CS971: AI for Finance Assignment 2

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Background and Project Overview

Background and Description of the Problem

The goal of this project is to build a trading system that leverages advanced machine learning techniques to forecast asset prices and execute trading decisions. The system first selects an optimal asset from the S&P 500 by evaluating risk-adjusted historical performance using daily returns and Sharpe ratios. Once the asset is chosen, its price data are pre-processed with technical indicators such as the RSI, MACD, and volume moving averages to capture market dynamics. An LSTM neural network which is well-known for its ability to model temporal dependencies is then employed to predict next-day prices. The model's hyperparameters are then finely tuned using both grid search and genetic algorithms. Finally, trading rules are applied to convert predictions (alone or in combination with RSI signals) into buy, sell, or hold actions in a simulated trading environment.

Related Work

Recent work on machine learning-based trading strategies spans deep neural models, technical analysis, and evolutionary optimization. Recurrent architectures like LSTM networks have been widely applied to stock price prediction and trading signal generation, leveraging their ability to capture temporal patterns and often outperforming traditional statistical models [1]. Many studies enhance such models by incorporating popular technical indicators such as RSI and MACD as input features, effectively fusing signals with data-driven learning to improve predictive accuracy [2]. In addition, optimization techniques like genetic algorithms have been used to fine-tune both model hyperparameters and strategy parameters. For example, GAs optimizing LSTM settings have achieved better forecasting performance than untuned benchmarks and similarly have been applied to calibrate indicator-based trading rules to maximize metrics like the Sharpe ratio [1]. These combined approaches demonstrate that integrating LSTM-driven prediction with technical indicators and applying evolutionary optimization can yield more robust, profitable trading strategies in practice which is precisely what our project aims to do.

Asset Selection

The initial assets were gathered using the S&P 500 index, a stock market index that tracks the performance of 500 of the largest trading companies in the United States. In addition to having an extensive collection of assets, this index represents a wide range of sectors including but not limited to technology, healthcare and finance. This serves as a solid foundation for selecting a significant asset for the project.

```
assets <- tq_index("SP500") # Load 500 assets from S&P
```

Furthermore, the daily returns for each asset are retrieved to calculate the Sharpe ratio.

```
load_daily_returns <- function(asset_symbols, startDate, endDate) { removed_assets <- c()
  assets_train <- lapply(asset_symbols, function(sym) {
    tryCatch(dailyReturn(getSymbols(sym, from = startDate, to = endDate, auto.assign = FALSE)),
      error = function(e) {removed_assets <<- append(removed_assets, sym); NULL})})
  asset_symbols <- setdiff(asset_symbols, removed_assets)
  df <- setNames(do.call(merge, c(assets_train, all = T)), asset_symbols)
  df <- na.omit(df); df <- df[, colSums(is.na(df)) < nrow(df)]; return(df)}
```

The start and end date for the period to be used to make next-day predictions has been set to two months. This is so that enough data is present to reflect vital patterns to make predictions, however, not a long enough time period whereby the large quantity of historic data will negatively skew results.

```
asset_symbols <- assets$symbol; startDate <- "2024-08-01"; endDate <- "2024-12-31"
df <- load_daily_returns(asset_symbols, startDate, endDate)
```

```
calc_sharpe_ratio <- function(returns, rf_rate) {mean_return <- mean(returns); risk <- sd(returns)
  sharpe_ratio <- ((mean_return - rf_rate) / risk) * sqrt(252); return(sharpe_ratio)}
```

The performance of all 500 assets is evaluated and compared to one another based on their Sharpe ratios. The Sharpe ratio serves as a valuable tool for measuring investment prospects for a specific asset as it enables the comparison of the expected return for the level of risk being taken (risk-adjusted return). In this case, a risk-free rate is dynamically retrieved and used within the Sharpe ratio calculation for each asset.

