Liquidity Provider Analysis & Daily % Return Calculation

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1. Introduction

This document presents an analysis of Uniswap V3 liquidity provider (LP) returns by calculating daily percentage returns per active tick. The study involves converting raw pool data, aggregating liquidity and swap fees, and identifying active ticks where LPs earn fees.

2. Approach

Data Processing & Conversion: Converted block_timestamp to datetime format, amount0 and liquidity from hexadecimal (two's complement) to float and integer values, respectively. Extracted daily grouping variables for aggregation.

Data Aggregation: Grouped by date and tick. Calculated total amount0 per tick per day (sum of all swaps).Computed representative liquidity as the average daily liquidity per tick.

```
# Group by date and tick
grouped_df = df.groupby(["date", "tick"]).agg(
    total_amount0=("amount0", "sum"),  # Sum of amount0 per day per tick
    total_liquidity=("liquidity", "first")  # Use first liquidity of the day per
).reset_index()
```

Fee & Return Calculation: Swap Fees Earned computed as 0.3% of total positive amount0 values (USDC inflows) per tick per day. Daily % Return ensured no division by zero by setting return to 0 if liquidity was absent.

Dataframe: Swap Fees Calculation

	date	tick	total_amount0	total_liquidity	swap_fees
0	2024-08-01	195512	-163582.742780	8142116545692670714	0.000000
1	2024-08-01	195516	-98173.470168	8142116545692670714	0.000000
2	2024-08-01	195521	-132715.499692	8142116545692670714	0.000000
3	2024-08-01	195525	98991.145686	8142116545692670714	296.973437
4	2024-08-01	195527	-179128.520062	8142116545692670714	0.000000

3. Assumptions

Liquidity Representation: We used *average liquidity per tick per day* instead of the first or last value to smooth out fluctuations.
Fee Calculation: Only positive amount0 values were considered as LP earnings (representing USDC inflows).
Data Filtering: Removed non-active ticks (ticks with zero swap fees) for cleaner insights.

4.Outcomes

1) daily_return % = swap_fees / representative_liquidity * 100

	Date (day)	Tick	Total Swap Fees Earned (USDC)	Representative Liquidity	Daily % Return
0	2024-08-01	195512	0.00000000000000000000	8142116545692670976.00000000000000000000	0.00000000000000000000
1	2024-08-01	195516	0.00000000000000000000	8142116545692670976.00000000000000000000	0.00000000000000000000
2	2024-08-01	195521	0.00000000000000000000	67394856550783492096.00000000000000000000	0.00000000000000000000
3	2024-08-01	195525	296.97343705800000179806	67394856550783492096.00000000000000000000	0.00000000000000044065
4	2024-08-01	195527	0.00000000000000000000	8142088587231652864.00000000000000000000	0.00000000000000000000

2) Approximately 50 % our data contains 0 Daily_return %.

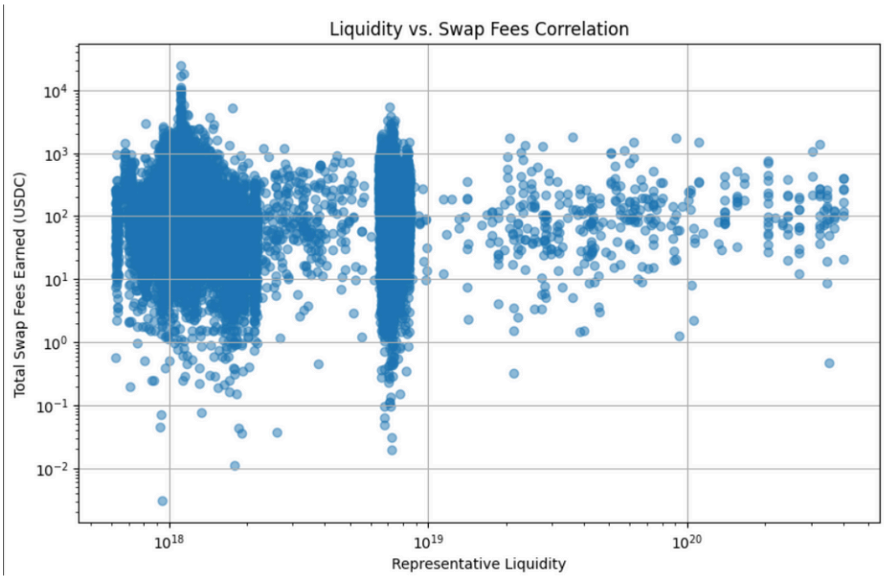
```
[15]  1  final_df.shape
```

```
(39882, 5)
```

