Analysis of Nasdaq Closing Cross auction dataset in Julia

Each trading day on the Nasdaq Stock Exchange concludes with the Nasdaq Closing Cross auction. This process establishes the official closing prices for securities listed on the exchange. There are a lot of factors in this roughly 10 minutes auction that affect the closing price. Bid price which determines the highest amount someone is willing to pay for the stock has a significant impact on the closing price of the stock

In this project the aim is to analyse the historic data for the daily ten minute closing auction on the NASDAQ stock exchange. And finding the parameters having maximum impact on bid_price using Julia. The data for this project was taken from the following [kaggle competition (https://www.kaggle.com/competitions/optiver-trading-at-the-close/data)](https://www.kaggle.com/competitions/optiver-trading-at-the-close/data).

A little description about the data:-

1. stock_id - A unique identifier for the stock.
2. date_id - A unique identifier for the date.
3. imbalance_size - The amount unmatched at the current reference price (in USD).
4. imbalance_buy_sell_flag - An indicator reflecting the direction of auction imbalance. a. buy-side imbalance; 1 b. sell-side imbalance; -1 c. no imbalance; 0
5. reference_price - The price at which paired shares are maximized, the imbalance is minimized and the distance from the bid-ask midpoint is minimized, in that order. Can also be thought of as being equal to the near price bounded between the best bid and ask price.
6. matched_size - The amount that can be matched at the current reference price (in USD).
7. far_price - The crossing price that will maximize the number of shares matched based on auction interest only.
8. near_price - The crossing price that will maximize the number of shares matched based auction and continuous market orders.
9. [bid/ask]_price - Price of the most competitive buy/sell level in the non-auction book.
10. [bid/ask]_size - The dollar notional amount on the most competitive buy/sell level in the non-auction book.
11. wap - The weighted average price in the non-auction book.
12. seconds_in_bucket - The number of seconds elapsed since the beginning of the day's closing auction, always starting from 0.
13. target - The 60 second future move in the wap of the stock, less the 60 second future move of the synthetic index. Only provided for the train set.

In [1]:
```
##to install any of the packeages imported below please uncomment t

# using Pkg
# Pkg.add("Package_name")
```

Importing packages

In [2]:
```
#import the follwoing packages

using CSV
using DataFrames
using Statistics
using Plots
using PyCall
using DataStructures
using StatsBase
using CategoricalArrays
using StatsPlots
using Random
using GLM
```

Fetching the Dataframe

In [3]:
```
df = CSV.read("train.csv", DataFrame)
first(df, 5)
```

Out[3]: 5×17 DataFrame

Row	stock_id	date_id	seconds_in_bucket	imbalance_size	imbalance_buy_sell_flag	refere
	Int64	Int64	Int64	Float64?	Int64	Float
1	0	0	0	3.1806e6	1	
2	1	0	0	1.66604e5	-1	
3	2	0	0	3.0288e5	-1	
4	3	0	0	1.19177e7	-1	
5	4	0	0	447550.0	-1	

In [4]:
```
size(df) #getting the size of the data frame
```

Out[4]: (5237980, 17)

