

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 = Sharpe Ratio E = Expected Return

R_a = Asset Return R_b = Risk Free Rate σ_a = 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

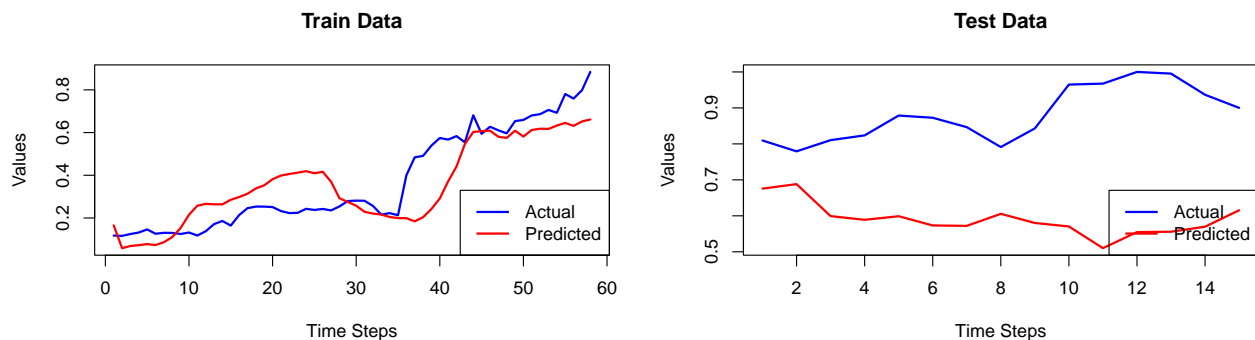
A genetic algorithm is an evolutionary process that mimics natural selection and genetics. This algorithm has been used to identify optimal hyperparameters within specified ranges (lower and upper). This implementation has a maximum of 100 iterations and will stop executing if the fitness does not improve 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
```

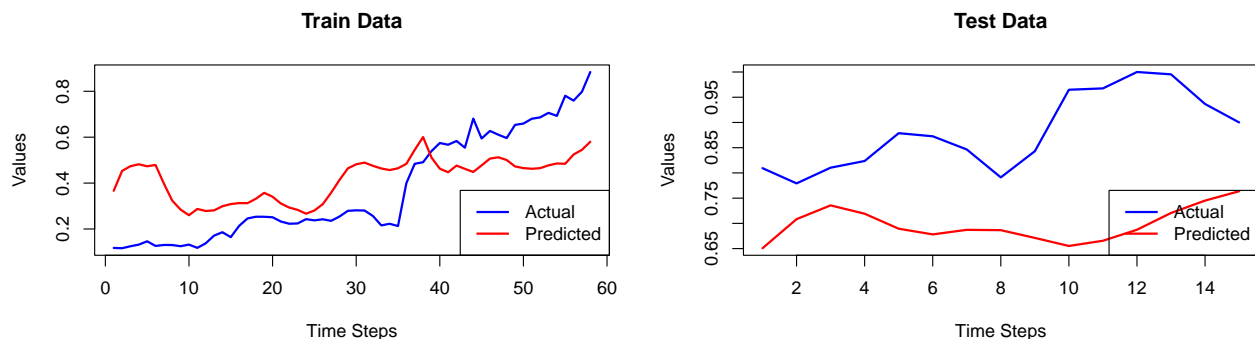
Optimisation Comparisons

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.

Grid Search Optimised Paramaters



Genetic Algorithm Optimised Paramaters



Tensorflow LSTM

```
# Build an LSTM model
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
)

