position of the weightings made no difference (i.e. whether the weightings for day, week, month were 20, 50, 30 were identical to that of 50, 20, 30 respectively). This was not a software issue but mathematical, as in practice the results of $f(3)$ to $f(30)$ would be identical regardless of the position of the weighting.

This issue can be seen more clearly in Table 3 where the top 12 set of results can be seen.

Day Weight	**Week Weight**	**Month Weight**	**Results (USD)**
3	31	66	1068.89
3	66	31	1068.89
31	3	66	1068.89
31	66	3	1068.89
66	3	31	1068.89
66	31	3	1068.89
3	44	53	1068.88
3	53	44	1068.88
44	3	53	1068.88
44	53	3	1068.88
53	3	44	1068.88
53	44	3	1068.88

Table 3: Top 12 results for the original algorithm with results rounded to the nearest cent

While it can be seen that a profit is made from a starting value of 1001.369USD to 1128.857USD, over the span of 2008-2015 this only gives us a Compound Annual Growth Rate (CAGR) of ∼0.823%. Compare this to the CAGR of ∼1.468% for the USD/RMB exchange rate over the same period with the Buy & Hold strategy, and it is clear that the algorithm in its current state is not effective in predicting forex price movements.

3.2 Backtesting Weighting Analysis

Plotting the results of the backtesting onto a 2D heatmap (where the third axis can be inferred from the X and Y, as the weightings must always sum to 100) we observe Figure 10. From the symmetrical pattern, our earlier findings that the respective order of the weightings is irrelevant to the algorithm compared to the actual numbers themselves is made visually evident.

3.3 Iterating on the Algorithm

Due to the poor performance of the original algorithm as well as the poor heatmap, it was iterated upon to be treat the initial starting point of the 'Day' value differently. This also solved the issue where the algorithm in practice traded the exact same way based on the combination of numbers rather than