$$S_a = \frac{E[R_a - R_b]}{\sigma_a}$$

$$Where: S_a = \text{Sharpe Ratio } E = \text{Expected Return}$$

$$R_a = \text{Asset Return } R_b = \text{Risk Free Rate } \sigma_a = \text{Asset Risk}$$

```
rf_rate <- as.numeric(last(getSymbols("DGS3MO", src = "FRED", auto.assign = FALSE)))/100 /252
best_res <- calc_sharpe_ratio(df[, 1], rf_rate); best_asset <- NULL
for (col in colnames(df)) { curr_sharpe <- calc_sharpe_ratio(df[, col], rf_rate)
  if (curr_sharpe > best_res) { best_res <- curr_sharpe; best_asset <- col}}
```

Once all assets have been compared, the best-performing asset is selected to be used to make next-day predictions in alignment with a comprehensive trading rule. All relevant data is then retrieved, this includes opening, high, low and closing prices.

```
best_asset_data <- getSymbols(best_asset, from = startDate, to = endDate, auto.assign = FALSE)
```

Data Preprocessing

Before training the LSTM-based model, we first enrich our data with technical indicators (RSI, MACD, and others), then remove any missing values and normalize each feature. Normalization helps ensure that the ranges of different variables do not negatively impact model training. Afterwards, we structure the data as sequences for the network by selecting the features of interest, choosing an appropriate sequence length and splitting into training and test sets.

We then add these new indicators as columns in our main dataset and remove any rows with missing values.

```
best_asset_data$RSI = rsi; best_asset_data$MACD = macd
best_asset_data$Volume_MA = volume_ma; best_asset_data = na.omit(best_asset_data)
```

Next, we normalize each column to the range [0,1] using a simple min-max scaling function to help the model converge more reliably during training.

```
data <- data.frame(best_asset_data[,1:9])
min_max_normalize <- function(x) {(x - min(x)) / (max(x) - min(x))}
data_scaled <- as.data.frame(lapply(data, min_max_normalize))
```

We now define a custom splitting function for time-series data. The idea is to convert our continuous dataset into overlapping sequences of length `seq_length`.

```
train_test_split <- function(asset, seq_length, target_feature, test_size = 0.2) {
  asset_matrix <- as.matrix(asset)
  num_seq <- nrow(asset_matrix) - seq_length + 1; num_features <- ncol(asset_matrix)
  seq_data <- array(dim = c(num_seq, seq_length, num_features))
  for (index in 1:(nrow(asset_matrix) - seq_length +1)) {
    seq_data[index, , ] <- asset_matrix[index:(index + seq_length - 1), ]}
  test_set_size <- round(test_size * nrow(seq_data)); train_set_size <- nrow(seq_data) - test_set_size
  x_train <- seq_data[1:train_set_size, 1:(seq_length - 1), , drop = FALSE]
  y_train <- seq_data[1:train_set_size, seq_length, target_feature, drop = FALSE]
  x_test  <- seq_data[(train_set_size + 1):nrow(seq_data), 1:(seq_length - 1), , drop = FALSE]
  y_test  <- seq_data[(train_set_size + 1):nrow(seq_data), seq_length, target_feature, drop = FALSE]
  return(list(x_train = x_train,y_train = y_train,x_test = x_test,y_test = y_test))}
```

With all preprocessing steps established, we can now select the columns to include and specify which feature to treat as our target for prediction. Below, we choose a sequence length of 8, meaning 7 steps for model inputs plus 1 step for the label.

```
open <- paste(best_asset, "Open", sep = ".");close <- paste(best_asset, "Close", sep = ".")
high <- paste(best_asset, "High", sep = ".");low <- paste(best_asset, "Low", sep = ".")
rsi = "RSI"; macd = "MACD"; volume_ma = "Volume_MA"; seq_length <- 8
features <- data_scaled[, c(open, high, low, close, macd, volume_ma)]
split_data <- train_test_split(features, seq_length, target_feature=4)
x_train <- split_data$x_train; y_train <- split_data$y_train
x_test <- split_data$x_test; y_test <- split_data$y_test
```