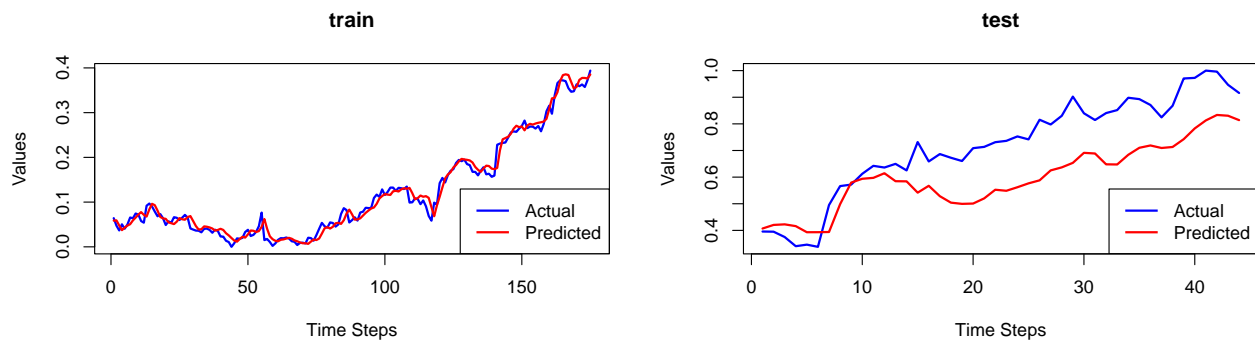
# Model summary
#summary(model)

```

```
## 6/6 - 1s - 532ms/epoch - 89ms/step
```

```
## 2/2 - 0s - 15ms/epoch - 7ms/step
```

Temp Message



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 - 16ms/epoch - 8ms/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

```



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

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

```
##
## Final Asset Value: $ 17159.5
```

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

```
## Profit/Loss: $ 7159.5
```

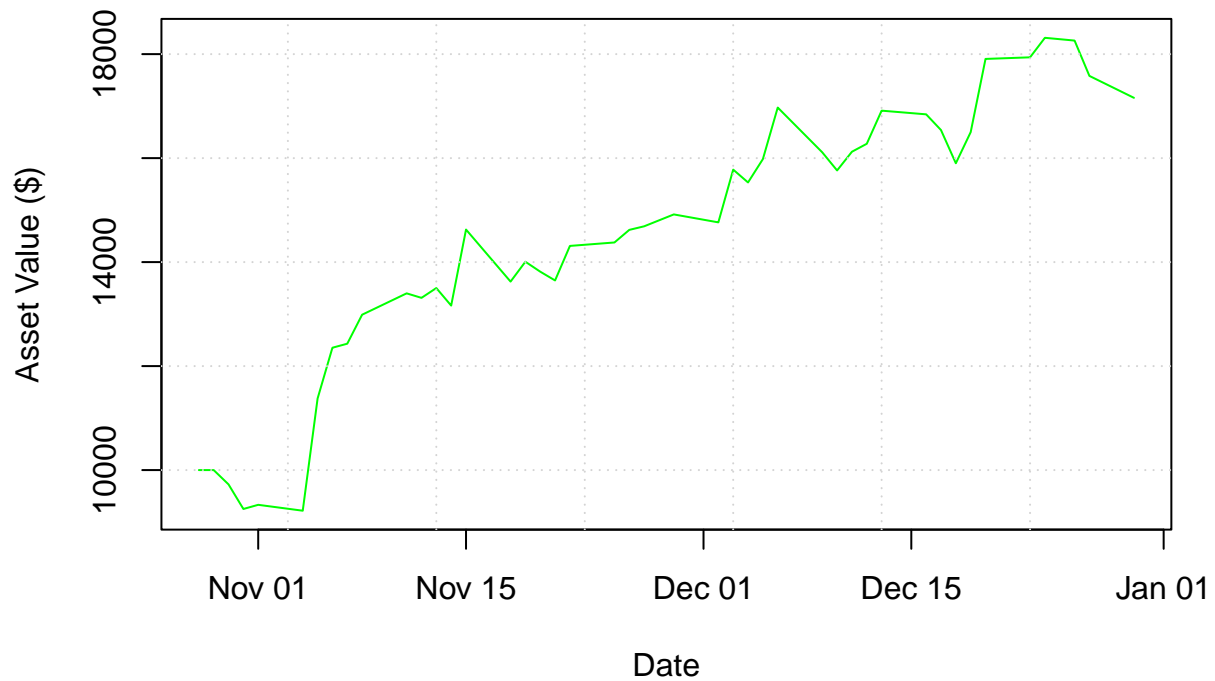
```
cat("Return on Investment (ROI): ", round(roi, 2), "%\n")
```

```
## Return on Investment (ROI): 71.6 %
```

```
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()
}

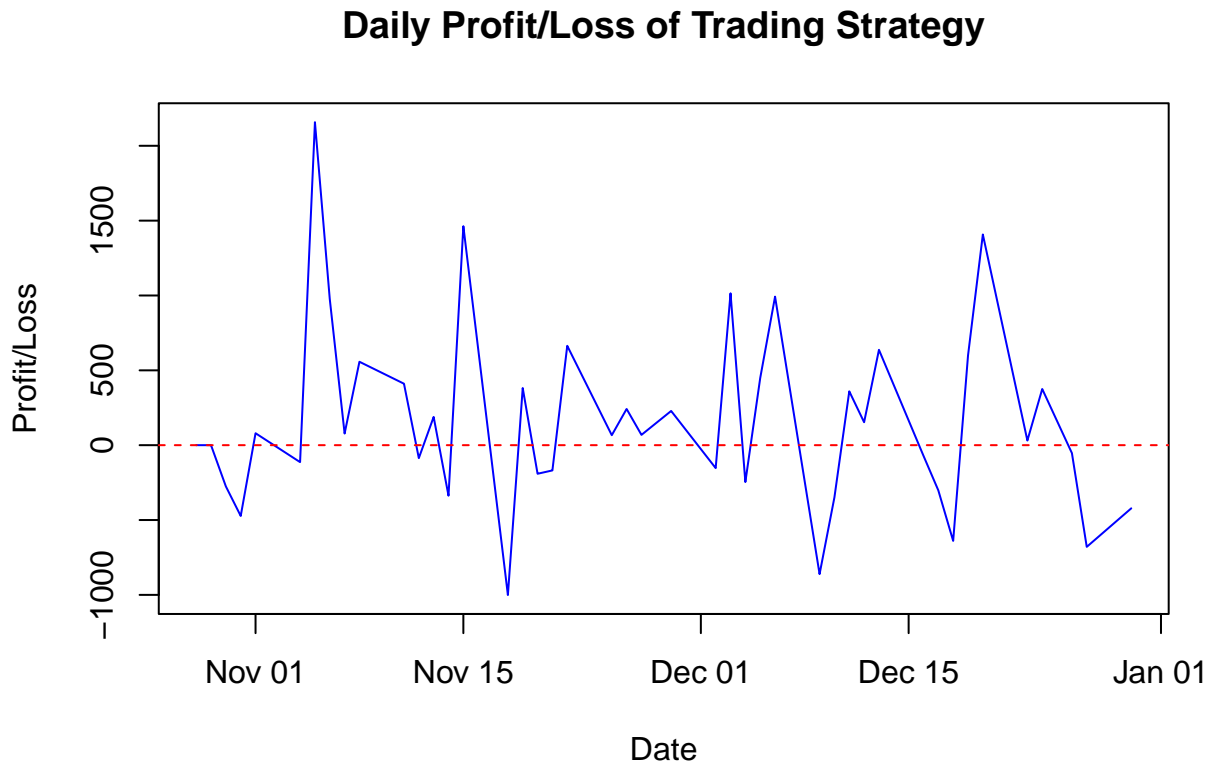
plot_trading_simulation(trade_log)
```

