Smart Portfolio Advisor

Group 11

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1.Introduction

There is a common saying that monkeys make better fund managers than humans. This was based on a series of experiments run, the most famous one being a Chimpanzee, Raven, who threw 10 darts to pick stocks from a basket of 133 internet companies. Her stock picks delivered a 213 per cent gain in 1999, outperforming more than 6,000 professional brokers on Wall Street.

How can the average investor make quality investment decisions? Other than cherry picking stocks, there are many options in the market today, from mutual funds, to index investing and roboadvisories. One way to assess a portfolio's health is by measuring its returns relative to its risk, to understand if the portfolio is generating a reasonable return for the risk it is assuming. The Sharpe Ratio, proposed by William Sharpe, is one of the most popular methods that is used to measure risk adjusted relative returns in Modern Portfolio Theory.

In this project, we demonstrate the use of Sharpe Ratio as a measure of portfolio fitness to evolve a portfolio of stocks using Genetic Algorithm. We also apply LSTM modeling to forecast future stock prices.

1.1. Business Value

Modern fund managers rely on a variety of finance tools, most of which are expensive products. Hence our offering is targeted at people who are interested to invest in an optimal way but cannot afford the tools and time to do so.

Through the use of Genetic Algorithms, our system is able to pick out good portfolio allocations with high Sharpe Ratios every day, which investors can compare against their own portfolio holdings, to see if anything can be adjusted for improvement, for example, by addition of a particular stock that performed well in the recommended portfolio.

They can also understand how optimal their current allocation is compared to other possibilities. For example, if their current portfolio has a Sharpe Ratio of 1.5, but the genetic algorithm is able to produce a few portfolio alternatives that have Sharpe Ratio above 1.5, that may signal that their current allocation can be further optimized under current market conditions.

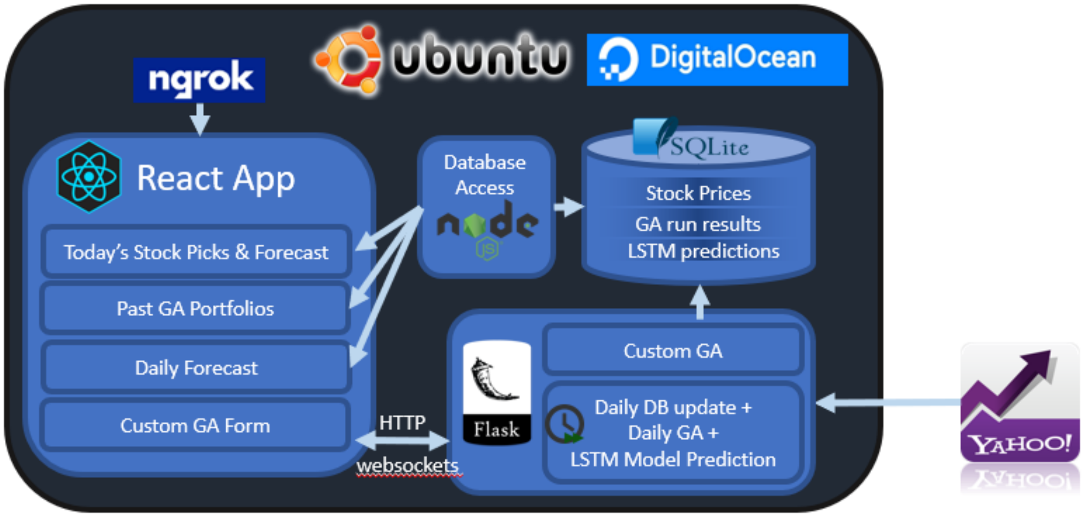
In addition to providing personalized and optimized portfolio, we also provide a rolling 2-week stock price forecast, based on the latest daily closing prices. Stock price prediction is often a complex and time-consuming activity, involving the collection and analysis of related company/industry updates, government policies and broad market sentiment. We aggregated key macroeconomic and technical indicators and applied deep learning techniques to offer our users exclusive insights into future market performance. For the purpose of this project, a long short-term memory (LSTM) was used for predicting the future two weeks stock price trend by considering past 40 days data. Users are able to save time from performing their own forecasting, and rest easy knowing that we provide highly accurate forecasts.

1.2. Project Aim

The aim of this system is to

(a) approximate the best return to risk portfolio allocation possible at any point in time based on historical returns.
(b) forecast the stock prices for the next 2 weeks

2.System Architecture



The Smart Portfolio Advisor is split into 5 parts. n-grok, a react app, a flask server, a database server, and an SQL lite database packaged into an Ubuntu Virtual Machine hosted in DigitalOcean, a cloud based infrastructure provider.

In the react application, all web pages pull preprocessed data from the SQLite database, except for the custom GA runs, which triggers a background thread on the server to run the GA for a basket of stocks picked by the user. As GA runs, the results of each epoch are published to the frontend via websocket communication after each epoch.

Within the flask server, there are 2 main services. Firstly, there is a service which responds to customized GA run requests from the frontend. Secondly, there is a cron job that does 3 functions. Firstly, it pulls the latest stock price information from Yahoo Finance on a daily basis. Secondly, it runs the daily GA to get the best portfolio for the day. Thirdly, it trains 1 LSTM model per ticker on the updated stock price information. It writes the results of all these 3 functions to the database, for the frontend to quickly pull out the desired information.

So, upon arriving at the Homepage, the user will get to see the Portfolio Recommendation of the day along with the Sharpe Ratio, percentage return of the investment and the risk percentage. These values are generated by pulling the daily stock price from Yahoo Financials and pushing those to the database (Daily DB Update) followed by running the daily GA and the LSTM Model Training on the updated dataset.

3. System Features

3.1. Stock Data Retrieval

We grabbed the data of 20 largest stocks in the S&P 500 in the past year from the Yahoo Finance API to form a dataset of historical stock data, and stored this in the database. 20 stocks were used for the run as a proof of concept. The daily stock prices are fetched from the Yahoo Financial API and the database is being updated using a CRON job scheduler on a daily basis as well.

3.2. Portfolio Recommendation of the day (based on Daily GA Run)

Daily GA Run refers to a series of runs which were done offline taking into consideration the latest daily data pulled from online finance APIs such as Yahoo Finance.

