AI For Finance (Assignment-2)

2023-04-03

```r
prepare_stock_data = function(stock_data) {
  # Close price
  close_price <- Cl(stock_data)

  # Simple Moving Average (SMA) - 10-day period
  sma <- SMA(close_price, n = 10)

  # Exponential Moving Average (EMA) - 10-day period
  ema <- EMA(close_price, n = 10)

  # Relative Strength Index (RSI) - 14-day period
  rsi <- RSI(close_price, n = 14)

  # Moving Average Convergence Divergence (MACD) - fast = 12 days, slow = 26 days, signal = 9 days
  macd_obj <- MACD(close_price, nFast = 12, nSlow = 26, nSig = 9, maType = "EMA")
  macd_signal <- macd_obj$signal

  # Bollinger Bands - 20-day period
  bbands <- BBands(close_price, n = 20)
  bbands_pct <- (close_price - bbands[,1]) / (bbands[,3] - bbands[,1])

  # Add volume for the stock
  volume = Vo(stock_data)

  # Merge all the features into a single dataset
  features <- merge(close_price, sma, ema, rsi, macd_signal, bbands_pct)
  colnames(features) <- c("Close_Price", "SMA", "EMA", "RSI", "MACD_Signal", "BBands_Pct")

  # Remove rows with NA values
  features_complete <- na.omit(features)
  return(features_complete)
}
```

```r
plot_stock = function(prepped_stock_data) {
  # Convert xts object to data frame
  features_df <- data.frame(Date = index(prepped_stock_data), coredata(prepped_stock_data))
  colnames(features_df) <- c("Date", "Close_Price", "SMA", "EMA", "RSI", "MACD_Signal", "BBands_Pct")

  # Reshape data frame to long format
  features_long <- features_df %>%
    tidyr::gather(key = "Feature", value = "Value", -Date)

  # Update the scale for the "Volume" feature
  features_long$Value <- ifelse(features_long$Feature == "Volume",
                                features_long$Value / 1e6, # Adjust the scale factor as needed
                                features_long$Value)