Trading Strategy Performance



```
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")
```



```
print(trading_rule)
```

##	Date	actual_price	predicted_price	action	asset_value	shares_held
## 1	2024-10-28	44.97	45.66500	HOLD	10000.00	0
## 2	2024-10-29	44.93	46.50472	BUY	10000.00	222
## 3	2024-10-30	43.69	46.63600	BUY	9724.72	222
## 4	2024-10-31	41.56	46.22412	BUY	9251.86	222
## 5	2024-11-01	41.92	44.80684	BUY	9331.78	222
## 6	2024-11-04	41.41	44.81494	BUY	9218.56	222
## 7	2024-11-05	51.13	44.85879	BUY	11376.40	222
## 8	2024-11-06	55.53	51.31705	HOLD	12353.20	222
## 9	2024-11-07	55.88	56.34809	HOLD	12430.90	222
## 10	2024-11-08	58.39	57.23377	HOLD	12988.12	222
## 11	2024-11-11	60.24	57.44696	HOLD	13398.82	222
## 12	2024-11-12	59.85	58.52187	HOLD	13312.24	222
## 13	2024-11-13	60.70	56.67074	HOLD	13500.94	222
## 14	2024-11-14	59.18	56.63294	HOLD	13163.50	222
## 15	2024-11-15	65.77	54.00882	HOLD	14626.48	222