Finally, we split part of the training set again for validation. This secondary split is helpful for hyperparameter tuning without contaminating our final test set.

```
split_validation <- function(x, y, valid_prop = 0.2) { total <- dim(x)[1]
  valid_size <- round(valid_prop * total);train_size <- total - valid_size
  x_train_tune <- x[1:train_size, , , drop = FALSE]
  x_val <- x[(train_size + 1):total, , , drop = FALSE]; y <- as.matrix(y)
  y_train_tune <- y[1:train_size, , drop = FALSE]
  y_val <- y[(train_size + 1):total, , drop = FALSE]
  return(list(x_train_tune = x_train_tune,y_train_tune = y_train_tune,
    x_val = x_val,y_val = y_val))}
split_data <- split_validation(x_train, y_train, valid_prop = 0.2)
x_train_tune <- split_data$x_train_tune; y_train_tune <- split_data$y_train_tune
x_val <- split_data$x_val; y_val <- split_data$y_val
```

Optimising LSTM Parameters

The LSTM parameters are optimised using two techniques: grid search and genetic algorithms. This was done to compare the results from utilising traditional versus evolutionary approaches and conclude the pros and cons of each. Furthermore, the optimised parameters identified from this process are used by the LSTM to make predictions in conjunction with the proposed trading rule.

```
tune_lstm <- function(learningrate, hidden_dim, num_layers, numepochs, batch_size) {
  model <- trainr( Y = y_train_tune, X = x_train_tune, learningrate = learningrate,
    hidden_dim = hidden_dim, num_layers = num_layers, numepochs = numepochs,
    network_type = "lstm", seq_to_seq_unsync = TRUE,batch_size = batch_size)
  predictions <- predictr(model, x_val)
  mse <- mean((predictions - y_val)^2, na.rm = TRUE); return(mse)}
```

Grid Search

Grid search is a traditional approach to identifying optimal hyperparameter values for machine learning models. In this approach, the key hyperparameters to be tested are listed inside a vector, which the algorithm then systematically iterates over each combination and records the result. In this case, the mean squared error (MSE) is used on validation data to determine the current performance.

```
lr_vals <- c(0.001, 0.005, 0.01); hd_vals <- c(8, 16, 32, 64, 128) # Grid parameters
nl_vals <- c(1, 2, 3); ne_vals <- c(50, 100, 150, 200); bs_vals <- c(8, 16, 32, 64)
```

```
run_grid_search <- function(lr_vals, hd_vals, nl_vals, ne_vals, bs_vals){
  for (lr in lr_vals) {for (hd in hd_vals) {for (nl in nl_vals) {
    for (ne in ne_vals) {for (bs in bs_vals) { current_mse <- tune_lstm(lr,hd,nl,ne,bs)
            log_results(lr, hd, nl, ne, bs, current_mse)}}}}}}
#run_grid_search(lr_vals, hd_vals, nl_vals, ne_vals, bs_vals)
#best_params_GS <- results[which.min(results$mse), ]
```

