CS971: AI for Finance Assignment 2

Stewart Macfarlane, Vladimir Lenkov, Alvee Kabir

11-04-2025

Project Background

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.

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

```
## # A tibble: 6 x 8
##   symbol company       identifier sedol weight sector shares_held local_currency
##   <chr>  <chr>         <chr>      <chr>  <dbl> <chr>        <dbl> <chr>
## 1 AAPL   APPLE INC     037833100  2046~ 0.0644 -        186857121 USD
## 2 MSFT   MICROSOFT CO~ 594918104  2588~ 0.0626 -         92470198 USD
## 3 NVDA   NVIDIA CORP   67066G104  2379~ 0.0604 -        304627187 USD
## 4 AMZN   AMAZON.COM I~ 023135106  2000~ 0.0389 -        117322921 USD
## 5 META   META PLATFOR~ 30303M102  B7TL~ 0.0277 -         27239796 USD
## 6 BRK-B  BERKSHIRE HA~ 084670702  2073~ 0.0206 -         22799710 USD
```

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

```r
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)
        cat("\nSkipping asset:", sym, "\n")
      }
    )
  })

  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)
```

```
## Warning: Failed to open
## 'https://query2.finance.yahoo.com/v8/finance/chart/-?period1=1722470400&period2=1735603200&interval=
## The requested URL returned error: 404

##
## Skipping asset: -
```

```
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

```
rsi = TTR::RSI(Cl(best_asset_data), n = 14)
ema_short = TTR::EMA(Cl(best_asset_data), n = 12)
ema_long = TTR::EMA(Cl(best_asset_data), n = 26)
macd = ema_short - ema_long
volume_ma = TTR::SMA(Vo(best_asset_data), n = 20)
```

```
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)
```

```
data <- data.frame(best_asset_data[,1], best_asset_data[,2], best_asset_data[,3], best_asset_data[,4], b
min_max_normalize <- function(x) {
  (x - min(x)) / (max(x) - min(x))
}

data_scaled <- as.data.frame(lapply(data, min_max_normalize))
```

```
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))
}
```

```
seq_length <- 8
open <- paste(best_asset, "Open", sep = ".")
high <- paste(best_asset, "High", sep = ".")
low <- paste(best_asset, "Low", sep = ".")
close <- paste(best_asset, "Close", sep = ".")
rsi = "RSI"
macd = "MACD"
volume_ma = "Volume_MA"
features <- data_scaled[, c(open, high, low, close, rsi, macd, volume_ma)]

split_data <- train_test_split(features, seq_length, ncol(features))
x_train <- split_data$x_train
y_train <- split_data$y_train
x_test <- split_data$x_test
y_test <- split_data$y_test
```

```
# For hyperparameter tuning, we split part of x_train/y_train to act as a validation set
# For example, we use 80% for training and 20% for validation
split_validation <- function(x, y, valid_prop = 0.2) {
  total <- dim(x)[1]
  valid_size <- round(valid_prop * total)
  train_size <- total - valid_size

  # Subset x without dropping dimensions
  x_train_tune <- x[1:train_size, , , drop = FALSE]
  x_val <- x[(train_size + 1):total, , , drop = FALSE]

  # Force y to be a matrix to ensure two dimensions
  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 the training data for tuning
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.

```r
# Define a tuning function that trains the LSTM and returns the mean squared error on the validation se
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
  )
  # Generate predictions on the validation set
  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.

```r
# Set up grid search parameters (you can adjust or expand the grid as needed)
lr_vals <- c(0.001, 0.005, 0.01)
hd_vals <- c(8, 16, 32, 64, 128)
nl_vals <- c(1, 2, 3)
ne_vals <- c(50, 100, 150, 200)
bs_vals <- c(8, 16, 32, 64)

# Initialize a data frame to store results
results <- data.frame(
  learningrate = numeric(0),
  hidden_dim = numeric(0),
  num_layers = numeric(0),
  numepochs = numeric(0),
  batch_size = numeric(0),
  mse = numeric(0)
)
```

```r
# Grid search
run_grid_search <- function(lr_vals, hd_vals, nl_vals, ne_vals, bs_vals){
```