  # Add a suffix to the "Volume" feature name to indicate the new scale
  features_long$Feature <- ifelse(features_long$Feature == "Volume",
                                  "Volume (Millions)",
                                  features_long$Feature)
  ggplot(features_long, aes(x = Date, y = Value, color = Feature, group = Feature)) +
    geom_line() +
    scale_color_discrete(name = "Features") +
    labs(title = "Stock Features over Time",
         x = "Date",
         y = "Value") +
    theme_minimal()
}
```

```r
train_test_split = function(stock_data) {
  # Calculate the number of rows for each set
  n_rows <- nrow(stock_data$data)
  train_size <- floor(0.70 * n_rows)
  validation_size <- floor(0.15 * n_rows)
  test_size <- n_rows - train_size - validation_size

  train_data <- stock_data$data[1:train_size]
  validation_data <- stock_data$data[(train_size + 1):(train_size + validation_size)]
  test_data <- stock_data$data[(train_size + validation_size + 1):n_rows]

  list(
    train = train_data,
    val = validation_data,
    test = test_data
  )
}
```

```r
normalize_data <- function(data) {
  col_mins <- apply(data, 2, min)
  col_maxs <- apply(data, 2, max)
  col_ranges <- col_maxs - col_mins

  normalized_data <- sweep(data, 2, col_mins, FUN = "-")
  normalized_data <- sweep(normalized_data, 2, col_ranges, FUN = "/")

  list(data = normalized_data, col_mins = col_mins, col_ranges = col_ranges)
}
```

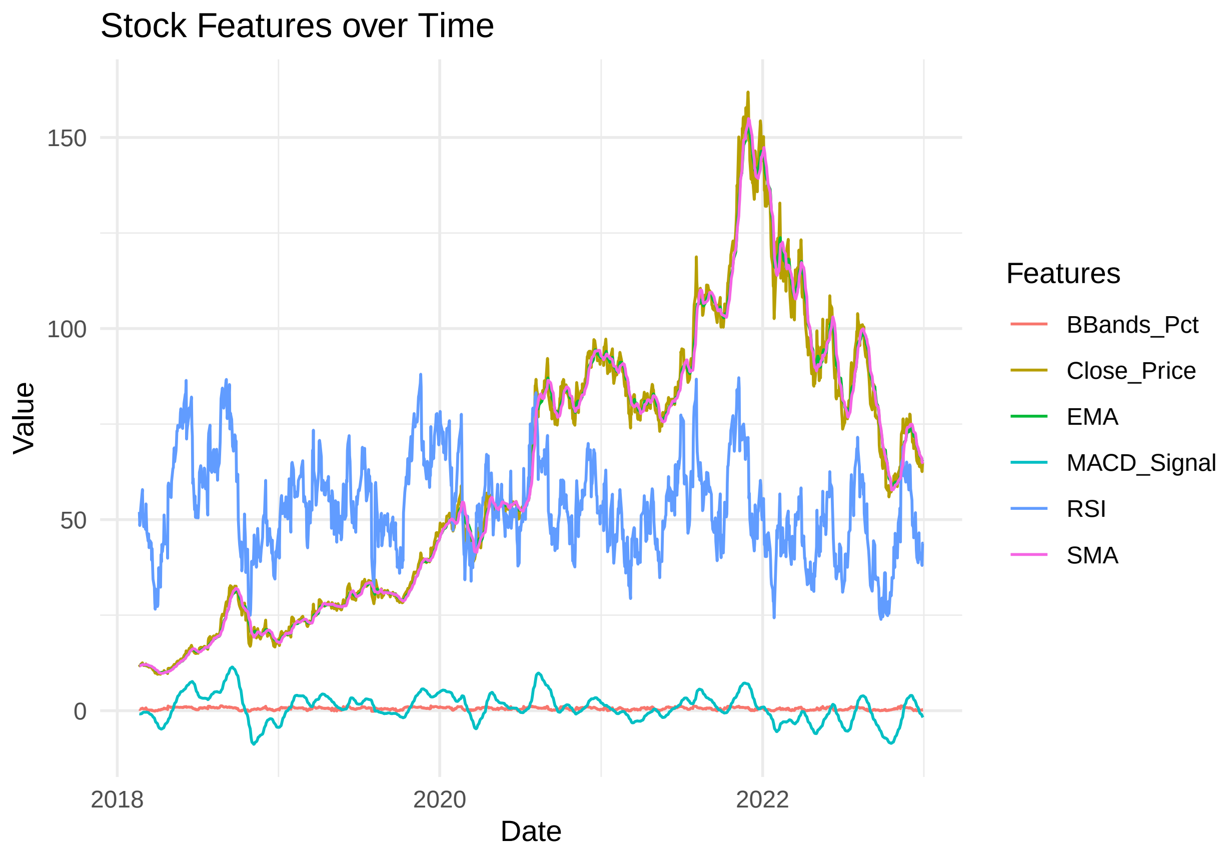
```r
denormalize_data <- function(normalized_data, col_mins, col_ranges) {
  denormalized_data <- sweep(normalized_data, 2, col_ranges, FUN = "*")
  denormalized_data <- sweep(denormalized_data, 2, col_mins, FUN = "+")

  denormalized_data
}
```

```r
preprocess_data <- function(data, lookback_window, horizon) {