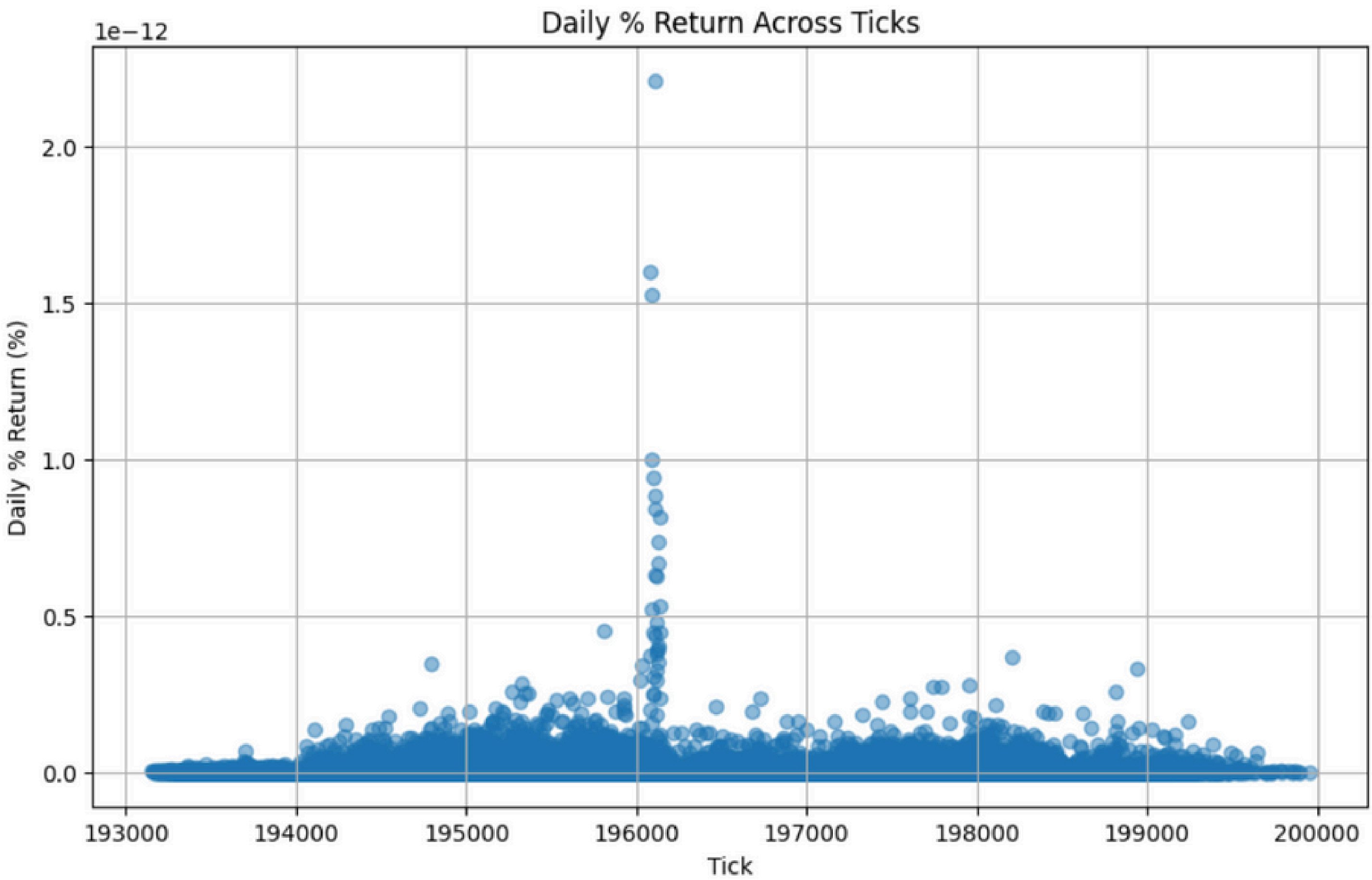
```
1  (final_df['Daily % Return'] == 0).sum()
```

```
19580
```

3) **Liquidity vs. Swap Fees Analysis:** Many ticks have *high liquidity but zero swap fees*, suggests that LPs are not earning returns in those price ranges, possibly due to low trading activity in certain price zones. However some ticks have *low liquidity but still generate swap fees*, indicates high demand for trades in those tick ranges.