```r
  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(learningrate = lr,
                                     hidden_dim = hd,
                                     num_layers = nl,
                                     numepochs = ne,
                                     batch_size = bs)
            results <<- rbind(results, data.frame(
              learningrate = lr,
              hidden_dim = hd,
              num_layers = nl,
              numepochs = ne,
              batch_size = bs,
              mse = current_mse
            ))
            #cat("Tested: lr=", lr, ", hd=", hd, ", nl=", nl, ", ne=", ne, ", bs=", bs,
            #    "-> MSE=", current_mse, "\n")
          }
        }
      }
    }
  }
}

#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.

```r
fitness_function <- function(params) {
  learningrate <- params[1]
  hidden_dim <- round(params[2])
  num_layers <- round(params[3])
  numepochs <- round(params[4])
  batch_size <- round(params[5])

  mse <- tune_lstm(
    learningrate = learningrate,
    hidden_dim = hidden_dim,
    num_layers = num_layers,
    numepochs = numepochs,
    batch_size = batch_size
  )
```

```r
  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
```

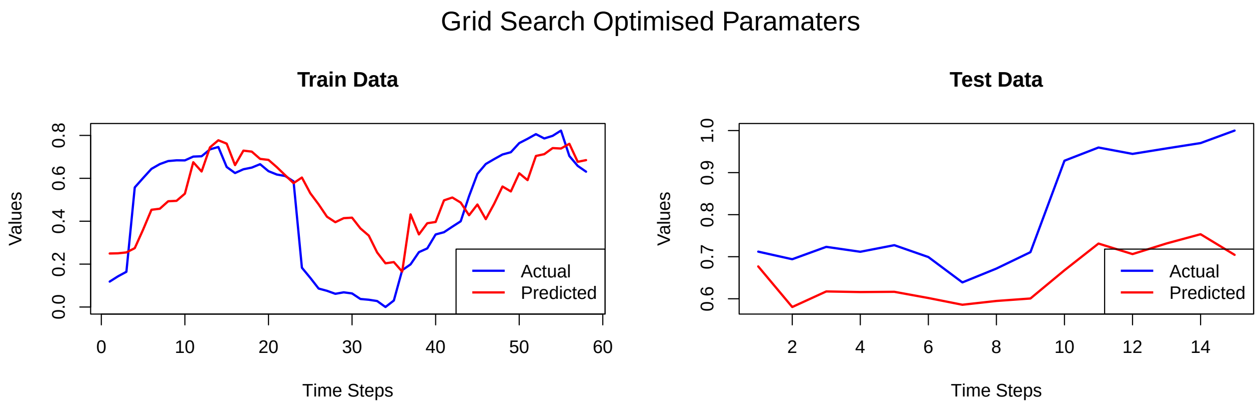
Optimisation Comparisons

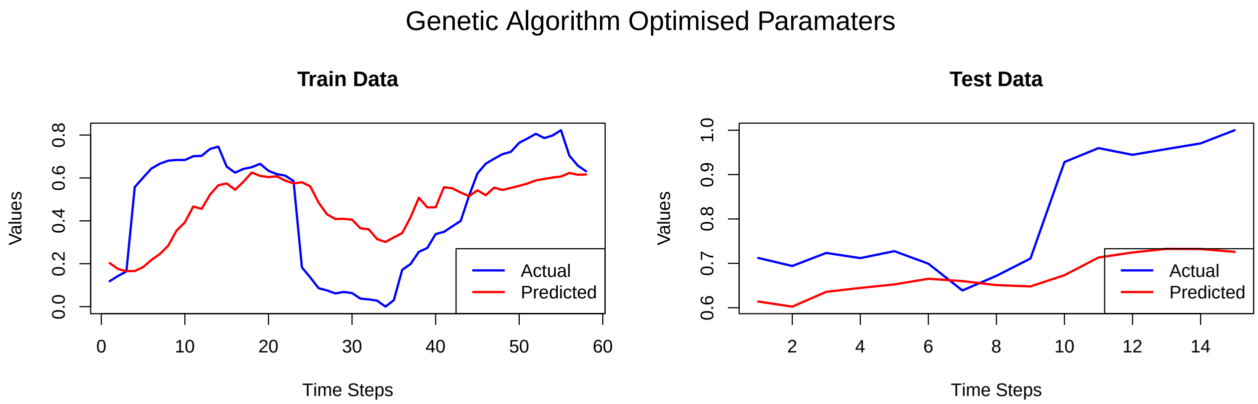
Through experimenting with both of the above approaches key benefits and downfalls of each have been identified. First, Grid search is strictly limited to searching the specified hyperparameters whereas the GA solution can navigate the search space more effectively only being restricted to lower and 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.