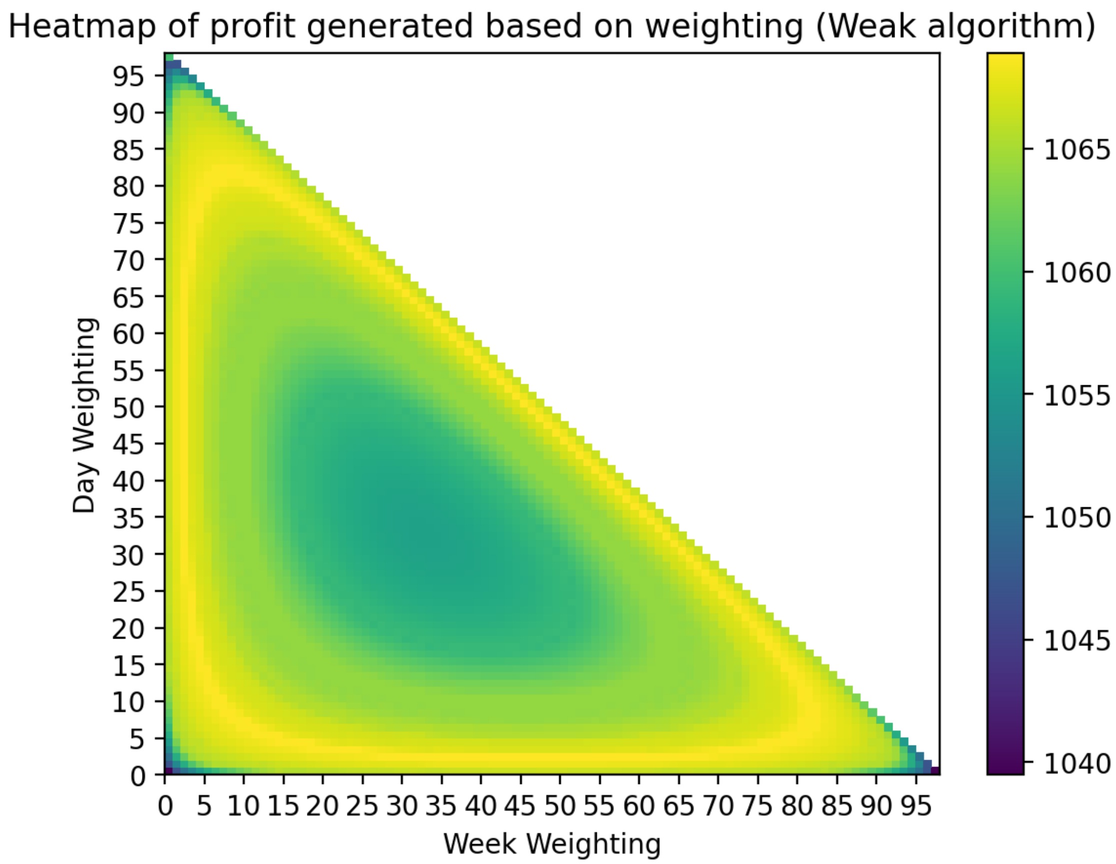

Figure 10: Weighting heatmap for the original algorithm (AKA 'Weak Algorithm') where temperature color represents the final currency value held after conversion to USD

the specific weightings they were applied to. The modified algorithm follow the same principles as the original, however has a modified trade signal formula. The new algorithm is as follows:

Trade signal:

$$\begin{aligned}
\alpha &= \text{Total Number of Values Observed in Dataset (so far)} \\
\beta &= x \text{ Size of window being observed in days} \\
\vartheta &= \text{Dataset being passed in (i.e. days, weeks, or months)} \\
p_x &= \text{Value at Position x in Dataset} \\
SMA_{\vartheta}(\beta) &= \frac{1}{\beta} \sum_{i=\alpha-\beta+1}^{\alpha} p_i \\
Day(x) &= SMA_{day}(x) * ((SMA_{day}(x) * Weight_{day}) + 1) \\
Week(x) &= Day(x) * ((SMA_{week}(x) * Weight_{week}) + 1) \\
Month(x) &= Week(x) * ((SMA_{month}(x) * Weight_{month}) + 1) \\
\textbf{TRADE IF: } & Month(3) > Month(30)
\end{aligned} \tag{2}$$

The trading amount is calculated in the same way as the old algorithm.

4 New Algorithm Data Analysis

4.1 Backtesting Results

Through running the background tests on the same 2008-2015 dataset, significantly better results were obtained. The data obtained can be seen in Table 4. Immediately, the core issue with the previous algorithm can be seen to be addressed; the results are different for every set of weightings, therefore – the respective position of the weighting matters.

Day Weight	**Week Weight**	**Month Weight**	**Results (USD)**
97	1	2	1117.29
97	2	1	1116.84
96	2	2	1115.00
96	1	3	1114.85
96	3	1	1114.73
95	4	1	1113.13
95	3	2	1112.90
95	2	3	1112.00
94	5	1	1111.92
95	1	4	1111.84
94	4	2	1111.69
93	6	1	1110.56

Table 4: Top 12 results for the new algorithm rounded to the nearest cent

While it can be seen that the results are significantly better than that of the previous algorithm, the CAGR is $\sim$1.383%. This is still worse than the CAGR of $\sim$1.468% for the USD/RMB exchange rate over the same period with the Buy & Hold strategy. However, the new algorithm is still a significant improvement over the original algorithm. On top of this, the new algorithm also has an incredibly low maximum drawdown peaking at just over 2% as seen in Figure 11.