As the GA runs took a long time to run, and the time increasing with the number tickers, the team decided to:

- limit the number of tickers to 20, and population size to 10 as a proof of concept,
- run the GA offline during non trade hours and write the results to database for easy retrieval
- parallelize certain operations (see runtime optimizations)

The “daily GA Runs” for a time period stretching back to 6 Sep 2021 was performed to simulate the algorithm performance on historical data. Each run uses 12 months of historical data to compute annualized return and annualized volatility (standard deviation).

3.3. Custom Portfolio Recommendation (based on Custom GA Run)

Custom GA run refers to a run which the user may trigger on the fly, for a custom basket of stocks of his choice, to observe the portfolio optimization process

This is meant to allow the users to optimize across a basket of stocks already in his portfolio. As the algorithm runs, the console output will be pushed to the web frontend after every epoch, so that the user can receive updates on his portfolio optimization process

3.4. Stock Price Forecasting

Using the stored stock historical data, we trained the LSTM model to predict the stock price trend in the next 10 days based on the last 40 days of data.

After having trained the model, we save the predicted stock price for the next 10 days to the database and the trained LSTM model as a .hdf5 file.

Since the stock database is updated everyday with new addition of daily stock price, we are re-training the LSTM models everyday too. Re-training the model everyday makes sure the latest changes in the stock prices are captured in the model. Hence, we can give sharper predictions for the future dates .

On the frontend, the stock forecasts for tickers that are being recommended by the GA algorithm are featured on the HomePage. There is also a separate page called Forecast where users can input which stocks they are interested in, and our backend will pull the necessary forecasts from the database. These forecasts will be the output of the daily offline LSTM model training process that are stored in the database.

3.5. Historical Portfolio Recommendations

Our server can return the previous recommended portfolio in the History Portfolio page. Once they pick a specific day, they can get our Portfolio recommendation of that day and compare it with the present day. This will help the user understand how the portfolio recommendations have evolved over the time.

3.6. Financial News

Users can also decide their own investment decisions in response to the latest financial news.

We provide our users with the latest and most comprehensive financial news to help them decide their investment strategies based on what happens every day.

4. GA Algorithm for Portfolio Recommendation

4.1. Knowledge Identification

4.1.1. Fitness Function Definition

The Sharpe Ratio is computed using the following formula:

$$\text{Sharpe} = (\mu - rf) / \sigma$$

Where μ is the return of the portfolio,

rf is the risk free rate,

σ is the standard deviation of the portfolio

From the formula, it can be understood that the aim of the Sharpe ratio is to maximise the excess returns on the portfolio compared to holding a risk-free asset such as Treasury bonds over a certain time period, in relation to the risk of that same portfolio, which is measured as volatility of the prices over that same time period.

The interpretation for Sharpe ratio is as follows:

Sharpe Value	Interpretation
<1	Not good, taking more risk than is proportionate for the return
1-1.99	OK
2-2.99	Really good
>3	Exceptional

4.1.2. Data specification

To compute the Sharpe ratio, the following were needed:

(a) Historical Adjusted Closing Stock prices for up to 2 years per ticker (for the 20 identified subset of tickers), since the historical GA were being backtested for a period of 1 year
(b) Risk Free rate benchmarked by the 10 year US Treasury bills for up to 2 years.

Both pieces of data could be obtained from Yahoo Finance API.

4.1.3. Hyperparameter specification

Each GA Run is initialized with the hyperparameters in the table below. These were arbitrarily set, and the frontend supports customization of some of these parameters.

Hyperparameter	Description	Frontend setting
Run date	Date which GA is run for. The system will pull 1 year of historical data based on this date	
Stock tickers	The basket of stocks which the GA should optimize over	Y
Max Stocks	Max number of stocks which should receive allocations within the stock tickers	
Max Epochs	Number of epochs which the GA should run for, if it did not converge prematurely	Y
Max Depth	Max number of recursions the GA should run for. Each recursion is performed on a freshly generated random population. Max Depth is 5 for Daily GA offline run and it is kept 0 for the Custom GA online run.	
Selection Rate	The top N% of chromosomes which should form the next generation	Y
Crossover rate	The rate at which crossover should be permitted	Y
Mutation Rate	The rate at which mutation should be permitted	Y
Risk Free Rate	The returns which the investor would have achieved if he had invested in a relatively risk free asset instead	

4.2. Knowledge specification

4.2.1. Chromosome

A chromosome is a vector containing the proportions allocated to each ticker.

For example, if there were 3 tickers, stock A, stock B, stock C, the chromosome could look like [0.2, 0.3, 0.5]. This means that 20% of the portfolio should be allocated to stock A, 30% to stock B, and 50% to stock C. As such, the sum of all the ticker allocations in the chromosome needs to be equal to 1, and this could be achieved by dividing each number in the vector by the sum of all the numbers in the vector.

In the sample github code, every stock had an allocation. But as we were considering to scale up the basket of available stocks to 100 or 500, we decided to implement a maxStocks hyperparameter to limit the number of stocks which would receive allocations, or the allocation would be spread too thinly over a large basket of stocks.

Hence the code to generate the chromosome was modified to only choose [maxStocks] stocks out of X number of possible tickers.

```
# Chromosome Definition
def chromosome(n, totalstocks):
    ''' Generates set of random numbers whose sum is equal to 1
        Input: n = number of stocks we want to invest out of
         totalstocks. totalstocks = universe of investible stocks
        Output: Array of random numbers'''

    ch = np.random.rand(n)
    ch = ch/sum(ch)
    #disperse ch across the available stocks
    portfolio = [0] * totalstocks
    i = 0
    while (i != n):
        #look for portfolio[index] == 0 to replace with chromosome
        index = np.random.randint(0, totalstocks)
        if (portfolio[index] == 0):
            portfolio[index] = ch[i]
            i = i + 1

    return portfolio
```

4.2.2. Fitness Value (Sharpe) Computation

The computation was done in accordance with a few online tutorials [4,5]

1. **Computation of Daily Return**

   Firstly, the daily return was computed for each stock using the adjusted closing price.

$$\text{Daily Return (\%)} = \frac{\text{Today's price} - \text{Yesterday's price}}{\text{Yesterday's price}}$$

This computation was done as the data is pulled from the source and written into the database to shorten GA computation time.

2. **Computation of Annualized Daily Return**

   Next, the annualized daily return was computed based on 1 year of daily return data.