LSTM

```r
#train_lstm <- function(params){
#  model <- trainr(
#    Y = y_train,
#    X = x_train,
#    learningrate = as.numeric(params[1]),
#    hidden_dim = as.numeric(round(params[2])),
#    num_layers = as.numeric(round(params[3])),
#    numepochs = as.numeric(round(params[4])),
#    bactch_size = as.numeric(round(params[5])),
#    network_type = "lstm",
#    activation = "tanh",
#    seq_to_seq_unsync = T
#  )
#  return(model)
#}
```

```r
lstm_GS <- readRDS("lstm_GS.rds")
lstm_GA <- readRDS("lstm_GA.rds")
```






```r
starting_funds = 10000
investment = starting_funds
shares = 0

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

predictions_scaled = predictr(lstm_GS, x_test)
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
```

```r
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))
```

```r
)

trading_rule$asset_value[1] = investment
trading_rule$shares_held[1] = shares
trading_rule$actual_price = actual_unscaled
trading_rule$predicted_price = predictions_unscaled

threshold_buy = 0.05
threshold_sell = -0.05

for(i in 1:nrow(trading_rule)){
  if(i>1){
    investment = trading_rule$asset_value[i-1]
    shares = trading_rule$shares_held[i-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 && investment > 0) {
      action = "BUY"
      buy_quantity = floor(investment / current_price)
      shares = shares + buy_quantity
      investment = investment - (buy_quantity * current_price)
    } else if (predicted_change_percentage < threshold_sell && shares > 0) {
      action = "SELL"
      sell_value = shares * current_price
      investment = investment + sell_value
      shares = 0
    }
  }

  trading_rule$action[i] = action
  trading_rule$asset_value[i] = investment + (shares * current_price)
  trading_rule$shares_held[i] = shares
}
```

```r
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))
)

trading_rule$asset_value[1] = investment
trading_rule$shares_held[1] = shares
trading_rule$actual_price = actual_unscaled
trading_rule$predicted_price = predictions_unscaled
```

```r
threshold_buy = 0.01
threshold_sell = -0.01

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){
      action = "BUY"
    } else if(predicted_change_percentage < threshold_sell){
      action = "SELL"
    } else if(predicted_change_percentage < threshold_buy && predicted_change_percentage > threshold_sel
      action = "HOLD"
    }
  }
  next_day_action[i + 1] = action
}

for(i in 1:nrow(trading_rule)){
  if(i > 1){
    investment = trading_rule$asset_value[i-1]
    shares = trading_rule$shares_held[i-1]
  }

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

  if(trade_action == "BUY" && investment > 0){
    buy_quantity = floor(investment / current_price)
    shares = shares + buy_quantity
    investment = investment - (buy_quantity * current_price)
  } else if(trade_action == "SELL" && shares > 0){
    sell_value = shares * current_price
    investment = investment + sell_value
    shares = 0
  }

  trading_rule$action[i] = trade_action
  trading_rule$asset_value[i] = investment + (shares * current_price)
  trading_rule$shares_held[i] = shares
}
```

```r
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
```

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

```
##
## Final Asset Value: $ 10000
```