  # Normalize the data
  normalized_data <- data
  num_samples <- nrow(data) - lookback_window - horizon + 1
  x <- array(0, dim = c(num_samples, lookback_window, ncol(normalized_data)))
  y <- array(0, dim = c(num_samples, horizon))

  for (i in 1:num_samples) {
    x[i, , ] <- normalized_data[i:(i + lookback_window - 1), ]
    y[i, ] <- normalized_data[(i + lookback_window):(i + lookback_window + horizon - 1), "Close_Price"]
  }

  list(x = x, y = y)
}
```

```r
build_lstm_model <- function(input_shape, learning_rate, regularization) {
  model <- keras_model_sequential() %>%
    layer_lstm(units = 20, input_shape = input_shape, return_sequences=TRUE, kernel_regularizer = regularizer_l2
    layer_dropout(rate=0.5) %>%
    layer_lstm(units = 10, kernel_regularizer = regularizer_l2(l = regularization)) %>%
    layer_dropout(rate=0.5) %>%
    layer_dense(units = 1)

  model %>% compile(
    loss = "mse",
    optimizer = optimizer_adam(learning_rate = learning_rate)
  )

  return(model)
}
```

```r
mse_fitness_function <- function(pso_params, train_data, val_data, horizon) {
  learning_rate <- pso_params[1]
  regularization <- pso_params[2]
  epochs = pso_params[3]
  lookback_window = pso_params[4]

  processed_train <- preprocess_data(train_data, lookback_window, horizon)
  processed_val <- preprocess_data(val_data, lookback_window, horizon)

  model <- build_lstm_model(
    input_shape = dim(processed_train$x)[-1],
    learning_rate = learning_rate,
    regularization = regularization
  )

  current_time <- format(Sys.time(), "%Y-%m-%d_%H-%M-%S")
  log_dir <- paste0("logs/fit/", current_time, "_lr_", learning_rate, "_reg_", regularization, "_epochs_", epoch

  # Initialize tensorboard callback with the unique log directory
  tensorboard_callback <- callback_tensorboard(log_dir = log_dir)