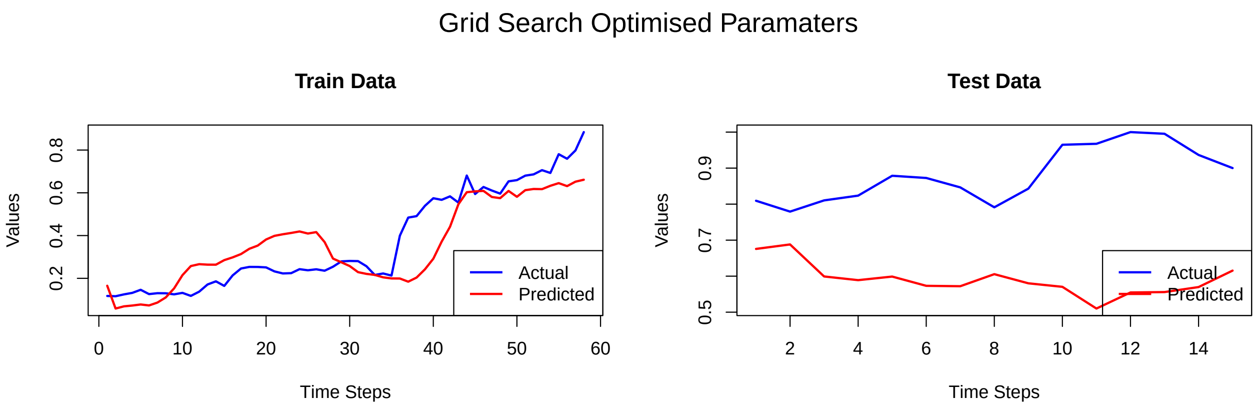
Genetic Algorithm

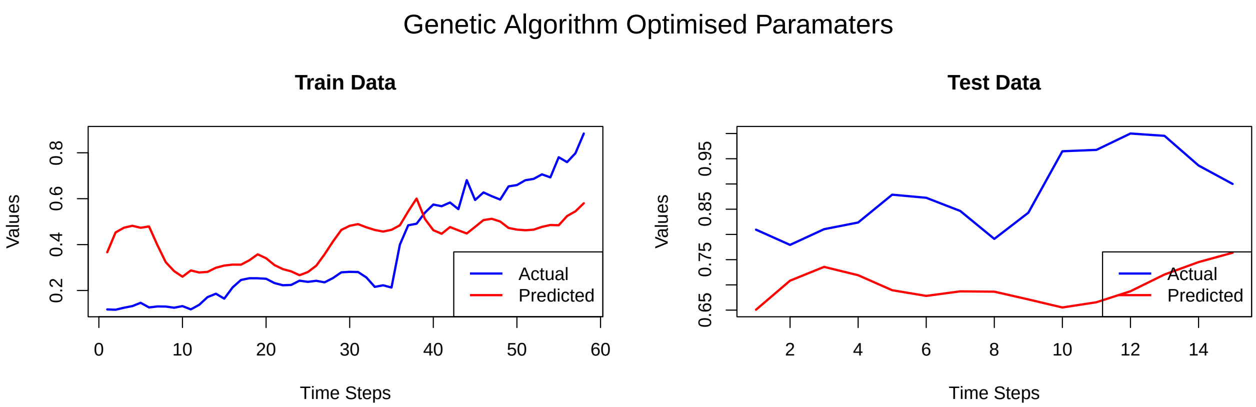
A genetic algorithm is an evolutionary process that mimics natural selection and genetics. This algorithm has been used to identify optimal hyperparameters within specified ranges (lower and upper). This implementation has a maximum of 100 iterations and will stop executing if the fitness does not improve after 20 iterations. The fitness is determined using the fitness function which evaluates performance against the MSE value.

```
fitness_function <- function(params) {
  lr <- params[1]; hd <- round(params[2]); nl <- round(params[3])
  ne <- round(params[4]); bs <- round(params[5])
  mse <- tune_lstm(lr, hd, nl, ne, bs); return(-mse)}
run_ga <- function(){ ga_result <- ga(type = "real-valued",fitness = fitness_function,
    lower = c(0.0001, 8, 1, 50, 8),upper = c(0.01, 128, 3, 200, 64),
    popSize = 20,maxiter = 100,run = 20); return(ga_result)}
#ga_result <- run_ga(); best_params_GA <- ga_result@solution
```

Optimisation Comparisons

Through experimenting with both of the above approaches key benefits and downfalls of each have been identified. First, Grid search is strictly limited to searching the specified hyperparameters whereas the GA solution can navigate the search space more effectively only being restricted to lower and upper bounds. Furthermore, both algorithms are computationally expensive, although, genetic algorithms have an edge as they can effectively terminate execution if the performance has not improved over a specified number of iterations, whereas grid search must evaluate all combinations. Finally, this difference between the two approaches is what sets them apart as a GA can get stuck in a local maximum and never converge to the optimal solution, on the other hand, grid search will evaluate all provided combinations guaranteeing the most optimal from the provided is found. Overall, both methods gain a similar performance using MSE. However, grid search slightly outperforms the GA result with an MSE score of 0.0161161 compared to 0.03577853 on the test (unseen) data, for this reason, the LSTM trained with optimised parameters from grid search will be used for algorithmic trading.