   The average of all the daily returns in 1 year was taken and multiplied by the number of trade days, which is commonly assumed to be 252 in most tutorials

$$\text{Annualized Daily Return (\%)} = \text{Mean (Daily Return)} \times \text{Number of Trade Days}$$

3. **Computation of Annualized Portfolio Variance**

   The computation of daily portfolio standard deviation was slightly more complex, because most Sharpe Ratio computation tutorials focused on the standard deviation for a single stock ticker, whereas we needed a weighted computation of portfolio standard deviation

   For an N-stock portfolio, portfolio variance is computed with the following formula:

$$\textbf{Portfolio variance} = \sum_{i=1}^{N} W_i \sigma_i + \left[\sum_{j=1}^{N} \sum_{k=1}^{N} W_j W_k \, COV_{j,k}\right]$$

   Then, the annualized Portfolio Standard Deviation was computed using the following formula:

$$\text{Annualized Standard Dev(\%)} = \sqrt{Portfolio\ Variance} \times \sqrt{\text{Number of Trade Days}}$$

4. **Computation of Risk Free Rate**

   The risk free rate was computed by taking the mean of the 10Y US Treasury bill yield (ticker: ^TNX) over the last 12 months.

5. **Computation of Annual Sharpe Ratio**

The excess return on the portfolio was computed by subtracting the risk free rate from the annualized daily return.

Finally the Sharpe ratio was computed by dividing the excess return by the volatility, which was measured by the annualized standard deviation of the portfolio.

$$\text{Sharpe Ratio} = \frac{\text{Annualized Daily Return} - \text{Risk Free Rate}}{\text{Annualized Std Dev of Portfolio}}$$

4.2.3. Population Selection and Generation

Each GA run had a default population size of 10. We opted to keep the population size smaller for faster runs, as we realized that computing the fitness function seemed to be a computation bottleneck (see runtime optimization).

At each epoch, the fitness values of all the population members would be computed. Then, we would **rank** them according to their fitness values, and take the top X portfolios according to [selectionRate]. For example, if [selectionRate] was 0.4, we would take the top 4 chromosomes (out of 10) for mutation and crossover.

With these 4 chromosomes, we would then replicate them until the desired population size (i.e. 10) is reached. So the new population would look like this before mutation and crossover:

[Top1, Top2, Top3, Top4, Top1, Top2, Top3, Top4, Top1, Top2]

We ran a few GA batches where we subjected all the chromosomes in this population to the crossover/mutation rate, and some succeeding generations got potentially worse results! Hence, to preserve the performance to be on par or better only, the first chromosome, which represented the best portfolio for the current generation, was excluded from crossover and mutation, in order to preserve a baseline Sharpe for the next generation that was at least as good as the current generation.

4.2.4. Crossover

In literature, there are many possible forms of crossover operations, e.g. single point crossover, two-point crossover, uniform crossover, arithmetic crossover and heuristic crossover.

We implemented **single point crossover** for simplicity. However, because we were intending to scale up the number of tickers, it was possible for the number of ticker allocations to increase until every possible ticker had a tiny allocation. Consider a worst case scenario where out of 20 stocks, parent 1 had all its 10 allocations in stock 1-10, and parent 2 had all its 10 allocations in stock 11-20. If crossover point is set at the midpoint of both stocks, the child will end up having 20 stock ticker allocations in the portfolio! The problem will get worse if not rectified in a larger basket of potential stocks, and as more crossovers are performed. [1]

To prevent the number of ticker allocations from increasing too much, we randomly dropped allocations if the number of ticker allocation exceeded [maxStocks]. We did not check if we picked the same random index, but the function does a reasonable job to keep the number of ticker allocations in check.

Then we had to re-normalize the final array to ensure that the sum of allocations was 1.

Below is the code for the crossover. We only performed the crossover on the chromosome that was selected for it, thus the function only returns 1 child instead of 2.

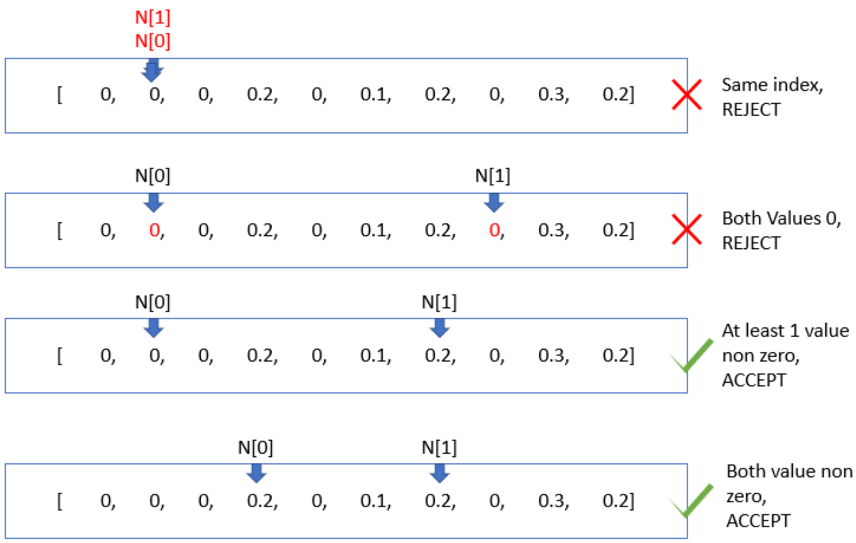
```
def crossover(parent1, parent2, maxStocks=10):
    length = len(parent1)
    crossoverPt = np.random.randint(0, length)
    child = [0] * length
    numStocks = 0
    stockLoc = []
    for i in range(length):
        if (i<crossoverPt):
            child[i] =  parent1[i]
        else:
            child[i] =  parent2[i]
        if (child[i] > 0.0):
            numStocks+=1;
            stockLoc.append(i)

    if (numStocks > maxStocks):
        toDrop = numStocks - maxStocks
        for j in range(toDrop):
            dropInd = stockLoc[np.random.randint(0, len(stockLoc))]
            child[dropInd] = 0.0
    sumOfChild = sum(child)
    if (sumOfChild > 0.0):
        child = [float(i)/sumOfChild for i in child]
    return child
```

[1] The reverse, where the stock ends up with zero allocations is also possible but not likely. In the event that there is zero allocations, the stock fitness will be low, hence it is likely to get excluded for the next epoch.