  history <- model %>% fit(
    x = processed_train$x,
    y = processed_train$y,
    validation_data = list(processed_val$x, processed_val$y),
    epochs = epochs,
    batch_size = 32,
    verbose = 0,
    callbacks=list(tensorboard_callback)
  )

  val_mse <- tail(history$metrics$val_loss, 1)
  return(val_mse)
}
```

```r
# Split the data into training, validation, and test sets

symbol <- "AMD"
start_date <- as.Date("2018-01-01")
end_date <- as.Date("2023-01-01")
stock_data <- getSymbols(symbol, src = "yahoo", from = start_date, to = end_date, auto.assign = FALSE)

prepped_stock_data = prepare_stock_data(stock_data)

plot_stock(prepped_stock_data)
```



```r
normal_data_training = normalize_data(prepped_stock_data)
split_data_training = train_test_split(normal_data_training)

train_data = split_data_training$train
validation_data = split_data_training$val
test_data = split_data_training$test
```

```r
lower_bounds <- c(0.0001, 0.001, 10, 5)
upper_bounds <- c(0.005, 0.01, 100, 50)
initial_weights <- runif(4, min=lower_bounds, max=upper_bounds)
```

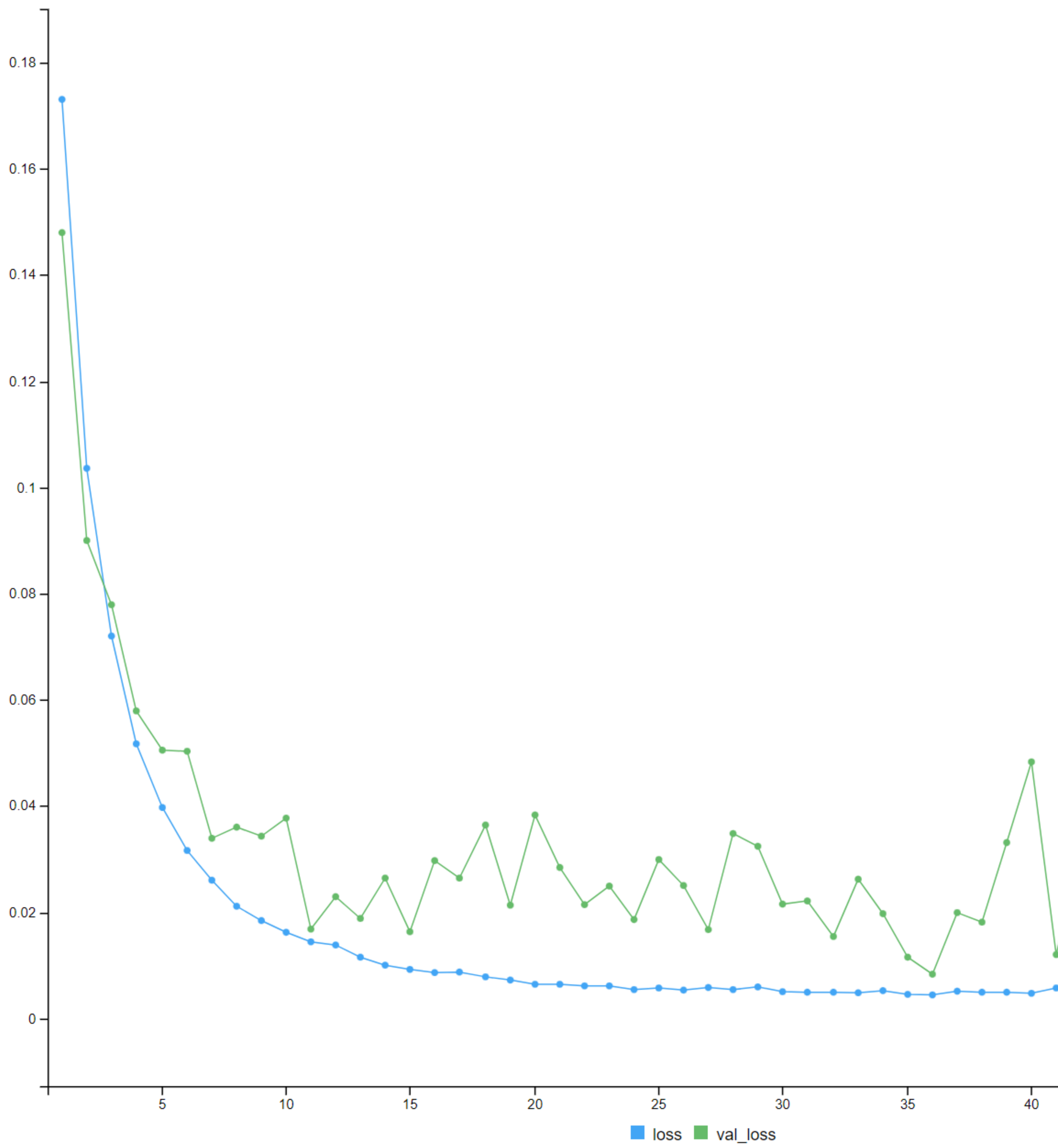
After running the PSO algorithm for 20 iterations, it found the below optimal parameters. We are putting them in here manually to avoid unnecessary time for re-computing the parameters by re-running the PSO process.

```r
optimal_params = c(0.00221, 0.00415, 55, 24) # LR, L2 regularisation, epochs, lookback window
```

```r
train_final_model = function(optimal_params, train_data, val_data, horizon) {
  # Extract the optimal parameters from the PSO result
  learning_rate <- optimal_params[1]
  regularization <- optimal_params[2]
  epochs = optimal_params[3]
  lookback_window = optimal_params[4]

  processed_train <- preprocess_data(train_data, lookback_window, horizon)