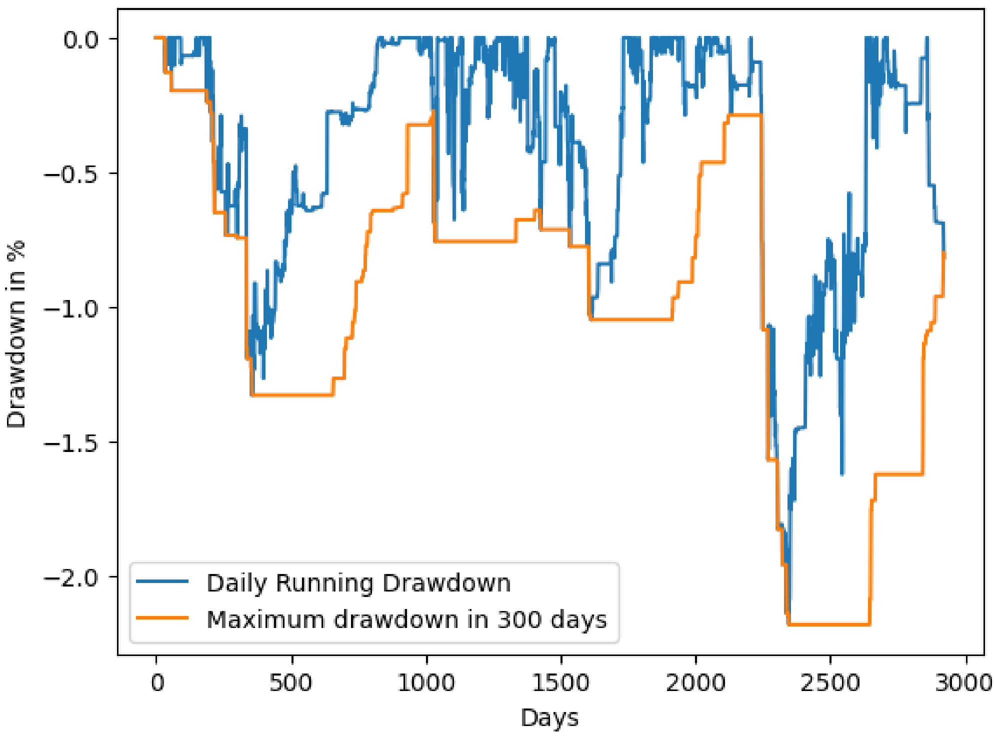

Figure 11: Daily running drawdown vs maximum drawdown from past 300 days

The total value of the currency held throughout the trading process can be seen in Figure 12.

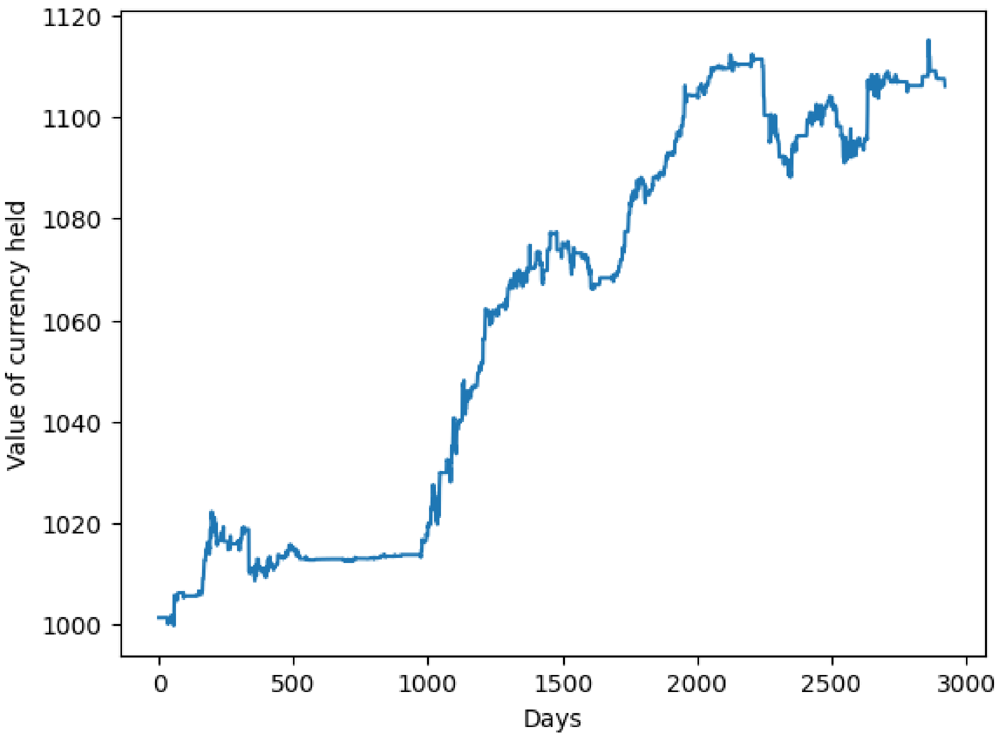

Figure 12: Total value of currency held over time

4.2 Backtesting Weighting Analysis

Plotting the results of the backtesting onto a similar 3D heatmap, much more interesting results are received. The heatmap for a day-week weighting comparison (where as before, month can be inferred) is shown in Figure 13. From these results, it can be seen that the algorithm is more effective when the day weight is higher than the week and month weight, as there is a clear yellow peak where the day weighting is at it's highest.