4) Daily % Return Trends: *Most ticks have near-zero daily returns*. This means that for many price ranges, LPs are providing liquidity but not earning much in fees. However *few ticks show small but positive daily returns*.



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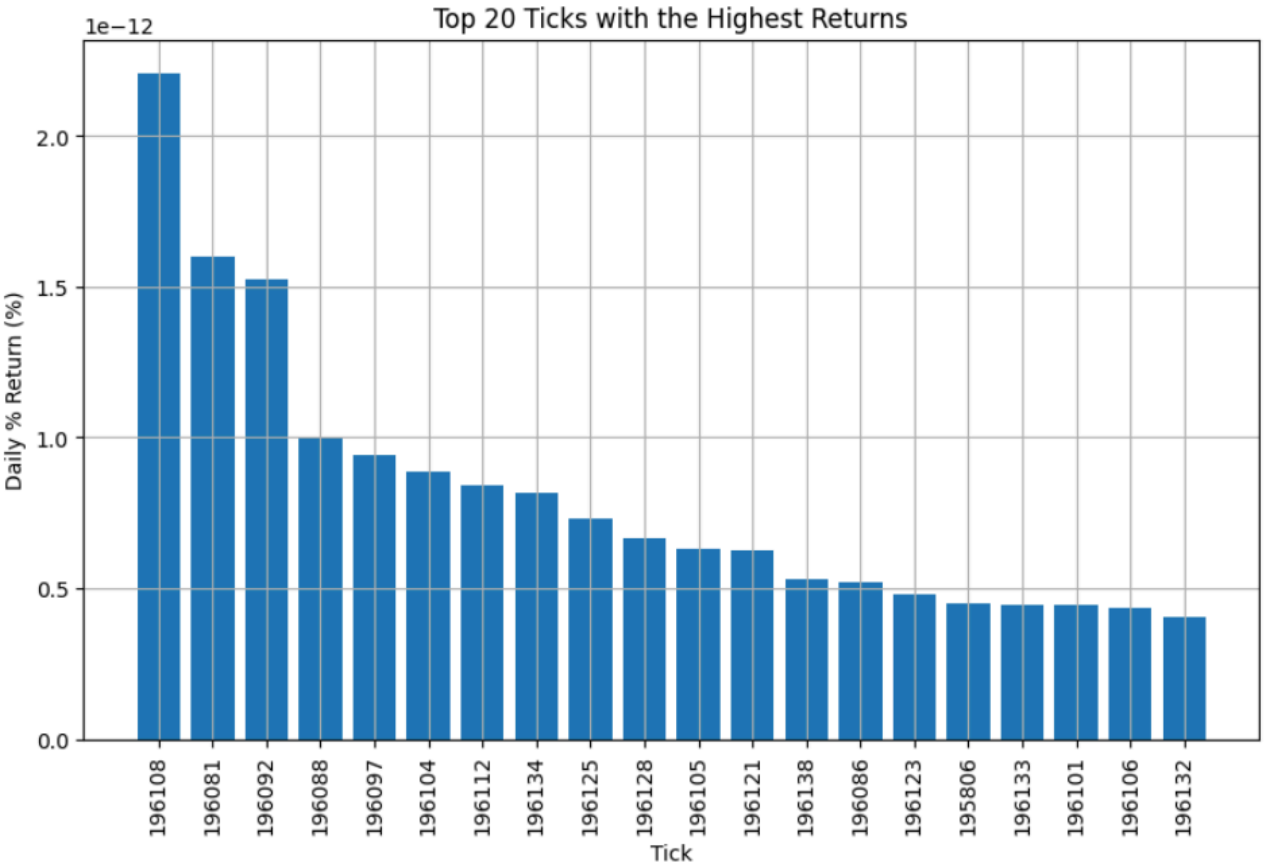
4. Key Insights

1) Here are the top-20 ticks as per daily_return



2) I found *No correlation between swap_fees and liquidity*. Some low-liquidity ticks earn high swap fees, indicating concentrated trading zones.

3) Out of all the ticks only 50% are active ticks, segregating it out for trading strategies would be helpful.