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

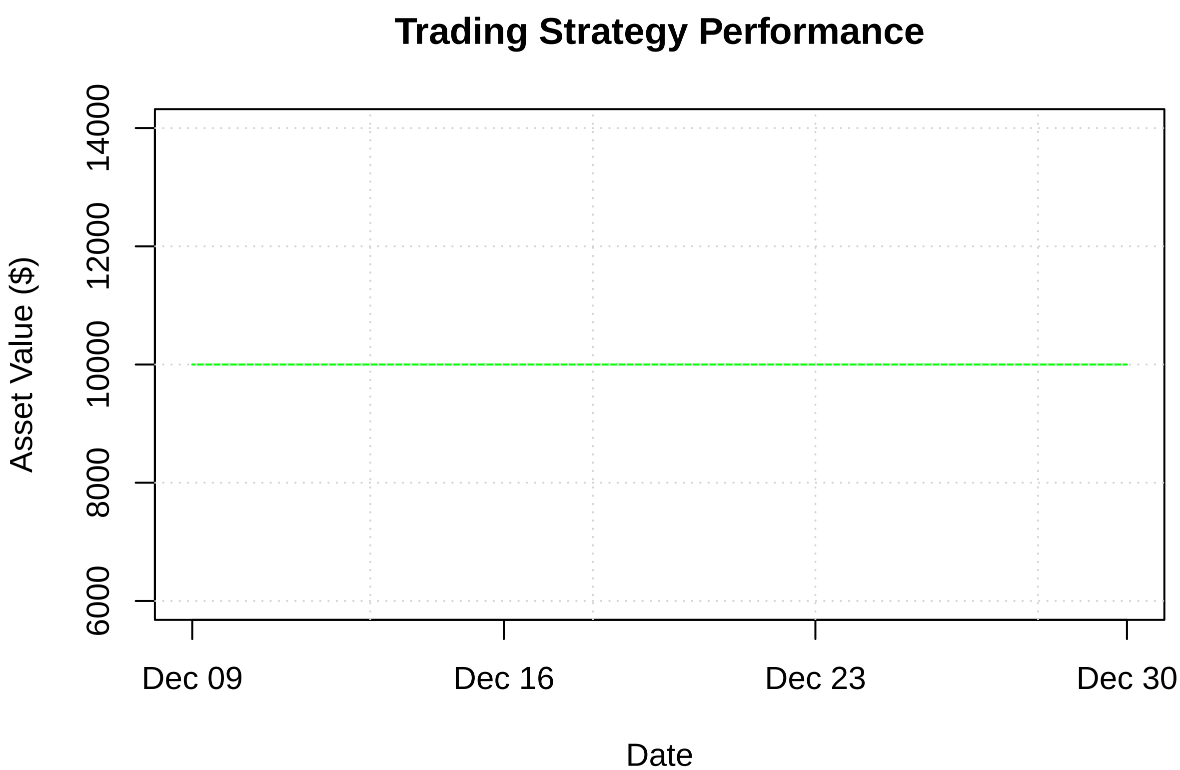
```
## Profit/Loss: $ 0
```

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

```
## Return on Investment (ROI):  0 %
```

```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
print(trading_rule)
```

```
##          Date actual_price predicted_price action asset_value shares_held
## 1  2024-12-09     67.39554        65.56744   HOLD       10000           0
```

```
## 2  2024-12-10     66.45506        60.53978    SELL       10000            0
## 3  2024-12-11     67.98600        62.46756    SELL       10000            0
## 4  2024-12-12     67.37810        62.39038    SELL       10000            0
## 5  2024-12-13     68.19372        62.42299    SELL       10000            0
## 6  2024-12-16     66.72497        61.65355    SELL       10000            0
## 7  2024-12-17     63.58379        60.81940    SELL       10000            0
## 8  2024-12-18     65.29941        61.28926    SELL       10000            0
## 9  2024-12-19     67.32994        61.59530    SELL       10000            0
## 10 2024-12-20     78.64948        65.08866    SELL       10000            0
## 11 2024-12-23     80.28217        68.39465    SELL       10000            0
## 12 2024-12-24     79.49410        67.09094    SELL       10000            0
## 13 2024-12-26     80.17125        68.40655    SELL       10000            0
## 14 2024-12-27     80.83242        69.55044    SELL       10000            0
## 15 2024-12-30     82.38000        66.99707    SELL       10000            0
```

```r
#Revised Dual-Indicator Trading Strategy

threshold_buy <- 0.005         # Predicted change > 0.5%
threshold_sell <- -0.005       # Predicted change < -0.5%
oversold_threshold <- 70       # For a BUY, require RSI < 70
overbought_threshold <- 30     # For a SELL, require RSI > 30

# Reinitialize simulation variables
investment_dual <- 10000
shares_dual <- 0

# Build the trading log for the dual-indicator strategy
trading_rule_dual <- data.frame(
  Date = index(tail(best_asset_data, nrow(y_test))),
  actual_price = as.numeric(actual_unscaled),
  predicted_price = as.numeric(predictions_unscaled),
  RSI = as.numeric(tail(best_asset_data$RSI, nrow(y_test))),
  action = character(nrow(y_test)),
  asset_value = numeric(nrow(y_test)),
  shares_held = numeric(nrow(y_test))
)

trading_rule_dual$asset_value[1] <- investment_dual
trading_rule_dual$shares_held[1] <- shares_dual

# Simulation loop with debug prints for the first few iterations
for (i in 1:nrow(trading_rule_dual)) {
  if (i > 1) {
    investment_dual <- trading_rule_dual$asset_value[i - 1]
    shares_dual <- trading_rule_dual$shares_held[i - 1]
  }
  current_price <- trading_rule_dual$actual_price[i]
  predicted_price <- trading_rule_dual$predicted_price[i]
  current_rsi <- trading_rule_dual$RSI[i]
  action <- "HOLD"

  if (!is.na(predicted_price) && !is.na(current_price) && !is.na(current_rsi)) {
    predicted_change_percentage <- (predicted_price - current_price) / current_price