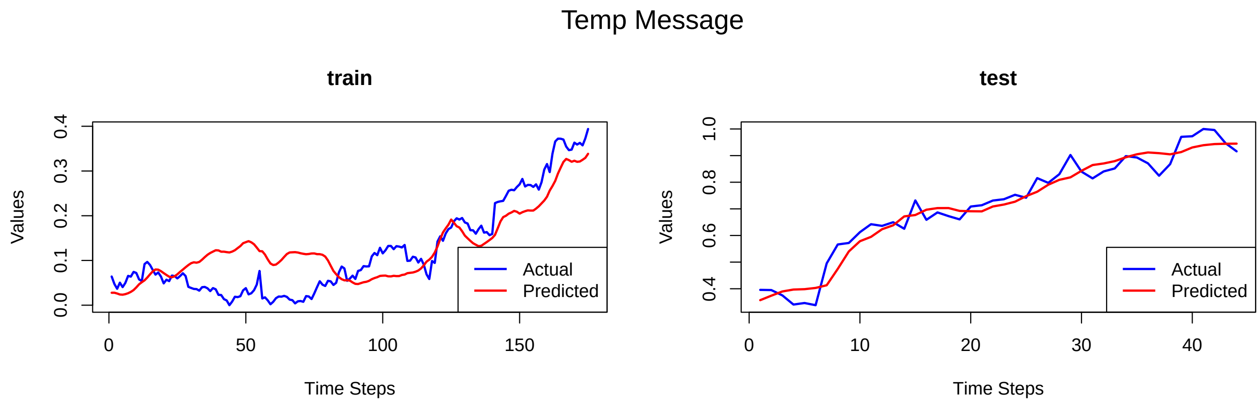
Tensorflow LSTM

```
lr <- 0.001
hd <- 64
ne <- 200
bs <- 8

model <- keras_model_sequential() %>%
  layer_lstm(units = 128, input_shape = c(7, 6), return_sequences = TRUE) %>%
  layer_lstm(units = 128, return_sequences = TRUE) %>%
  layer_lstm(units = 128) %>%
```

```
  layer_dense(units = 1, activation = "tanh")

# Compile the model
model %>% compile(
  optimizer = "adam",
  loss = "mse",
  metrics = c("mse")
)

# Train the model
model %>% fit(
  x_train, y_train,
  epochs = 200, batch_size = 32,
  verbose = 0
)

#save_model_hdf5(model, "tensorflow_lstm.keras")
model <- load_model_hdf5("tensorflow_lstm.keras")
```

```
## 6/6 - 1s - 526ms/epoch - 88ms/step
```

```
## 2/2 - 0s - 16ms/epoch - 8ms/step
```