Descriptive Statistics

In [5]:
```
describe(df) #getting a full description of the data frame
```

Out[5]: 17×7 DataFrame

Row	variable	mean	min	median	max	nmissing	eltype
	Symbol	Union…	Any	Union…	Any	Int64	Type
1	stock_id	99.2886	0	99.0	199	0	Int64
2	date_id	241.51	0	242.0	480	0	Int64
3	seconds_in_bucket	270.0	0	270.0	540	0	Int64
4	imbalance_size	5.71529e6	0.0	1.1136e6	2.98203e9	220	Union{I Float64
5	imbalance_buy_sell_flag	-0.0118962	-1	0.0	1	0	Int64
6	reference_price	0.999996	0.935285	0.999967	1.07749	220	Union{I Float64
7	matched_size	4.51002e7	4316.61	1.28826e7	7.71368e9	220	Union{I Float64
8	far_price	1.00171	7.7e-5	0.999883	437.953	2894342	Union{I Float64
9	near_price	0.99966	0.786988	0.999889	1.30973	2857180	Union{I Float64
10	bid_price	0.999726	0.934915	0.999728	1.07749	220	Union{I Float64
11	bid_size	51813.6	0.0	21969.0	3.02878e7	0	Float64
12	ask_price	1.00026	0.939827	1.00021	1.07784	220	Union{I Float64
13	ask_size	53575.7	0.0	23017.9	5.4405e7	0	Float64
14	wap	0.999992	0.938008	0.999997	1.07767	220	Union{I Float64
15	target	NaN	NaN		NaN	0	Float64
16	time_id	13310.1	0	13345.0	26454	0	Int64
17	row_id		0_0_0		9_90_99	0	String1

In [6]:
```
names(df) #names of all the features (columns)
```

Out[6]:
```
17-element Vector{String}:
 "stock_id"
 "date_id"
 "seconds_in_bucket"
 "imbalance_size"
 "imbalance_buy_sell_flag"
 "reference_price"
 "matched_size"
 "far_price"
 "near_price"
 "bid_price"
 "bid_size"
 "ask_price"
 "ask_size"
 "wap"
 "target"
 "time_id"
 "row_id"
```

In [7]:
```
# Extract numerical columns

numerical_data = select(df, Not([eltype(df[!, col]) <: AbstractStri
first(numerical_data, 5)
```

Out[7]: 5×16 DataFrame

Row	stock_id	date_id	seconds_in_bucket	imbalance_size	imbalance_buy_sell_flag	refere
	Int64	Int64	Int64	Float64?	Int64	Float(
1	0	0	0	3.1806e6	1	
2	1	0	0	1.66604e5	-1	
3	2	0	0	3.0288e5	-1	
4	3	0	0	1.19177e7	-1	
5	4	0	0	447550.0	-1	

Statistical Analysis of the data using heatmap

Performing statistical analysis to drive insights from the data.

In [8]:
```
# Replace missing values with 0.0
numerical_data .= coalesce.(numerical_data, 0.0)
first(numerical_data, 5)
```

Out[8]: 5×16 DataFrame

Row	stock_id	date_id	seconds_in_bucket	imbalance_size	imbalance_buy_sell_flag	refere
	Int64	Int64	Int64	Float64?	Int64	Float
1	0	0	0	3.1806e6	1	
2	1	0	0	1.66604e5	-1	
3	2	0	0	3.0288e5	-1	
4	3	0	0	1.19177e7	-1	
5	4	0	0	447550.0	-1	

In [9]:
```
# Identify integer columns
int_columns = names(numerical_data, Int)


# Convert integer columns to float
numerical_data[!, int_columns] .= float.(numerical_data[!, int_colu
first(numerical_data, 5)
```