    if (predicted_change_percentage > threshold_buy && current_rsi < oversold_threshold && investment_du
```

```r
      action <- "BUY"
      buy_quantity <- floor(investment_dual / current_price)
      shares_dual <- shares_dual + buy_quantity
      investment_dual <- investment_dual - (buy_quantity * current_price)
    } else if (predicted_change_percentage < threshold_sell && current_rsi > overbought_threshold && sha
      action <- "SELL"
      sell_value <- shares_dual * current_price
      investment_dual <- investment_dual + sell_value
      shares_dual <- 0
    }
  }

  trading_rule_dual$action[i] <- action
  trading_rule_dual$asset_value[i] <- investment_dual + (shares_dual * current_price)
  trading_rule_dual$shares_held[i] <- shares_dual
}

# Calculate final performance metrics
final_asset_value <- tail(trading_rule_dual$asset_value, 1)
profit_loss <- final_asset_value - 10000
roi <- (profit_loss / 10000) * 100

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

```
##
## Final Asset Value: $ 10000
```

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

```
## Profit/Loss: $ 0
```

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

```
## Return on Investment (ROI): 0 %
```

```r
# Print the full table
print(trading_rule_dual)
```

```
##          Date actual_price predicted_price      RSI action asset_value
## 1  2024-12-09     67.39554        65.56744 69.07233   HOLD       10000
## 2  2024-12-10     66.45506        60.53978 65.25666   HOLD       10000
## 3  2024-12-11     67.98600        62.46756 67.26606   HOLD       10000
## 4  2024-12-12     67.37810        62.39038 68.11199   HOLD       10000
## 5  2024-12-13     68.19372        62.42299 71.42037   HOLD       10000
## 6  2024-12-16     66.72497        61.65355 70.54158   HOLD       10000
## 7  2024-12-17     63.58379        60.81940 66.78071   HOLD       10000
## 8  2024-12-18     65.29941        61.28926 59.54137   HOLD       10000
## 9  2024-12-19     67.32994        61.59530 63.53262   HOLD       10000
## 10 2024-12-20     78.64948        65.08866 70.81358   HOLD       10000
## 11 2024-12-23     80.28217        68.39465 70.95150   HOLD       10000
```

```
## 12 2024-12-24     79.49410        67.09094 72.63272    HOLD       10000
## 13 2024-12-26     80.17125        68.40655 71.99547    HOLD       10000
## 14 2024-12-27     80.83242        69.55044 64.25471    HOLD       10000
## 15 2024-12-30     82.38000        66.99707 59.94499    HOLD       10000
##    shares_held
## 1            0
## 2            0
## 3            0
## 4            0
## 5            0
## 6            0
## 7            0
## 8            0
## 9            0
## 10           0
## 11           0
## 12           0
## 13           0
## 14           0
## 15           0
```

```r
# Plot the performance of the dual-indicator trading strategy
plot_dual <- function(trade_log) {
  plot(trade_log$Date, trade_log$asset_value, type = "l", col = "purple",
       xlab = "Date", ylab = "Asset Value ($)",
       main = "Dual-Indicator Strategy Performance")
  grid()
}
plot_dual(trading_rule_dual)
```