  processed_val <- preprocess_data(val_data, lookback_window, horizon)

  # Build the LSTM model with the optimal parameters
  model <- build_lstm_model(input_shape = dim(processed_train$x)[-1],
                            learning_rate = learning_rate,
                            regularization = regularization)

  current_time <- format(Sys.time(), "%Y-%m-%d_%H-%M-%S")
  log_dir <- paste0("logs/test/", current_time, "_lr_", learning_rate, "_reg_", regularization, "_epochs_", epoc
  # Initialize tensorboard callback with the unique log directory
  tensorboard_callback <- callback_tensorboard(log_dir = log_dir)

  # Train the LSTM model with the optimal parameters
  history <- model %>% fit(
    processed_train$x, processed_train$y,
    epochs = epochs,
    batch_size = 32,
    validation_data = list(processed_val$x, processed_val$y),
    callbacks = list(tensorboard_callback)
  )
  return(model)
}
```

```
train_model = train_final_model(optimal_params, train_data, validation_data, horizon=1)
```

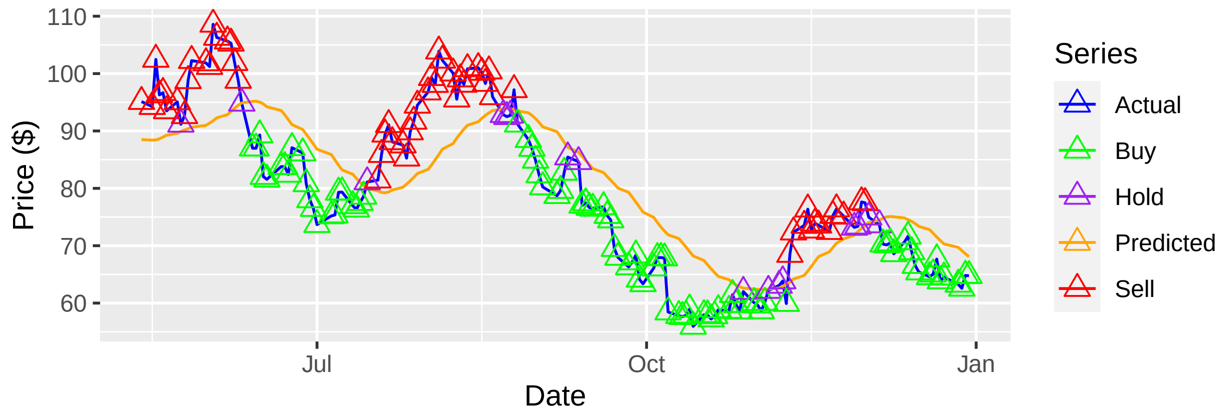
```
knitr::include_graphics("./final_train_amd.png")
```

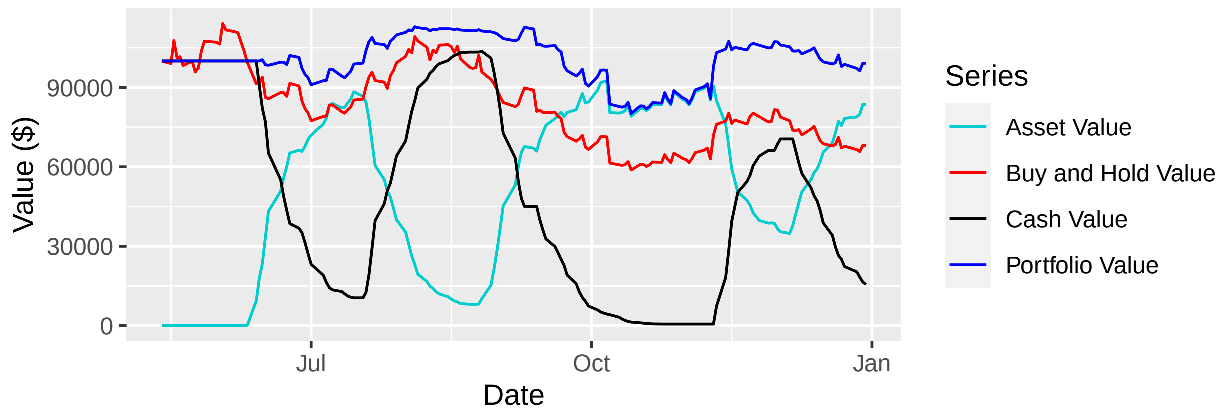


```
evaluate_final_model = function(optimal_params, model, test_data, horizon) {
  learning_rate <- optimal_params[1]
  regularization <- optimal_params[2]
  lookback_window = optimal_params[4]

  processed_test <- preprocess_data(test_data, lookback_window, horizon)
  # Evaluate the performance of the LSTM model on the test data
  test_loss <- model %>% evaluate(processed_test$x, processed_test$y)

  # Generate predictions for the test data
  predicted_test_prices <- model %>% predict(processed_test$x)

  # Convert the test data and predictions to data frames
  actual_test_prices <- as.data.frame(processed_test$y)