Out[9]: 5×16 DataFrame

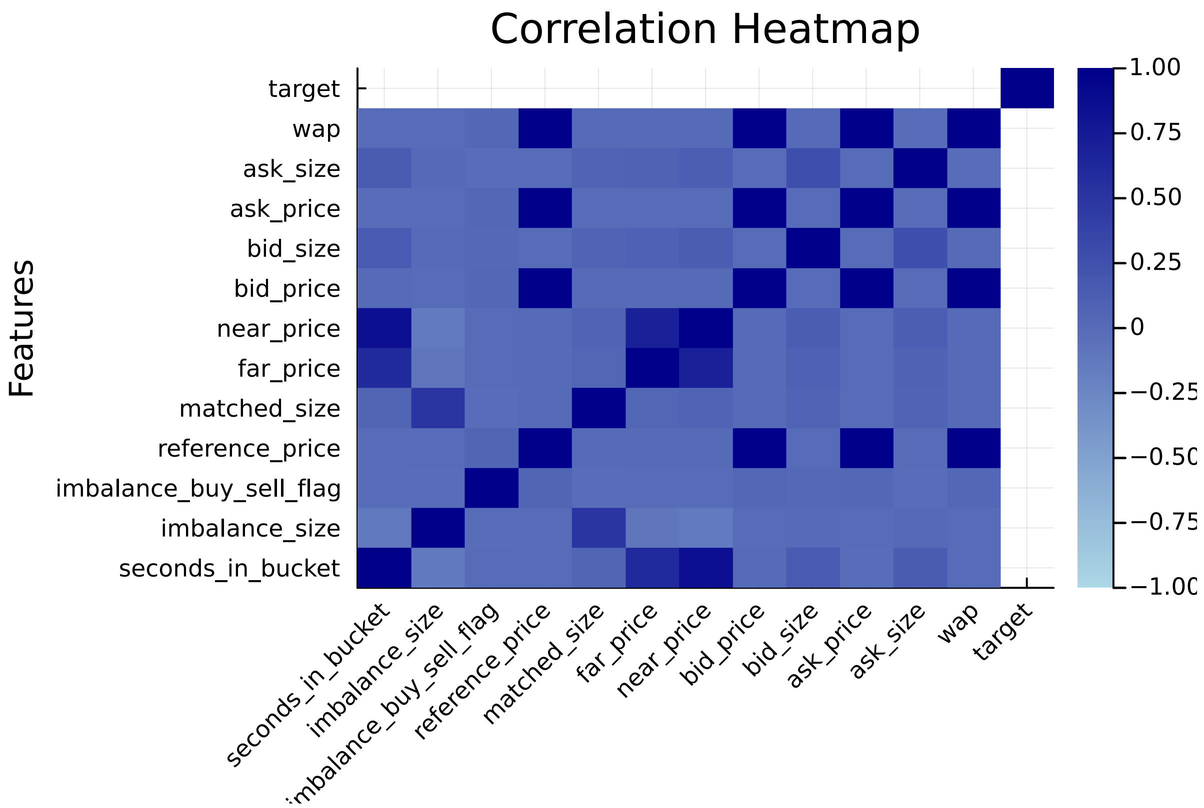
Row	stock_id	date_id	seconds_in_bucket	imbalance_size	imbalance_buy_sell_flag	refere
	Float64	Float64	Float64	Float64?	Float64	Float
1	0.0	0.0	0.0	3.1806e6	1.0	
2	1.0	0.0	0.0	1.66604e5	-1.0	
3	2.0	0.0	0.0	3.0288e5	-1.0	
4	3.0	0.0	0.0	1.19177e7	-1.0	
5	4.0	0.0	0.0	447550.0	-1.0	

In [10]:
```
names(numerical_data)
```

Out[10]:
```
16-element Vector{String}:
 "stock_id"
 "date_id"
 "seconds_in_bucket"
 "imbalance_size"
 "imbalance_buy_sell_flag"
 "reference_price"
 "matched_size"
 "far_price"
 "near_price"
 "bid_price"
 "bid_size"
 "ask_price"
 "ask_size"
 "wap"
 "target"
 "time_id"
```

In [11]:
```
# Select relevant columns
selected_columns = ["seconds_in_bucket", "imbalance_size", "imbalan
                    "matched_size", "far_price", "near_price", "bid
                    "ask_size", "wap", "target"]

# Create a correlation matrix
correlation_matrix = cor(Matrix(numerical_data[:, selected_columns]

# Plot heatmap


#### blue color is used to show variation in correlation kindly cha
#### if there is any difficulty in understandin the variation

heatmap(selected_columns, selected_columns, correlation_matrix,
        title="Correlation Heatmap",
        xlabel="Features",
        ylabel="Features",
        xrotation=45,
        c=:blues,
        clim=(-1, 1))
```

Out[11]:



Taking a subsample of the data

As it can be seen the data set we have at hand here is huge, with more than 5 million rows. Due to limitation of computational power we will try working on a sub-sample of the data-set, we will reduce the size and try to work on it, to not deviate by a significant margin from the properties of current data set we will compare the heatmap and descriptive statistics of the subsampled and original datasets.