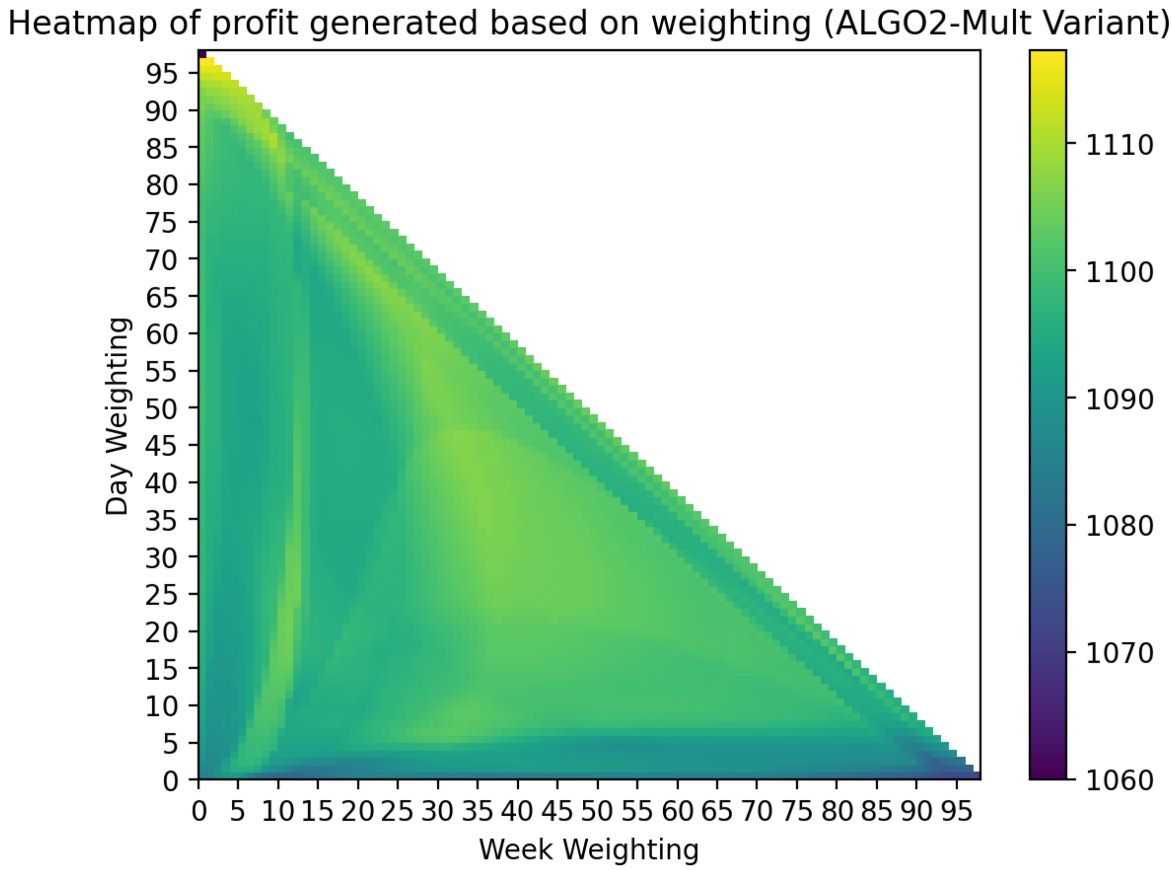

Figure 13: Weighting heatmap for the modified algorithm (AKA 'Algo-2 Mult' for day vs week) where temperature color represents final converted USD held

Even though the third axis can be inferred, to gain a better visual understand as the results vary based on the assignment, two more heatmaps can be seen in Figures 14 and 15. Similar to Figure 13, Figure 15 clearly reinforces the fact that the day weighting is critical, as while both of the other heatmaps have a dark spot at the origin, Figure 15 observes a bright spot – implying a high value of Day yields the highest results. This aligns clearly with the results seen in Table 4 where all the highest results have an exceedingly high weighting value for the day.