  colnames(actual_test_prices) <- c("Actual_Price")
  predicted_test_prices <- as.data.frame(predicted_test_prices)
  colnames(predicted_test_prices) <- c("Predicted_Price")

  # Combine the actual and predicted test prices
  price_comparison <- cbind(actual_test_prices, predicted_test_prices)

  # Calculate the error between the actual and predicted test prices
  error <- mean((price_comparison$Actual_Price - price_comparison$Predicted_Price)^2)

  list(actual = actual_test_prices, predicted = predicted_test_prices)
}

backtest_results = function(predicted, actual, normalized_data, buy_threshold = 0.05, sell_threshold = -0.05, in
  denormalize_data <- function(normalized_data, col_min, col_range) {
    denormalized_data <- normalized_data * col_range + col_min
    denormalized_data
  }

  shift_and_denormalize = function(predicted, actual) {
    # Implement your trading strategy and backtest it using the predicted_test_prices
    shifted_predicted <- predicted[-1,] # Remove the first element
    actual_trimmed <- actual[-length(actual),] # Remove the last element

    # This is so that instead of it being today predicted : today actual for signal, it is
    # tomorrow predicted : today actual

    shifted_predicted = denormalize_data(shifted_predicted, normalized_data$col_mins["Close_Price"], normalized_
    actual_trimmed = denormalize_data(actual_trimmed, normalized_data$col_mins["Close_Price"], normalized_data$c
    list(predicted = shifted_predicted, actual = actual_trimmed)
  }

  shifted_and_trimmed = shift_and_denormalize(predicted, actual)
  shifted_predicted = shifted_and_trimmed$predicted
  actual_trimmed = shifted_and_trimmed$actual

  # Calculate the predicted profit percentage
  predicted_profit_pct <- (shifted_predicted - actual_trimmed) / actual_trimmed