In [18]:
```
original_rows = size(numerical_data, 1)  # Get the original number
desired_sample_size = 10000  # Desired sample size

# Randomly select rows
random_indices = rand(1:original_rows, desired_sample_size)
sampled_df = numerical_data[random_indices, :]
first(sampled_df, 5)
```

Out[18]: 5×16 DataFrame

Row	stock_id	date_id	seconds_in_bucket	imbalance_size	imbalance_buy_sell_flag	refere
	Float64	Float64	Float64	Float64?	Float64	Float
1	196.0	388.0	40.0	0.0	0.0	
2	81.0	392.0	10.0	4.95694e6	-1.0	
3	180.0	461.0	150.0	2.04817e6	1.0	
4	160.0	263.0	200.0	1.93657e7	-1.0	
5	91.0	100.0	280.0	3.70198e6	-1.0	

Descriptive statistics of subsampled data

In [13]:
```
describe(sampled_df)
```

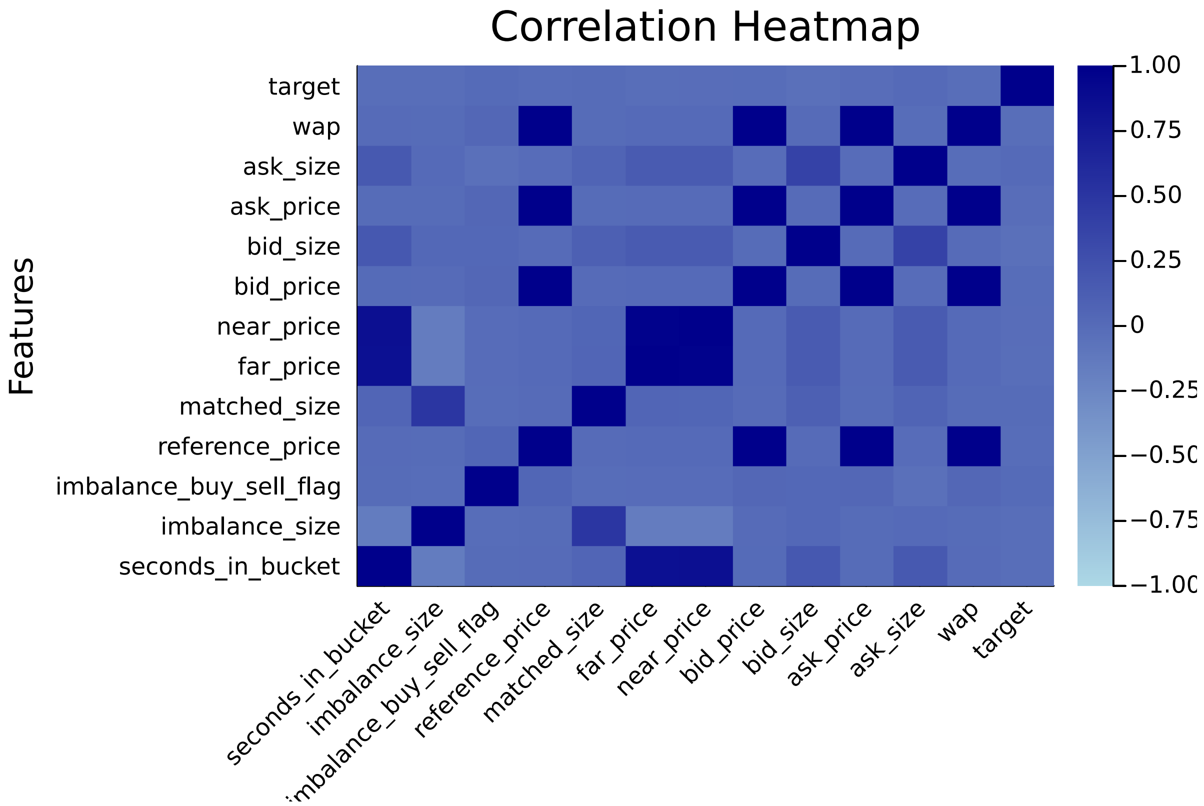
Out[13]: 16×7 DataFrame

Row	variable Symbol	mean Float64	min Float64	median Float64	max Float64	nmissing Int64	eltype Type
1	stock_id	99.1608	0.0	98.0	199.0	0	Float6
2	date_id	241.66	0.0	242.0	480.0	0	Float6
3	seconds_in_bucket	270.31	0.0	270.0	540.0	0	Float6
4	imbalance_size	5.82078e6	0.0	1.08599e6	7.58501e8	0	Union{ Float6
5	imbalance_buy_sell_flag	-0.0109	-1.0	0.0	1.0	0	Float6
6	reference_price	0.999891	0.0	0.99995	1.05354	0	Union{ Float6
7	matched_size	4.57211e7	0.0	1.29903e7	6.41694e9	0	Union{ Float6
8	far_price	0.455472	0.0	0.0	1.27784	0	Union{ Float6
9	near_price	0.463129	0.0	0.0	1.10229	0	Union{ Float6
10	bid_price	0.999618	0.0	0.999716	1.05063	0	Union{ Float6
11	bid_size	51368.2	31.74	22506.9	1.8416e6	0	Float6
12	ask_price	1.00016	0.0	1.00019	1.05487	0	Union{ Float6
13	ask_size	53137.4	18.43	22628.7	3.41093e6	0	Float6
14	wap	0.999888	0.0	0.999996	1.05102	0	Union{ Float6
15	target	-0.0579486	-89.2401	-0.0602007	74.4903	0	Float6
16	time_id	13318.3	5.0	13325.0	26448.0	0	Float6

Heatmap of the subsampled data

In [14]:
```
# Select relevant columns
selected_columns = ["seconds_in_bucket", "imbalance_size", "imbalan
                    "matched_size", "far_price", "near_price", "bid
                    "ask_size", "wap", "target"]

# Create a correlation matrix
correlation_matrix = cor(Matrix(sampled_df[:, selected_columns]))

# Plot heatmap

#### blue color is used to show variation in correlation kindly cha
#### if there is any difficulty in understandin the variation

heatmap(selected_columns, selected_columns, correlation_matrix,