Interestingly, it can also be observed that the month weighting should generally be higher than that of week. Not only at a more nuanced extent as seen in Table 4 but in general for all weightings, as it can be observed that the heatmap with the darkest spot at the origin is seen in Figure 14 where the origin values represent a heatmap with a high week value.

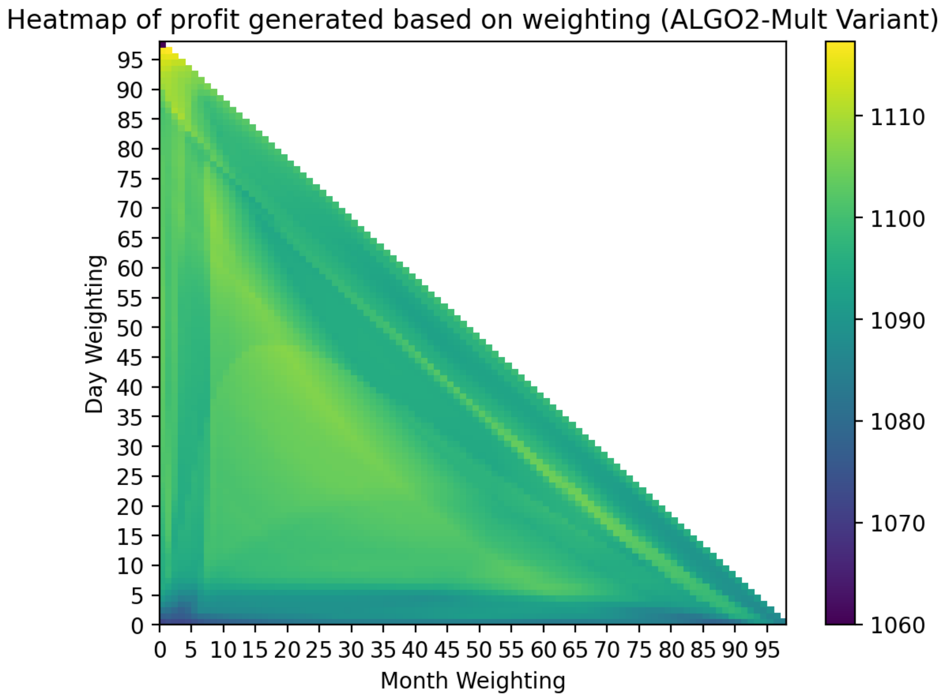

Figure 14: Weighting heatmap for the modified algorithm (AKA 'Algo-2 Mult' for day vs month), temperature represents final currency value held in USD