  trading_signals <- ifelse(predicted_profit_pct > buy_threshold, "Buy",
                            ifelse(predicted_profit_pct < sell_threshold, "Sell", "Hold"))

  backtest_loop = function(predicted_profit_pct, portfolio_value, signals, actual_value) {
    cash <- portfolio_value
    num_shares <- 0
    # Initialize the cash_value vector
    cash_value <- rep(NA, length(signals))
    asset_value = rep(NA, length(signals))
    total_portfolio_value = rep(NA, length(signals))
    buy_and_hold_value = rep(NA, length(signals))
    buy_and_hold_shares = floor(cash / actual_value[1])

    # Backtesting loop
```

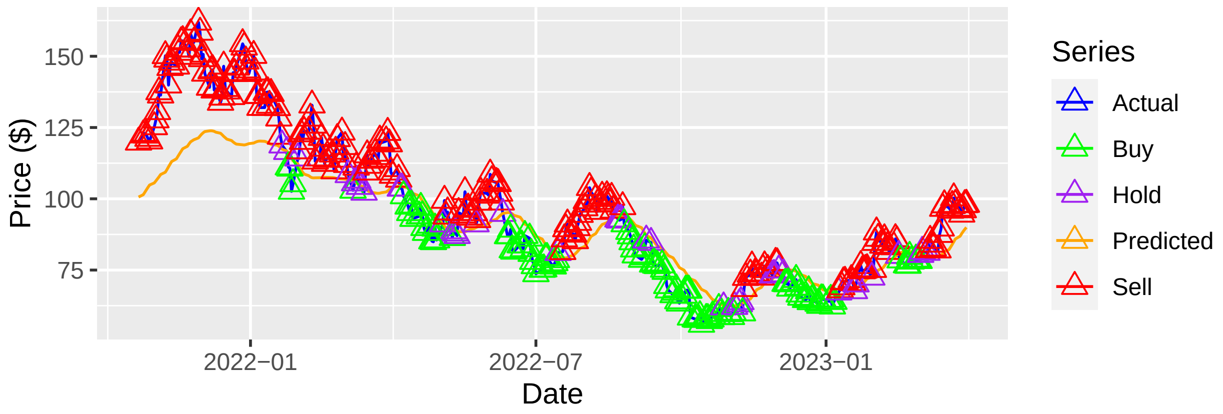
```r
    for (i in 1:(length(signals) - 1)) {
      cash_value[i] <- cash
      buy_and_hold_value[i] = buy_and_hold_shares * actual_value[i]

      if (signals[i] == "Buy" && cash >= actual_value[i]) {
        investment_amount <- cash * predicted_profit_pct[i]
        num_shares_bought <- floor(investment_amount / actual_value[i])
        num_shares <- num_shares + num_shares_bought
        cash <- cash - (num_shares_bought * actual_value[i])
      } else if (signals[i] == "Sell" && num_shares > 0) {
        sell_amount <- num_shares * actual_value[i] * (-predicted_profit_pct[i])
        num_shares_sold <- floor(sell_amount / actual_value[i])
        num_shares <- num_shares - num_shares_sold
        cash <- cash + (num_shares_sold * actual_value[i])
      }

      asset_value[i] = num_shares * actual_value[i]
      total_portfolio_value[i] = cash + asset_value[i]
    }

    # Add the final cash value
    cash_value[length(signals)] <- cash
    asset_value[length(signals)] = num_shares * actual_value[length(actual_value)]
    total_portfolio_value[length(signals)] = cash + (num_shares * actual_value[length(actual_value)])