4.2.5. Mutation

For mutation, we swapped 2 indices within a chromosome. However, as we expected that our chromosome could be potentially "sparse", i.e. with only [maxStocks] ticker allocations out of a big basket, to make the mutation useful, we avoided swapping ticker allocations for tickers with 0 allocations, as that would have no impact on the chromosome allocation.



Below is the code for the mutation. The highlighted condition in the while loop will stay true until the 2 selected indexes are different, and either or both indexes are pointing to non-zero ticker allocations.

```
def mutation(parent):
    child=parent.copy()
    n=np.random.choice(range(len(parent)),2)
    while (n[0]==n[1] or (child[n[0]]==0.0 and child[[n[1]]==0.0])):
        n=np.random.choice(range(len(parent)),2)
    child[n[0]],child[n[1]]=child[n[1]],child[n[0]]
    return child
```

4.2.6. Termination Criteria

4.2.6.1. Single run termination criteria (convergence or max epoch)

There are 2 termination criteria for each GA run, the run will terminate when either is fulfilled.

The first criteria is convergence. At every epoch, the population is sorted according to their fitness, and the elite chromosomes are compared against the elite chromosomes from the previous epoch. In this case, with a selection rate of 0.4, the number of elite chromosomes per epoch was 4 (out of 10). The pairwise Euclidean distance is computed, and if the Euclidean distance does not exceed 0.0001, a convergence counter is incremented. If the convergence counter is incremented 3 times, we terminate the run. By examining the portfolios, it can be seen that the best portfolios of the last 3 epochs of any GA run may not be exact duplicates, but close enough.

The second criteria is max epoch. When the GA fails to converge, we cut it off when maxEpochs exceed 40 as usually by this time, the increment in Sharpe is not significant (due to population homogenity) and running with another seed population can potentially introduce more improvements compared to continuing along the current epoch.

4.2.6.2. Multi-run termination criteria (Sharpe Ratio 2, recursion depth of 5)

A GA Run starts off with a randomly initialized population of pop_size, typically 10 members. Usually after 1 run (up to 40 epochs), the Sharpe ratio may not be ideal because the run converges at a local maxima that does not yield a good Sharpe ratio. For daily GA runs, a portfolio allocation with Sharpe Ratio > 2 was desired, as it signaled a good return to risk ratio. Since the daily GA run was done offline, the program was made to rerun recursively for a maximum of 5 times (recursion depth <= 5), in the hopes of hitting a good start search point (initial population) which can eventually find a good local maxima with a minimum Sharpe Ratio of 2. While recursing 5 times did not always result in the target Sharpe Ratio of 2, it almost always resulted in an improved Sharpe Ratio, compared to increasing the number of epochs, selection rate, mutation rate, or crossover rate.

We found that the data influenced how easily the desired Sharpe ratio could be achieved. In particular, dates that were more recent yielded lower Sharpe ratios compared to dates in 2021. Before we enforced a maximum depth of 5, the algorithm would recurse for many times for portfolios in Jun to Oct 2022, being unable to reach the target Sharpe ratio of 2.

This could be due to the fact that the 1 year return (e.g. Oct 22 compared with Oct 21) started to turn negative on May 22, making it harder to find a decent performing portfolio in the limited basket of stocks that would give a high return.

Below is a summary of Daily GA Runs for 06-Sep-21 to 25-Oct-22, capped at 5 runs per day

Month	Av. Sharpe	Runs	S&P500 1-yr %change
Oct-22	0.847959	90	-15.531
Sep-22	1.123859	110	-15.5536
Aug-22	1.261385	115	-11.2369
Jul-22	1.192506	105	-4.68113
Jun-22	1.31393	95	-10.6377
May-22	1.700427	73	-0.31593
Apr-22	2.360509	26	0.090374
Mar-22	2.540174	23	15.55188
Feb-22	2.585688	21	16.40865
Jan-21	2.972397	21	23.30379
Dec-21	3.307817	23	28.84886
Nov-21	3.61518	22	27.78956
Oct-21	3.033292	21	42.82695
Sep-21	2.897593	19	30.16647

4.3. Knowledge Refinement

4.3.1. Algorithm Tuning

Some tweaks were made to the algorithm to run more efficiently. Some of these included:

(a) At first we employed Generational GA, where we attempted to perform crossover/mutation on all chromosomes in the next generation according to the crossover rate and mutation rate. However, upon examining the results, we quickly realised that subsequent epochs could yield less optimal portfolios, hence we opted to do Steady State GA instead. We excluded the fittest individual from crossover/mutation possibility as we did not want to lose our best portfolio, the rest of the portfolio was subject to high crossover/mutation rate as we only had 9 other members, and it was critical to try as many permutations as possible to figure out possible portfolio improvement.

(b) We introduced recursion to restart the GA runs when the desired Sharpe ratio was not met, and also capped the GA runs when they failed to achieve a good result after 5 runs. The reason it was done this way was because we realised that given our population size of 10, the GA runs tend to get stuck if local maxima very easily, yielding suboptimal sharpe portfolios. Hence it is better to restart the GA, as starting from a different start point can be more helpful to improve the GA rather than continuing along the current epoch, as the GA could have been evolving along a path with many suboptimal local maximas.

(c) From(a), we also considered if getting a better quality initial population would be helpful and experimented with increasing the population size. The hypothesis was that more random chromosomes present would increase the quality of the fittest individual from the first epoch, and hence set the stage for better subsequent Sharpe ratio. However, after a few runs, we realized that increasing the population size came at a cost of fitness computation, ranking, additional crossover/mutation computation, and these added significantly to the runtime overhead. What was worse was that the random allocation of stock tickers often resulted in the generation of many low quality chromosomes, and hence did not contribute to the betterment of the Sharpe ratio significantly. We ended up expending a lot of computation on examining and tweaking low quality chromosomes. Hence, the conclusion was that expending extra effort to get a better initial population may not benefit much as due to significant performance issues.

(d) Instead, we found that choosing a smaller population size rather than larger one allows for faster convergence, even at high mutation and crossover rates. This was the preferred strategy because it was "fail-fast". A convergence counter was implemented to detect early convergence so that computation time of subsequent epochs could be saved when the improvement in sharpe was minimal. Early run termination, coupled with restarting at different initial populations, helped to bring up the portfolio Sharpe in an acceptable timeframe.

(e) Last but not least, we also experimented with changing selection rates to between 0.3 to 0.6 and increasing mutation/crossover rates to as much as 0.9, but no significant improvement in Sharpe was observed.