## 16	2024-11-18	61.26	55.60256	HOLD	13625.26	222
## 17	2024-11-19	62.98	53.18673	HOLD	14007.10	222
## 18	2024-11-20	62.12	51.68058	HOLD	13816.18	222
## 19	2024-11-21	61.36	51.39984	HOLD	13647.46	222
## 20	2024-11-22	64.35	51.47355	HOLD	14311.24	222
## 21	2024-11-25	64.65	52.67278	HOLD	14377.84	222
## 22	2024-11-26	65.74	54.68488	HOLD	14619.82	222
## 23	2024-11-27	66.05	54.44204	HOLD	14688.64	222
## 24	2024-11-29	67.08	55.26766	HOLD	14917.30	222
## 25	2024-12-02	66.39	56.16704	HOLD	14764.12	222
## 26	2024-12-03	70.96	56.86935	HOLD	15778.66	222
## 27	2024-12-04	69.85	59.18051	HOLD	15532.24	222
## 28	2024-12-05	71.87	59.88251	HOLD	15980.68	222
## 29	2024-12-06	76.34	60.93317	HOLD	16973.02	222
## 30	2024-12-09	72.46	63.26394	HOLD	16111.66	222
## 31	2024-12-10	70.89	63.11032	HOLD	15763.12	222
## 32	2024-12-11	72.51	60.59196	HOLD	16122.76	222
## 33	2024-12-12	73.20	60.55599	HOLD	16275.94	222
## 34	2024-12-13	76.07	62.80646	HOLD	16913.08	222
## 35	2024-12-16	75.75	64.43609	HOLD	16842.04	222
## 36	2024-12-17	74.39	64.97705	HOLD	16540.12	222
## 37	2024-12-18	71.51	64.38987	HOLD	15900.76	222
## 38	2024-12-19	74.21	64.62558	HOLD	16500.16	222
## 39	2024-12-20	80.55	66.43797	HOLD	17907.64	222
## 40	2024-12-23	80.69	68.94150	HOLD	17938.72	222
## 41	2024-12-24	82.38	70.80321	HOLD	18313.90	222
## 42	2024-12-26	82.14	72.06900	HOLD	18260.62	222
## 43	2024-12-27	79.08	71.89277	HOLD	17581.30	222
## 44	2024-12-30	77.18	70.86497	SELL	17159.50	0
##	cash_held daily_profit_loss					
## 1	10000.00000	0.00000				
## 2	25.53993	0.00000				
## 3	25.53993	-275.28037				
## 4	25.53993	-472.85939				
## 5	25.53993	79.91929				
## 6	25.53993	-113.21963				
## 7	25.53993	2157.84027				
## 8	25.53993	976.79949				
## 9	25.53993	77.70051				
## 10	25.53993	557.21963				
## 11	25.53993	410.70051				
## 12	25.53993	-86.58071				
## 13	25.53993	188.70051				
## 14	25.53993	-337.44010				
## 15	25.53993	1462.97919				
## 16	25.53993	-1001.21963				
## 17	25.53993	381.84027				
## 18	25.53993	-190.92014				
## 19	25.53993	-168.71963				
## 20	25.53993	663.77953				
## 21	25.53993	66.60068				
## 22	25.53993	241.97919				
## 23	25.53993	68.82115				
## 24	25.53993	228.65973				

## 25	25.53993	-153.18054
## 26	25.53993	1014.53993
## 27	25.53993	-246.42014
## 28	25.53993	448.44095
## 29	25.53993	992.33858
## 30	25.53993	-861.35939
## 31	25.53993	-348.53993
## 32	25.53993	359.64061
## 33	25.53993	153.17885
## 34	25.53993	637.14061
## 35	25.53993	-71.03993
## 36	25.53993	-301.92014
## 37	25.53993	-639.35939
## 38	25.53993	599.39932
## 39	25.53993	1407.48088
## 40	25.53993	31.07986
## 41	25.53993	375.17885
## 42	25.53993	-53.27953
## 43	25.53993	-679.31946
## 44	17159.50000	-421.80034

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