    buy_and_hold_value[length(signals)] = buy_and_hold_shares * actual_value[length(actual_value)]

    return(
      data.frame(Cash = cash_value,
                 Assets = asset_value,
                 Portfolio = total_portfolio_value,
                 BuyAndHold = buy_and_hold_value,
                 Actual = actual_value,
                 Signals = signals,
                 Predicted = shifted_predicted)
    )
  }

  backtest_series = backtest_loop(predicted_profit_pct, initial_cash, trading_signals, actual_trimmed)
  return(backtest_series)
}
```

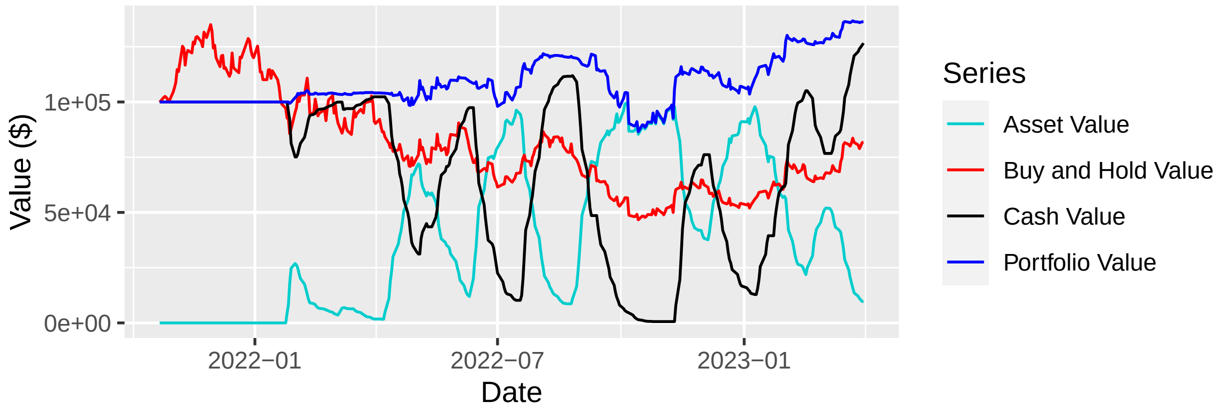
```r
full_evaluation(optimal_params, train_model, test_data, normal_data_training)
```



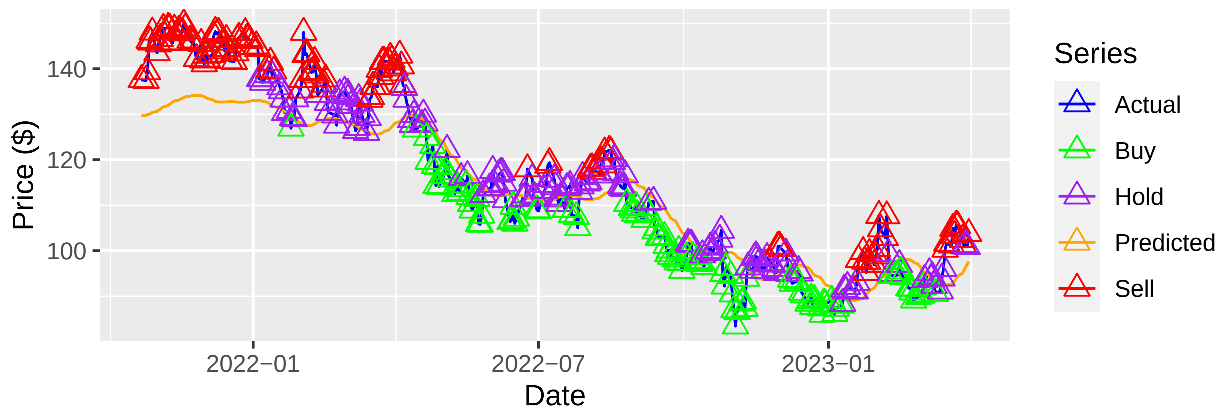


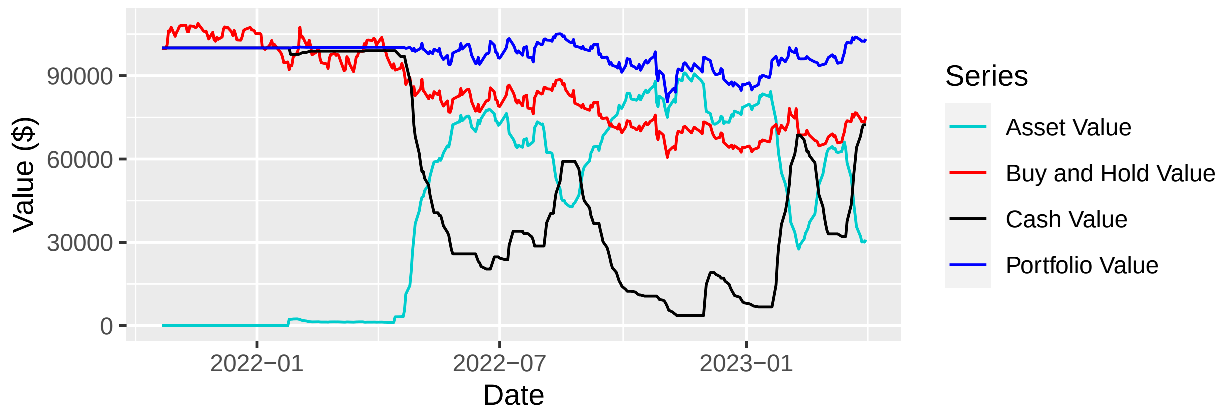
```r
symbol <- "AMD"
start_date <- as.Date("2021-08-01")
end_date <- as.Date("2023-04-01")
stock_data_test <- getSymbols(symbol, src = "yahoo", from = start_date, to = end_date, auto.assign = FALSE)


normal_data2 = normalize_data2(prepare_stock_data(stock_data_test), normal_data_training$col_mins, normal_data_t
full_evaluation(optimal_params, train_model, normal_data2, normal_data_training, cash=100000)
```





```
symbol <- "GOOGL"
start_date <- as.Date("2021-08-01")
end_date <- as.Date("2023-04-01")
stock_data_aapl <- getSymbols(symbol, src = "yahoo", from = start_date, to = end_date, auto.assign = FALSE)

normal_data_aapl = normalize_data(prepare_stock_data(stock_data_aapl))
full_evaluation(optimal_params, train_model, normal_data_aapl$data, normal_data_aapl, cash=100000, buy_threshold
```


Price ($)
140
120
100
2022−01
2022−07
2023−01
Date
Series
Actual
Buy
Hold
Predicted
Sell


Value ($)
90000
60000
30000
0
2022−01
2022−07
2023−01
Date
Series
Asset Value
Buy and Hold Value
Cash Value
Portfolio Value