4.3.2. Key Performance Indicators

Some performance measures are described below

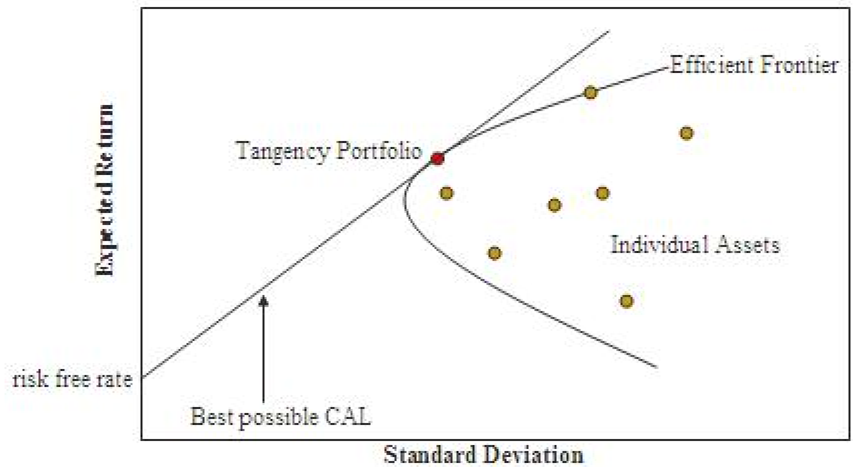
Measure	**Sharpe**	**Remark**

	Improvement	
Average Sharpe Improvement per Epoch	+ 0.588	Evaluated by taking the fittest individual at each epoch (popid=0) and comparing from epoch 0 to maxEpoch, for each run in a day. The average across all runs in a year from 02-Sep-2021 to 06-Sep-2022 was computed
Average Sharpe Improvement due to restart	+ 0.913	For each day, if there was more than 1 GA run, the min and max final Sharpes were extracted and their difference computed. The average range (divided by number of days with GA runs > 1) was then taken to be an indicator of the Sharpe improvement
Average Difference versus 1000 Randomly Generated Portfolios	- 0.099	This was a surprising result. Visually the GA generated portfolio appeared to lie near the Efficient Frontier, indicating a relatively efficient allocation (see below). However, 91/260 days, GA generated portfolio underperformed randomly generated portfolios. More discussion below

Efficient Frontier Hypothesis

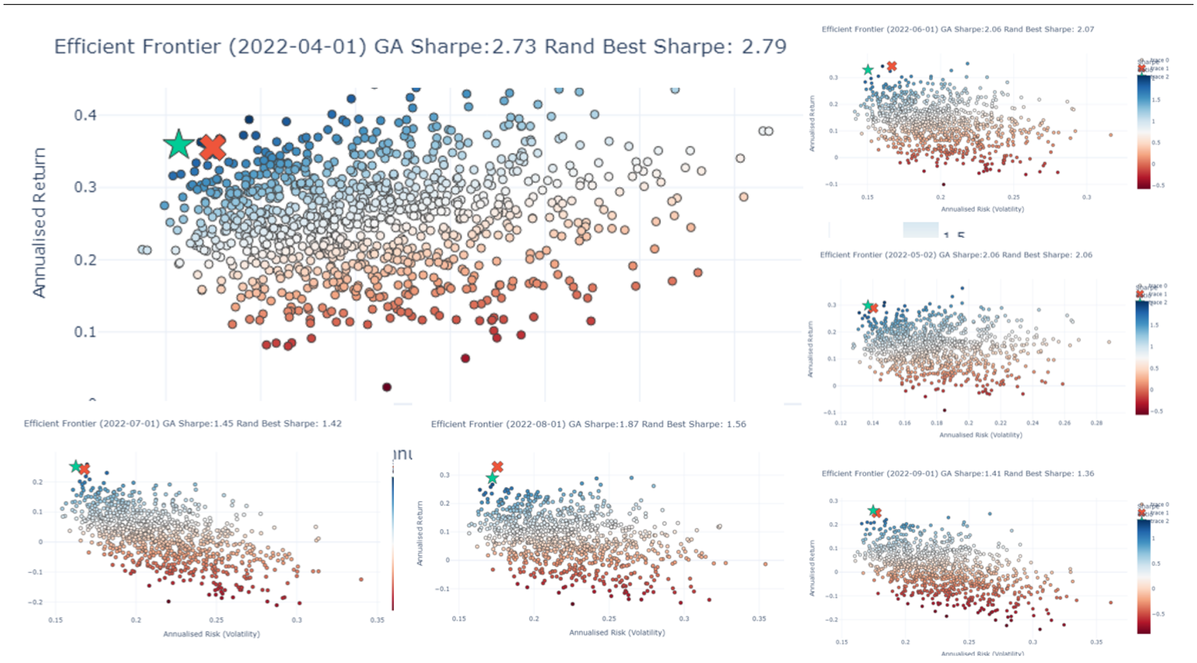
The efficient frontier is the set of optimal portfolios that offer the highest expected return for a defined level of risk or the lowest risk for a given level of expected return. [6]

It is typically plotted as a risk versus return graph. Each point in the graph represents a portfolio allocation. Portfolios below the curve are sub optimal, so only the upper part of the curve is considered. Portfolios to the right are high risk and also not recommended



We adapted a python notebook to generate out the efficient frontier for the days that the daily GA was run. The notebook generated 1000 random portfolios with the 20 tickers we defined, and calculated the excess risk and returns for these portfolios to plot on the graph. Most of the days, the GA generated portfolio consistently appeared to sit near the Efficient Frontier, indicating that it was a near optimal portfolio for the risk assumed. However, in terms of Sharpe ratio, it couldn't beat the best of the randomly generated portfolios.

The Efficient Frontier diagrams below are a sampling from the set of 260 images generated. The green star represents the best random portfolio, and the red cross represents the portfolio recommendation by the GA Run. The rest of the datapoints are the randomly generated portfolios (999) and the colour scheme of the datapoints indicates the desirability of the Sharpe Ratio (red=poor, bl `ue= good)



We try to explain why this happens. One possibility was that GA uses less random portfolios, hence unable to approximate the global optimum better. The minimum number of portfolios generated by GA runs is 50, and the maximum is less than 2000. However, in general, the number of portfolios generated would not hit 2000 due to constraints such as the fittest chromosome in each generation being omitted from crossover/mutation, and portfolios generated by crossover/mutation have more limitations than a truly random distribution as they are constrained by the crossover/mutation operations. Hence GA is limited in its ability to extend over the search space compared to random portfolio picking.