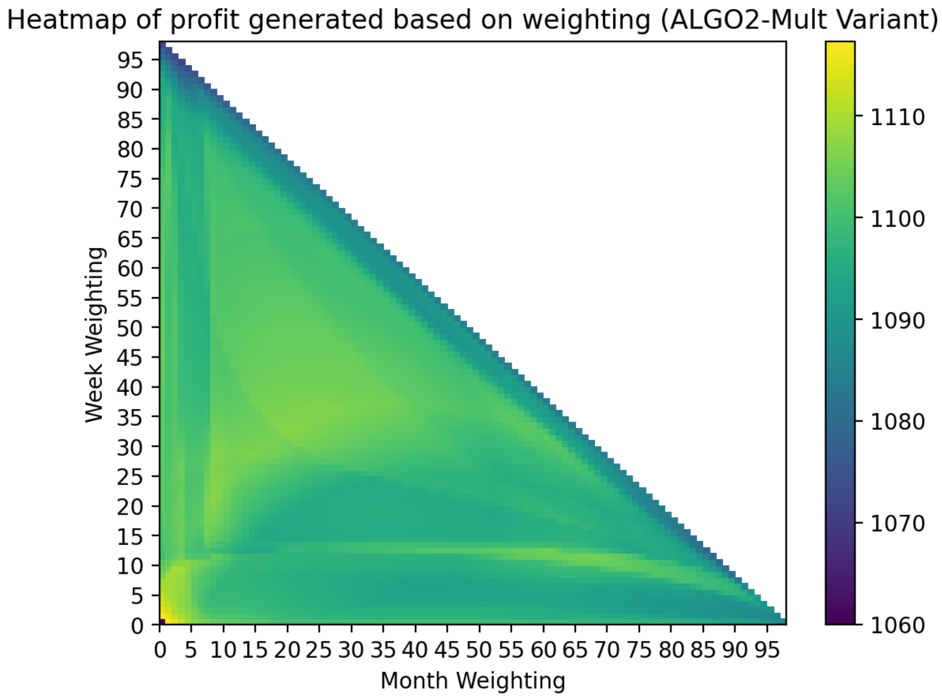

Figure 15: Weighting heatmap for the modified algorithm (AKA 'Algo-2 Mult' for week vs month), temperature represents final currency value held in USD

4.3 Algorithm Confluence and Concluding

Due to the still relatively poor results of the modified algorithm compared to just buying and holding RMB, it was decided to try and improve the results by using a confluence method.

The two main methods employed were: Using the results of the modified algorithm as a filter for the original algorithm, and vice versa, for a more nuanced buy/sell signal and; Applying some simple TensorFlow Keras Long Short-Term Memory (LSTM) neural network analysis to predict future stocks rather than using linear regression to decide whether to buy/sell and how much to buy/sell.

Unfortunately, in both cases the results obtained were worse than that without confluence. A summary of the results of all the different trading algorithms attempted can be seen in Table 5, the results achieved through confluence methods are highlighted in bold. Of note is that the LSTM neural network is incredibly rudimentary and did not have sufficient expertise or insight put into it, however the visible takeaway is that regardless of that – once confluence was employed, the CAGR decreased.

Table 5: Results of the confluence methods

Algorithm	**Variant**	**CAGR**
Buy & Hold	Holding RMB	1.468%
First Iteration AKA ‘Weak’	–	0.824%
Second iteration AKA ‘Algo2’	Mult-Variant	1.383%
Second iteration AKA ‘Algo2’	Mult-Variant -1	0.919%
Second iteration AKA ‘Algo2’	Sum-Variant	0.976%
Simple LSTM	-	1.304%
Confluence	**Weak + Algo2 Mult-Variant**	**1.149%**
Confluence	**LSTM + Algo2 Mult-Variant**	**1.231%**

5 Conclusion and Further Actions

5.1 Concluding

This report used Google Trends in order to receive trade signals and to determine the magnitude of these actions. A series of different algorithms were created and tested in order to determine the most effective method of trading, ranging from simple algorithms to applying confluence to multiple algorithms. While a consistent profit was generated, the algorithms that were attempted in this project were not able to outperform the buy and hold strategy of just holding RMB.

A takeaway based on these results calls back to the analogy mentioned at the beginning of this report on animals fleeing the site of an oncoming storm. Based on the results achieved, it can be determined that perhaps it is disadvantageous to allow yourself to be too swayed or manipulated by the news cycle – even the financial news cycle. It is important to note that this is not to say that the news cycle should be ignored, but rather that it should be taken with a grain of salt.

5.2 Limitations

A key limitation of this project is the difficulty of data collection. While USD/RMB was chosen due to it's high popularity in the news cycle from the trade war, it would have been preferable to do comparisons versus other popular exchanges that have different geopolitical natures such as USD/HKD or USD/EUR. The nature of the algorithm and Trends also lends itself to extensibility to not just other foreign exchanges, but trading on regular stocks as well as Web3 assets, and it may have offered more cohesive insights to test these as well. In all of these cases however, the limiting factor of testing is the lack of high quality harvesting APIs for Google Trends, leading to manual data collection being required for long term historical backtesting. This is a time-intensive process, and as such, the data collected is limited by the time period of the project.

Another limitation is the lack of an advanced trading algorithm. The algorithms used in this project are simple linear regressions, and while they do yield a profit, they can almost certainly be improved on to yield a higher profit, which is explored further in Section 5.3.