        title="Correlation Heatmap",
        xlabel="Features",
        ylabel="Features",
        xrotation=45,
        c=:blues,
        clim=(-1, 1))
```

Out[14]:



As it can be seen from the two heat maps that features having a correlation of more than 50% are consistent in the two data-sets, also from the descriptive statistics of the two data-sets it is clear that they do not deviate by much so can move ahead with the subsampled dataframe.

Performing regression analysis

This is done to get an uderstanding of 2 things:-

1. P-value which helps in gauging the imporatnce of the associated predictors of the target variable (bid_price) in our case.
2. R-squared value which determines the proportion of variance in the dependent variable that can be explained by the independent variable

First lets start with taking all the feature vectors for predicting the target at once.

In [15]:
```
# Define the model
model = lm(@formula(bid_price ~ stock_id + date_id + seconds_in_buc
                     imbalance_buy_sell_flag + reference_price + ma
                     near_price + bid_size + ask_price + ask_size +
           sampled_df)

# Summarize the regression results
println("Regression Summary:")
println(coef(model))
println("The last value represents the p-value.\n")

#Drawing more Statistical insight
println("Statistical information:\n")

println("R-squared value")
println("\nR-squared:", r2(model))

print("\nAdjusted-R-squared value\n")
println("\nAdjusted R-squared: ", adjr2(model))
```

```
Regression Summary:
[0.0, 0.00291101542948181, 0.0, 0.0010895434920524024, 2.696325491
5229403e-9, 0.0, 0.0, -1.0324330063338554e-10, 0.0, 0.0, 1.1884598
139185719e-7, 0.0, 4.348093928208455e-8, 0.0, 2.2435104058071236e-
5]
The last value represents the p-value.

Statistical information:

R-squared value

R-squared:-924.6856936917196

Adjusted-R-squared value

Adjusted R-squared: -925.2414941682682
```

The p-value is less than 0.05 which supports our hypothesis of using all the features at once for predicting bid_price. But if we notice the R-squared-value is -944.5227623062601 which indicates there is something wrong with either the model or the data as the R-squared value lie between 0 and 1.