The other theory is that the stock markets have been quite volatile for the past 1 year. There are many fluctuations in the stock prices and risk free rates, and these have caused there to be many local maxima that the GA got stuck at and 5 permitted restarts were not sufficient to locate better maximas.

You may have recalled that we decided not to increase the population size because it resulted in more computation (e.g. ranking, crossover, mutation, low convergence). Increasing population size would mean that more random portfolios would be generated at the first epoch, mirroring the random portfolio picking strategy. However, the subsequent runtime cost in terms of performing all those operations to evolve the portfolio also increases. Since random portfolio picking seems to work better and run faster, it seems to suggest perhaps GA is not quite suited for this task after all.

4.3.3. Run time optimizations

We observed that computing the fitness values for each population was taking up a significant amount of time. The console printout for each population member's sharpe ratio took about 2 seconds and the original GA run took about 20 minutes to complete 1 run. Hence, we decided to parallelize the fitness value computation across the population using Python's multiprocessing library. This cut down the runtime for a full GA run (40 epochs) significantly from 20 minutes to less than 4. Parallelization was also attempted for the crossover and mutation functions for each chromosome, but the time savings was not significant.

Parallelization for python worked differently on Unix systems versus Windows systems. On Unix, a fork was made with the parent's thread context duplicated to the child thread, whereas in Windows a new python interpreter was "spawned", which was lacking in the parent thread context. This meant that certain functions were missing in memory, and the only way around it was to refactor all the code into a python file and read it back into the child thread. For ease of deployment, we decided to field the backend into a Unix based OS (Ubuntu) instead.

To produce the database of GA runs for a year since Sep 2021, the python notebook was uploaded to a 4 core VM in DigitalOcean and 3 notebook duplicates[2] were made to run GAs for different time frames (e.g. Jun - Sep 22, Mar - Jun 22, Sep 21 - Mar 22) while writing to the same sqlite database file. This way, the entire database could be generated fairly quickly (< 12 hours). This mode of working also facilitated bug fixes in the code, which would otherwise have been rather cumbersome to implement.

4.4. Limitations and Improvements

4.4.1. Too Slow!

The greatest limitation of the Genetic Algorithm is speed, or the lack of it. The algorithm takes very long to run. It requires further optimization which we were not in time to do. Our lack of familiarity with python APIs led us to code the algorithm to perform in relatively inefficient ways. Towards the tailend of the project, when running the Efficient hypothesis notebooks, we saw that it is possible to generate many portfolios and

[2] 3 Notebooks were observed to bring CPU utilization to 100%. 1 notebook (60%) and 2 notebooks (80%). The workload was split arbitrarily according to observation that earlier timeframes (Sep 2021 to Mar 2022) seemed to run faster due to lower recurse depths

evaluate them quickly with certain optimizations in place. However we were not in time to replicate these changes to our main system setup.

4.4.2. Overly-dynamic portfolio recommendations

There is a cost to buy and sell stocks to be in line with the portfolio recommendation. Depending on the data, the allocation could look vastly different from day to day, confusing investors. Investors are not day traders so their strategy might not involve buying/selling on a daily basis and in fact, excessive buying and selling could eat into their returns due to trading fees imposed by any trading platform of their choice.

Some things we could try to give stability to the recommendation would be firstly, to introduce a penalty to the fitness function that penalizes it for any buy/sell decisions. We could reference an existing trading platform's fee structure (e.g. SGX's) to compute a penalty based on the buy/sell volume.

Secondly, we could also try to use yesterday's recommended portfolio as a starting point for today's GA run. This approach may be limited in reaching the efficient frontier, but given a good "yesterday" portfolio that sits relatively near the efficient frontier, and further, computing today's "best random portfolio" as a guide to an achievable Sharpe, it might be possible to find an intermediate portfolio between the "today's best random" and "yesterday's GA recommendation" that has a buy/sell penalty of less than some penalty threshold

4.4.3. Only Linux

As mentioned, the code can only run in Linux, it would be good to refactor the code so that we can run it on Windows too

5. LSTM Model for Stock Price Forecasting

5.1. Knowledge Identification

Stock price can be influenced by many interconnected factors, it is not only directly impacted by the business financial status, reputation and future planning of an enterprise, it will also be impacted by numerous external factors such as natural disasters, global economic situation, interest rate and so on. To make a reliable prediction on stock future trends, multivariate information has to be gathered to train the model. For the purpose of this project, we collected the data in three aspects: the historical data that show the basic information of the stocks; the macroeconomic indicators which reflect overall health of the economy and have long-term impacts of stock market; and the technical indicators which are the mathematical pattern derived from historical data widely used by professional investors to make trading decisions.

Category	Indicator	Description	Source/ Formula
Historical Data	Volume	Stock volume is counted as the total number of shares that are actually traded (bought and sold) during the trading day. Volume can indicate market activity. For example, stocks with high volume are usually viewed to have less Volatility and higher liquidity (Mitchell, 2022).	Yahoo Finance
	Adjusted Close Price (Adjclose)	The adjusted closing price amends a stock's closing price to reflect that stock's value after accounting for any corporate actions, which is often used when examining historical returns or doing a detailed analysis of past performance (Ganti, 2021).	Yahoo Finance
Macroeconomic Indicators	CBOE Volatility Index (VIX)	The Chicago Board Options Exchange (CBOE) Volatility Index measures stock market volatility by tracking trading in S&P 500 options. For example, if the VIX value declines, the S&P 500 is predicted to be stable in the near future, while if the VIX value increases, it may indicate that S&P 500 is falling (Kuepper, 2022).	Yahoo Finance
	U.S. Dollar Index (USDX)	The U.S. dollar index (USDX) is a measure of the value of the U.S. dollar relative to six of America's most significant trading partners (the Euro, Swiss franc, Japanese yen, Canadian dollar, British pound, and Swedish krona). The USDX value can indicate the U.S. dollar’s value in global markets (Lee, 2022).	Yahoo Finance