5.3 Further Actions

Based on the data received, it can be observed that while using Trends to trade does yield a consistent profit, the profit is less compared to that of simply holding RMB. However, this is not to say that Trends cannot be used to trade, but rather that the algorithm used in this project is not the most optimal. It can be noted that the algorithm produces a significant profit over simply holding USD, as we only know holding RMB generates a higher profit than trading with Trends with hindsight. Further steps could be taken to refine the method in two key aspects:

1. The triggering of the buy/sell signal

   The triggering of this signal could be refined by having a more intelligent, long-term algorithm feed information back into itself – as for the purposes of this report the algorithm simply compared a 3 day running average to a 30 day running average. This leads to the window being considered by the algorithm being quite short

   Furthermore, as discussed earlier in 2.3, the algorithm in its current state is unable of taking into account whether the spike is preceding volatility or succeeding it. This problem could be solved by using an algorithm that considers not just the Trends volatility and trading on it, but how far ago the last trade volatility was – thus checking whether the spike in Trends is simply just reporting on a recent trade spike

2. The buy/sell amount

   Similar to the buy/sell signal, this could be refined by devising an algorithm that feeds into itself and looks at the trends of previous buy/sell signals.

References

[1] Google. "Google trends." (2022), [Online]. Available: http://www.google.com/trends.

[2] R. Wood, *Final fantasy 14 endwalker is so successful they had to stop selling it*, Dec. 2021. [Online]. Available: https://www.techradar.com/news/final-fantasy-14-endwalker-is-so-successful-they-had-to-stop-selling-it.

[3] S. Subin, *Activision blizzard shares drop after report ceo allegedly knew about sexual misconduct*, Nov. 2021. [Online]. Available: https://www.cnbc.com/2021/11/16/activision-blizzard-shares-drop-after-reports-allege-sexual-misconduct.html.

[4] I. Group. "Top 10 most traded currency pairs." (2022), [Online]. Available: https://www.ig.com/en/trading-strategies/top-10-most-traded-currency-pairs-191206#usdcny.

[5] U. G. Treasury. "Second meeting of the u.s.-china strategic economic dialogue joint u.s.-china economic track fact sheet." (May 2010), [Online]. Available: https://home.treasury.gov/system/files/136/SEDjointeconfactsheet072910.pdf.

[6] Netease. "Translated name: The political bureau of the central committee of the communist party of china held a meeting to study the "thirteenth five-year plan" issue." (Oct. 2015), [Online]. Available: https://www.163.com/news/article/B5OJ39NA00014PRF.html.

[7] J. Howard. "Markets in perspective october 2015 in review: Russell investments." (2015), [Online]. Available: https://russellinvestments.com/us/blog/markets-in-perspective-october-2015-in-review.

[8] "Tianjin explosion: China sets final death toll at 173, ending search for survivors." (Sep. 2015), [Online]. Available: https://www.theguardian.com/world/2015/sep/12/tianjin-explosion-china-sets-final-death-toll-at-173-ending-search-for-survivors.

A Example Segment of Data Collected

Date	Raw daily interest	Raw weekly interest	Raw monthly interest	Price	Change %
1/1/2008	0	0	10	7.3041	0
2/1/2008	34	0	10	7.2938	-0.0014
3/1/2008	0	0	10	7.2729	-0.0029
4/1/2008	0	0	10	7.273	0
5/1/2008	0	0	10	7.273	0
6/1/2008	0	0	10	7.273	0
7/1/2008	0	38	10	7.2694	-0.0005
8/1/2008	0	38	10	7.2647	-0.0006
9/1/2008	0	38	10	7.2636	-0.0002
...	...	...	...	...	...
22/12/2015	0	17	62	6.4788	-0.0003
23/12/2015	0	17	62	6.4778	-0.0002
24/12/2015	0	17	62	6.4773	-0.0001
25/12/2015	0	17	62	6.4764	-0.0001
26/12/2015	0	17	62	6.4764	0
27/12/2015	5	17	62	6.4764	0
28/12/2015	8	17	62	6.4886	0.0019
29/12/2015	4	17	62	6.4848	-0.0006
30/12/2015	8	17	62	6.4912	0.001
31/12/2015	9	17	62	6.4936	0.0004

Table 6: Example segment of data collected