Trading

```
starting_funds = 10000
investment = starting_funds
cash_on_hand = starting_funds
shares = 0

inverse_scale <- function(scaled_value, unscaled_min, unscaled_max) {
  scaled_value * (unscaled_max - unscaled_min) + unscaled_min
}

predictions_scaled = model %>% predict(x_test)
```

```
## 2/2 - 0s - 14ms/epoch - 7ms/step
```

```
unscaled_min_close = min(data[, paste(best_asset, "Close", sep = ".")])
unscaled_max_close = max(data[, paste(best_asset, "Close", sep = ".")])

predictions_unscaled = inverse_scale(predictions_scaled, unscaled_min_close, unscaled_max_close)
actual_unscaled = inverse_scale(y_test, unscaled_min_close, unscaled_max_close)
#predictions_unscaled
#actual_unscaled
```

```
trading_rule = data.frame(
  Date = index(tail(best_asset_data, nrow(y_test))),
  actual_price = rep(NA, nrow(y_test)),
  predicted_price = rep(NA, nrow(y_test)),
  action = character(nrow(y_test)),
  asset_value = numeric(nrow(y_test)),
  shares_held = numeric(nrow(y_test)),
  cash_held = numeric(nrow(y_test)),
  daily_profit_loss = numeric(nrow(y_test)) # New column for daily P/L
)

trading_rule$asset_value[1] = starting_funds
trading_rule$shares_held[1] = shares
trading_rule$cash_held[1] = cash_on_hand
trading_rule$daily_profit_loss[1] = 0
trading_rule$actual_price = actual_unscaled
trading_rule$predicted_price = predictions_unscaled

threshold_buy = 0.01
threshold_sell = -0.01
loss_minimisation_threshold = -0.05
last_buy_price = 0

next_day_action = character(nrow(trading_rule))
next_day_action[1] = "HOLD"

for(i in 1:(nrow(trading_rule) - 1)){
  current_price = trading_rule$actual_price[i]
  predicted_price = trading_rule$predicted_price[i]
  action = "HOLD"

  if(!is.na(predicted_price) && !is.na(current_price)){
    predicted_change_percentage = (predicted_price - current_price) / current_price
    if(predicted_change_percentage > threshold_buy && cash_on_hand > predicted_price){
      action = "BUY"
    } else if(predicted_change_percentage < threshold_sell && shares > 0){
      action = "SELL"
    }
  }
  next_day_action[i + 1] = action
}

for(i in 1:nrow(trading_rule)){
  previous_asset_value = trading_rule$asset_value[i]
  if(i > 1){
```

```
    cash_on_hand = trading_rule$cash_held[i-1]
    shares = trading_rule$shares_held[i-1]
    previous_asset_value = trading_rule$asset_value[i-1]
  }

  trade_action = next_day_action[i]
  current_price = trading_rule$actual_price[i]

  if(trade_action == "BUY" && cash_on_hand > 0){
    buy_quantity = floor(cash_on_hand / current_price)
    if(buy_quantity > 0){
      shares = shares + buy_quantity
      cash_on_hand = cash_on_hand - (buy_quantity * current_price)
      last_buy_price = current_price
    }
  } else if(trade_action == "SELL" && shares > 0){
    sell_value = shares * current_price
    # Loss minimisation sell
    if (last_buy_price > 0 && (current_price - last_buy_price) / last_buy_price < loss_minimisation_thre
      cash_on_hand = cash_on_hand + sell_value
      shares = 0
      last_buy_price = 0
      trade_action = "SELL OUT"
    } else {
      cash_on_hand = cash_on_hand + sell_value
      shares = 0
      last_buy_price = 0
    }
  }

  trading_rule$action[i] = trade_action
  trading_rule$asset_value[i] = cash_on_hand + (shares * current_price)
  trading_rule$shares_held[i] = shares
  trading_rule$cash_held[i] = cash_on_hand

  # Calculate daily profit/loss
  if (i > 1) {
    trading_rule$daily_profit_loss[i] = trading_rule$asset_value[i] - previous_asset_value
  }

  # Sell all on the final day
  if (i == nrow(trading_rule) && trading_rule$shares_held[i] > 0) {
    final_sell_value = trading_rule$shares_held[i] * current_price
    trading_rule$asset_value[i] = trading_rule$cash_held[i] + final_sell_value
    trading_rule$cash_held[i] = trading_rule$cash_held[i] + final_sell_value
    trading_rule$shares_held[i] = 0
    trading_rule$action[i] = "SELL"
  }
}
```

```
final_asset_value = tail(trading_rule$asset_value, 1)
initial_investment = starting_funds
profit_loss = final_asset_value - initial_investment
```

```r
roi = (profit_loss / initial_investment) * 100

cat("\nFinal Asset Value: $", round(final_asset_value, 2), "\n")
```

```
##
## Final Asset Value: $ 18548.8
```

```r
cat("Profit/Loss: $", round(profit_loss, 2), "\n")
```