Technical Indicators	Moving average convergence divergence (MACD)	Moving average convergence divergence (MACD) is a trend-following momentum indicator that is calculated by subtracting the 26-period exponential moving average (EMA) from the 12-period EMA. And EMA is a type of moving average (MA) that places a greater weight and significance on the most recent data points. MACD's histogram is often used to identify potential failure and reversal of stock price. For instance, MACD crossing above zero is considered bullish, while crossing below zero is bearish, and the further from the zero line the stronger the signal (Dolan, 2022).	MACD = 12_Period_EMA - 26_Period_EMA
	Relative strength indicator (RSI)	The Relative Strength Index (RSI) is one of the widely used momentum oscillators on a scale of 0 to 100 which measures both the speed and rate of change in price movements within the market. Usually, RSI above 70 means the market condition is overbought, and RSI below 30 means market condition is oversold (Fernando, 2022).	RSI = 100 – [100 / (1 + (Average of Upward Price Change / Average of Downward Price Change)]
	Average True Range (ATR)	The average true range (ATR) is an indicator for price volatility showing the average price variation of a stock within a given time period, generally using 14 days. ATR is used by investors to determine when to trade(Hayes, 2022).	TR = max [(high - low), abs(high - $close_{prev}$), abs(low - $close_{prev}$)] $ATR = \frac{1}{n}\sum_{i=1}^{n} TR_i$

To get the stock information and the value of macroeconomic indicators, a python module called yahoofinancials is used to fetch the relevant data from Yahoo Finance. And the definition and formula about technical indicators are based on financial websites such as Investopedia.

5.2. Knowledge Specification

5.2.1. Data preprocessing

It is necessary to standardize data before training the model as values of input features may vary from one to another. For example, the AAPL stock volume is much higher than its relative strength indicator which has values from 0 to 100. MinMaxScaler was implemented to ensure the value of each feature is normalized to a scale of 0 to 1.

Moreover, calculating the technical indicators needs a certain amount of data. For instance, the average true range (ATR) evaluates the average price variation of a stock within a 14 days period, therefore, at least 14 days data is needed and the first 13 rows would not have values. Enough data should be obtained for calculating the technical indicators and NaN data should be removed in the data preprocessing stage. Following is a snapshot of the dataset:

date	volume	VIX	USDX	MACD	RSI	ATR	adjclose
2017-12-05	0.167850	0.029644	0.336613	0.482733	0.273053	0.039151	0.000000
2017-12-06	0.167945	0.025428	0.352776	0.482518	0.379945	0.041202	0.004436
2017-12-07	0.138825	0.013734	0.366128	0.481350	0.352007	0.043078	0.003355
2017-12-08	0.151584	0.005847	0.373156	0.487047	0.481156	0.049701	0.009581
2017-12-11	0.135631	0.002584	0.371047	0.495740	0.519986	0.055034	0.013570

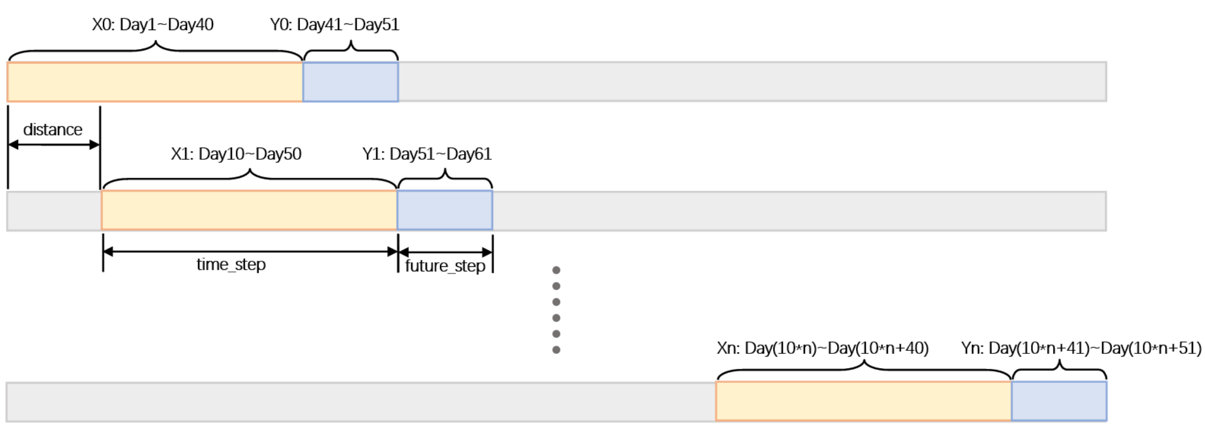
5.2.2. Dataset creation

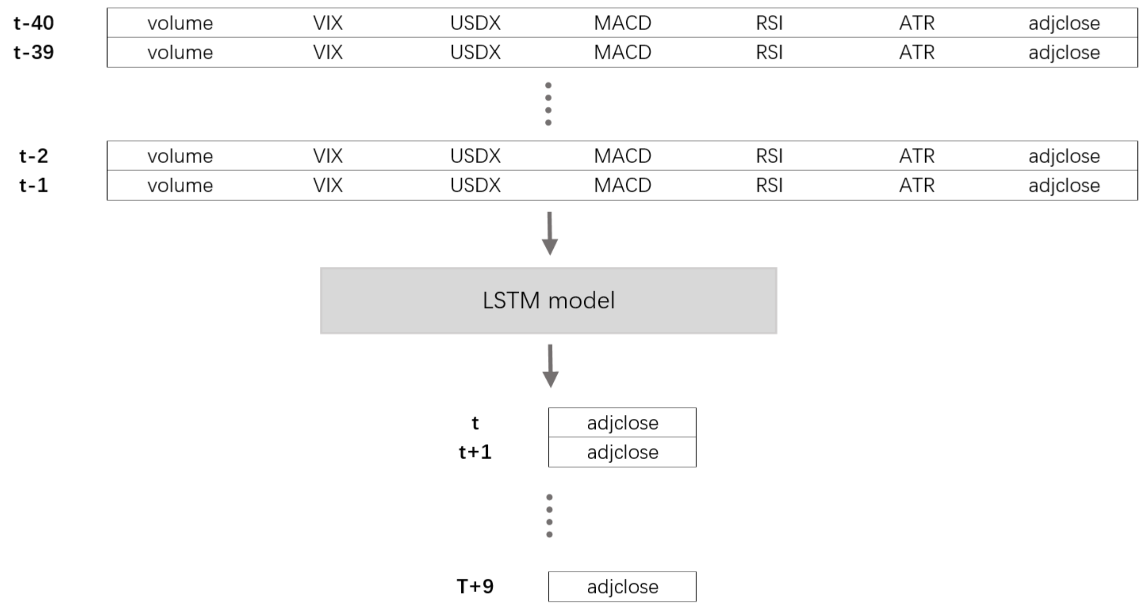
Our input data would be 40 days values and output data is the further 10 days adjclose value. The dataset is created in the following way using a sliding window with a step of 10. 10 days corresponds to roughly 2 weeks of data (weekends being non trade days)