Let's try using those features which as per the heatmaps have a correlation of more than or equal to 75% with the bid_price.

These will be:- reference_price, ask_price, wap,

In [16]:
```
# Define the model
model = lm(@formula(bid_price ~ reference_price + ask_price + wap),

# Summarize the regression results
println("Regression Summary:")
println(coef(model))
println("The last value represents the p-value.\n")

#Drawing more Statistical insight
println("Statistical information:\n")

println("R-squared value")
println("\nR-squared:", r2(model))

print("\nAdjusted-R-squared value\n")
println("\nAdjusted R-squared: ", adjr2(model))
```

```
Regression Summary:
[0.0008508902149638224, 0.4426379842144153, -0.3866462938540647, 0
.9429915860395669]
The last value represents the p-value.

Statistical information:

R-squared value

R-squared:0.998982995645371

Adjusted-R-squared value

Adjusted R-squared: 0.9989826904219752
```

This time we have a R-squared value of 99.9% which indicates that any movement in bid_price can be explained by the features taken into consideration to very significant extent. However we have a p value which is > 0.05 which hints that these features are not a statistically significant predictor of bid_price.

Let's try taking more features into account this time all those that have a correlation of more than 50%. These will be - reference_price, ask_price, wap, imbalance_buy_sell_flag, far_pice, near_price.

In [17]:
```
# Define the model
model = lm(@formula(bid_price ~ reference_price + ask_price + wap +

# Summarize the regression results
println("Regression Summary:")
println(coef(model))
println("The last value represents the p-value.\n")

#Drawing more Statistical insight
println("Statistical information:\n")

println("R-squared value")
println("\nR-squared:", r2(model))

print("\nAdjusted-R-squared value\n")
println("\nAdjusted R-squared: ", adjr2(model))
```

```
Regression Summary:
[0.000559516151971252, 0.5079613644294192, -0.4009385750278202, 0.
8922361837269409, -8.317216193638194e-5, 8.70984208810989e-5, -4.5
71247915893844e-5]
The last value represents the p-value.

Statistical information:

R-squared value

R-squared:0.999032322244667

Adjusted-R-squared value

Adjusted R-squared: 0.9990317412313044
```

This gives us a p-value less than 0.05 and R-squared value of 99.9% suggesting the following:-

Coefficient Significance: The P-value is suggesting that the corresponding features (independent variables) are likely a statistically significant predictor of the target (dependent variable).

R-squared Value: An R-squared value of 99.9% indicates that the model explains a very high percentage of the variability in the dependent variable. This is a strong indicator that the model fits the data extremely well.

Overall Model Fit: The combination of a low p-value and a high R-squared value suggests that the model is statistically significant and provides an excellent fit to the data.

Conclusion

From this limited statistical analysis we were able to conclude that reference_price, ask_price, wap, imbalance_buy_sell_flag, far_pice, near_price can be used to explain variation in bid_price.

Scope of improvement

Overfitting: Extremely high R-squared values may sometimes indicate overfitting, where the model fits the training data too closely and may not generalize well to new, unseen data.

Domain Knowledge: While statistical significance is crucial, the ultimate interpretation should also consider the theoretical or practical significance of the findings within the specific domain or field of study.

Assumptions: Regression models have assumptions, and violations of these assumptions could affect the validity of the results. It's important to check for assumptions such as linearity, independence of residuals, and normality.

Future work

I would like to do a thorough statistical analysis of this dataset deploying other methods. FSurther I want to develop robust prediction models to be able to predict bid_price and eventually closing price using real time data during the last 10 minutes of closing auction of a trading day.