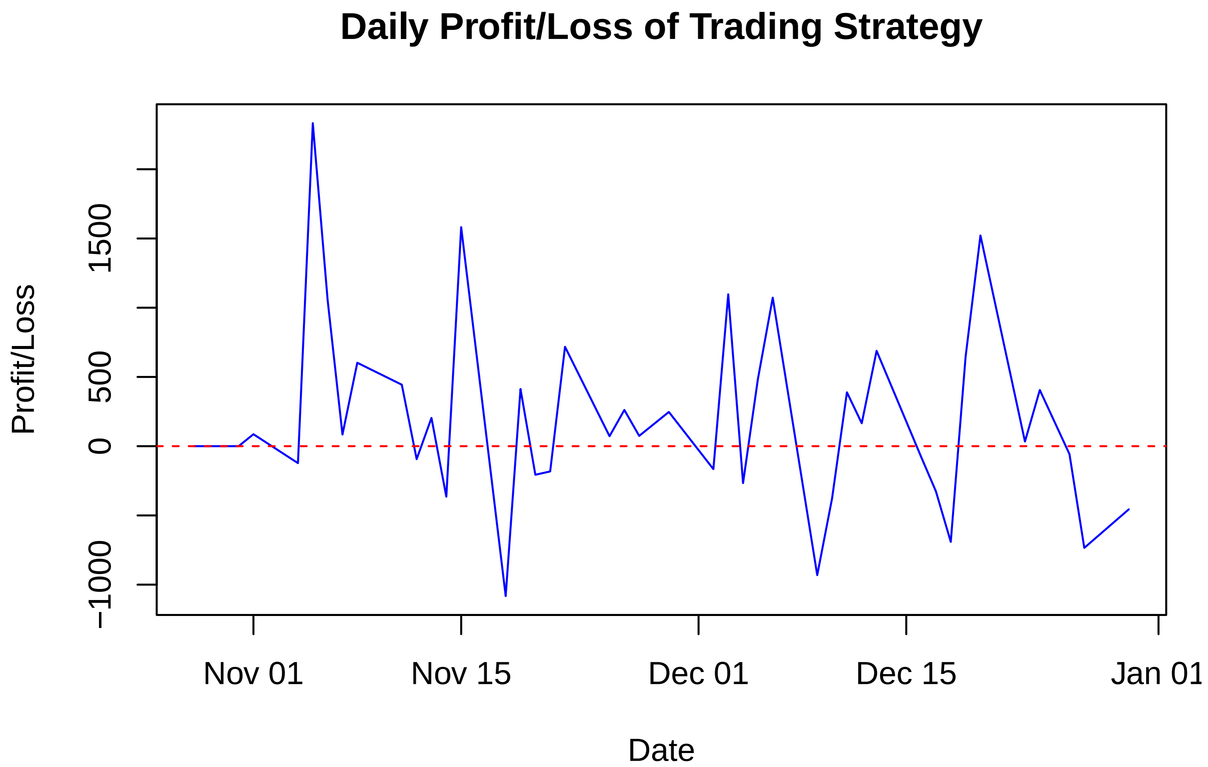
```
## Profit/Loss: $ 8548.8
```

```r
cat("Return on Investment (ROI): ", round(roi, 2), "%\n")
```

```
## Return on Investment (ROI):  85.49 %
```

```r
plot_trading_simulation = function(trade_log) {
  plot(trading_rule$Date, trading_rule$asset_value, type = "l", col = "green",
       xlab = "Date", ylab = "Asset Value ($)",
       main = "Trading Strategy Performance")
  grid()
}

plot_trading_simulation(trade_log)
```

```r
plot(trading_rule$Date, trading_rule$daily_profit_loss,
     type = "l",  # "l" for line plot
     xlab = "Date",
     ylab = "Profit/Loss",
     main = "Daily Profit/Loss of Trading Strategy",
     col = "blue")

# Add a horizontal line at zero for reference
abline(h = 0, lty = "dashed", col = "red")
```




```r
print(trading_rule)
```

```
##          Date actual_price predicted_price action asset_value shares_held
## 1  2024-10-28        44.97        42.57995   HOLD     10000.0           0
## 2  2024-10-29        44.93        43.61868   HOLD     10000.0           0
## 3  2024-10-30        43.69        44.60440   HOLD     10000.0           0
## 4  2024-10-31        41.56        45.04613    BUY     10000.0         240
## 5  2024-11-01        41.92        45.13572    BUY     10086.4         240
## 6  2024-11-04        41.41        45.42277    BUY      9964.0         240
## 7  2024-11-05        51.13        46.04648    BUY     12296.8         240
## 8  2024-11-06        55.53        49.85334   HOLD     13352.8         240
## 9  2024-11-07        55.88        53.91362   HOLD     13436.8         240
## 10 2024-11-08        58.39        56.28394   HOLD     14039.2         240
## 11 2024-11-11        60.24        57.29688   HOLD     14483.2         240
## 12 2024-11-12        59.85        59.07224   HOLD     14389.6         240
## 13 2024-11-13        60.70        59.98659   HOLD     14593.6         240
## 14 2024-11-14        59.18        62.05689   HOLD     14228.8         240
## 15 2024-11-15        65.77        62.37537    BUY     15810.4         240
```

```
## 16 2024-11-18       61.26       63.60989  HOLD     14728.0          240
## 17 2024-11-19       62.98       63.98779   BUY     15140.8          240
## 18 2024-11-20       62.12       63.99312   BUY     14934.4          240
## 19 2024-11-21       61.36       63.33074   BUY     14752.0          240
## 20 2024-11-22       64.35       63.25457   BUY     15469.6          240
## 21 2024-11-25       64.65       63.22497  HOLD     15541.6          240
## 22 2024-11-26       65.74       64.35862  HOLD     15803.2          240
## 23 2024-11-27       66.05       64.81548  HOLD     15877.6          240
## 24 2024-11-29       67.08       65.47330  HOLD     16124.8          240
## 25 2024-12-02       66.39       66.76006  HOLD     15959.2          240
## 26 2024-12-03       70.96       67.78797  HOLD     17056.0          240
## 27 2024-12-04       69.85       69.41929  HOLD     16789.6          240