time_step = 40

future_step = 10

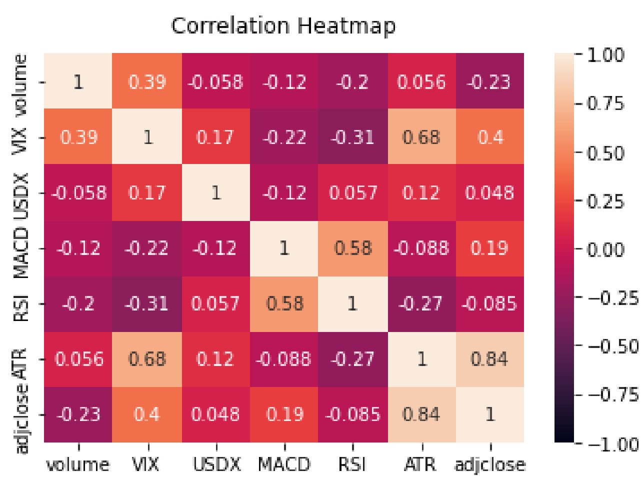
distance = 10





5.3. Knowledge Refinement

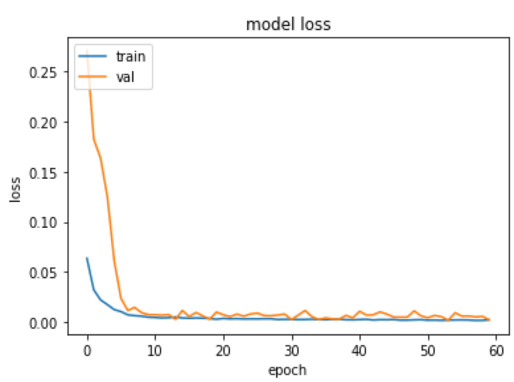
To select an appropriate set of data, we want the factors that contribute to the stock price fluctuation but do not include duplicates. Therefore, to identify the features that have potential influence and remove duplicate features, a correlation heatmap of all input features is generated. In this project, features that have high correlation coefficient with our target "Adjusted Close Price" are considered as influential features and features that have high correlation coefficient above 0.7 is considered as duplicate features to be removed. It is validated that none of the pairwise correlations between the chosen features exceeds the threshold.



To identify optimal model architecture and hyperparameters, we trained the models with different combinations of number of layers, learning rates and batch sizes, and compared the mean squared error (MSE) on both training and validation sets to evaluate their performance. Optimizer Adam and epoch size of 60 was used, and each combination of hyperparameters was executed 5 times to get the average test loss and average validation loss. The following table shows the results:

Neuron number	Batch size	Learning Rate	Average test loss	Average validation loss
(64)	5	0.1	0.005010980	0.0171092
		0.01	0.000838538	0.006069266
		0.001	0.001719581	0.005473279
	10	0.1	0.010183932	0.026804345
		0.01	0.00088972	0.00523274
		0.001	0.00151668	0.00367822
(128, 64)	5	0.1	0.08221204	0.1908787
		0.01	0.0009692	0.017170
		0.001	0.00156414	0.00922018
	10	0.1	0.06777188	0.31198183
		0.01	0.0010267	0.01713104
		0.001	0.00138937	0.004644903
(128, 64, 30)	5	0.1	0.0346339	0.268277
		0.01	0.00149486	0.051282045
		0.001	0.0022146	0.012507
	10	0.1	0.03024959	0.214945
		0.01	0.0012523	0.054831
		0.001	0.00226974	0.01361636

The results indicate that the model with batch size 10, learning rate 0.001 and single layer LSTM shows the best performance compared to all other models.



5.4. Limitations and improvements

Due to the time limitation of this project, we only collected and analyzed the historical data and macroeconomic indicators that can be obtained easily and freely from platforms such as Yahoo Finance, and the technical indicators that can be calculated from historical data. But the enterprise's internal factors such as business financial status was not analyzed in this project, as such information is not open to the public generally. And also, other potential influencers such as an enterprise's reputation and future planning, international events, natural disasters which are difficult to be quantified are also not included in this project.

Another issue is that in practice, the factors that impact stock price trends are continually changing, which means that using past 5 years data would not be suitable to train a model to predict today's stock market. For example, USDX considers six currencies of most significant trading partners of America, but these six currencies are not always static: the German mark and many European currencies had been replaced by the euro. It is possible that in the near future other currencies will supplant the currencies in the index as the global economics is continuously changing. Consequently, using the data many years ago may not accurately reflect today's stock market situation.

Future improvements could be done in the following aspects:

(a) Denoising using wavelet transform

In practice, stock price fluctuation is full of uncertainty, and the existence of the high noise will lead to the poor performance of the prediction model. It is suggested that Haar wavelet transform can be used to denoise the time-series data such as stock price data, and usually models can perform better with denoised data (Ortega & Khashanah, 2013).

(b) Further hyperparameter tuning

For this project, we evaluated the LSTM models by using MSE as loss function. In the future, more indexes can be used to measure the accuracy and reliability of the prediction such as Root Mean Squared Error(RMSE) or R-Squared. Moreover, more could be explored about optimization methods and neural network architectures and different neuron numbers.

(c) More data

Stock price forecasts could be a sophisticated task in reality when considering daily events and news. Additional techniques such as topic modeling can be applied to quantify the news gathered from various platforms such as newspapers, blogs and social media. With multifaceted data, our system can give our user more valuable guidance on stock investment.

6. Conclusion

In conclusion, the team has developed and delivered a prototype portfolio recommendation system that is able to advise the users how to invest their monies in an optimal manner.

The team learnt how to evaluate portfolio allocations to maximize rewards to risk ratios, and how to apply GA to solve optimization problems, as well as apply LSTM to do stock price forecasting. The team also gained hands-on experience in deploying applications to the web.

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