## 28 2024-12-05       71.87       70.55688  HOLD     17274.4          240
## 29 2024-12-06       76.34       71.13356  HOLD     18347.2          240
## 30 2024-12-09       72.46       72.65619  HOLD     17416.0          240
## 31 2024-12-10       70.89       73.99567  HOLD     17039.2          240
## 32 2024-12-11       72.51       74.36299   BUY     17428.0          240
## 33 2024-12-12       73.20       74.90540   BUY     17593.6          240
## 34 2024-12-13       76.07       75.80090   BUY     18282.4          240
## 35 2024-12-16       75.75       76.49621  HOLD     18205.6          240
## 36 2024-12-17       74.39       76.91988  HOLD     17879.2          240
## 37 2024-12-18       71.51       76.75684   BUY     17188.0          240
## 38 2024-12-19       74.21       76.48797   BUY     17836.0          240
## 39 2024-12-20       80.55       77.01410   BUY     19357.6          240
## 40 2024-12-23       80.69       78.08290  HOLD     19391.2          240
## 41 2024-12-24       82.38       78.60502  HOLD     19796.8          240
## 42 2024-12-26       82.14       78.87057  HOLD     19739.2          240
## 43 2024-12-27       79.08       78.94579  HOLD     19004.8          240
## 44 2024-12-30       77.18       78.97081  SELL     18548.8            0
##      cash_held daily_profit_loss
## 1  10000.00000           0.00000
## 2  10000.00000           0.00000
## 3  10000.00000           0.00000
## 4     25.59967           0.00000
## 5     25.59967          86.39923
## 6     25.59967        -122.39960
## 7     25.59967        2332.80029
## 8     25.59967        1055.99945
## 9     25.59967          84.00055
## 10    25.59967         602.39960
## 11    25.59967         444.00055
## 12    25.59967         -93.60077
## 13    25.59967         204.00055
## 14    25.59967        -364.80011
## 15    25.59967        1581.59912
## 16    25.59967       -1082.39960
## 17    25.59967         412.80029
## 18    25.59967        -206.40015
## 19    25.59967        -182.39960
## 20    25.59967         717.59949
## 21    25.59967          72.00073
## 22    25.59967         261.59912
## 23    25.59967          74.40125
## 24    25.59967         247.19971
```

```
## 25    25.59967        -165.60059
## 26    25.59967        1096.79993
## 27    25.59967        -266.40015
## 28    25.59967         484.80103
## 29    25.59967        1072.79846
## 30    25.59967        -931.19934
## 31    25.59967        -376.79993
## 32    25.59967         388.80066
## 33    25.59967         165.59875
## 34    25.59967         688.80066
## 35    25.59967         -76.79993
## 36    25.59967        -326.40015
## 37    25.59967        -691.19934
## 38    25.59967         647.99927
## 39    25.59967        1521.60095
## 40    25.59967          33.59985
## 41    25.59967         405.59875
## 42    25.59967         -57.59949
## 43    25.59967        -734.39941
## 44 18548.79974        -456.00037
```

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