HF-data

September 19, 2023

1 High-Frequency Data

[3]:
```python
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
```

[5]:
```python
header = ['trade_id','price','quantity','order_id','timestamp','is_buyer_maker']
df = pd.read_csv('./BTCUSDT-trades-2023-05-31.csv',header=0 , names = header)
df.head()
```

[5]:

	trade_id	price	quantity	order_id	timestamp	is_buyer_maker
0	3765419375	27680.0	0.400	11072.0000	1685491200110	True
1	3765419376	27680.0	0.006	166.0800	1685491200156	True
2	3765419377	27680.0	0.300	8304.0000	1685491200157	True
3	3765419378	27680.1	0.003	83.0403	1685491200244	False
4	3765419379	27680.1	0.003	83.0403	1685491203809	False

2 Introduction

In many High-Frequency Trading papers, it is common to make the following assumptions:

- The time duration Δt is sufficiently small.
- The terminal time T is also small.

Therefore, it is necessary to investigate the characteristics of high-frequency trading data.

[6]:
```python
def closed_time_series(df, time_interval):
    """
    Change tick data to OHLCV data
    """
    df['timestamp'] = pd.to_datetime(df['timestamp'], unit='ms')
    df = df.set_index('timestamp')
    df['quantity'] = df['quantity'] * df['price']
    df['buy_quantity'] = np.where(df['is_buyer_maker'], df['quantity'], 0)
    df['sell_quantity'] = np.where(df['is_buyer_maker'], 0, df['quantity'])
    df = df.resample(str(time_interval)+'S').agg({'price':'last', 'quantity':
 ↪'sum', 'buy_quantity':'sum', 'sell_quantity':'sum'})
```

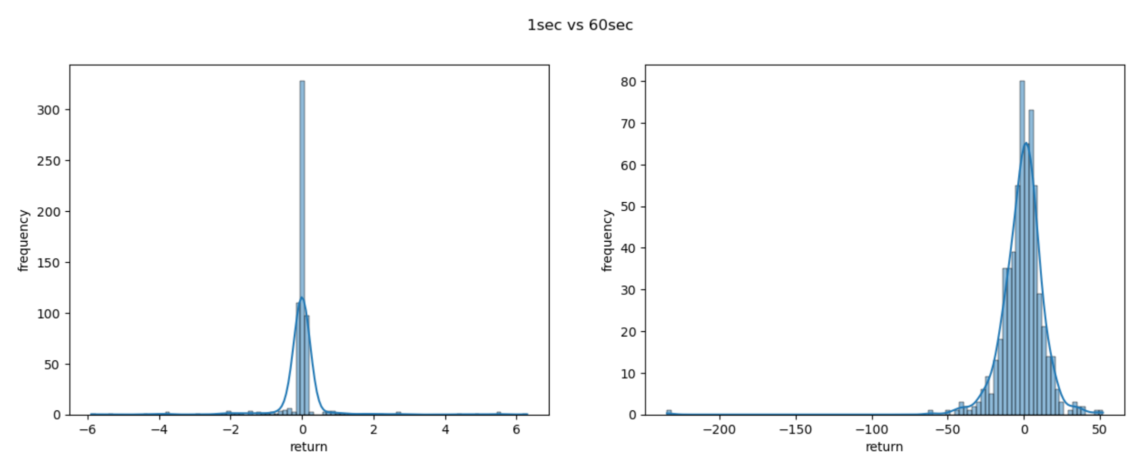
```
    df['return'] = df['price'].diff()
    df['log_return'] = np.log(df['price']) - np.log(df['price'].shift(1))
    df = df.dropna()
    df['volatility'] = df['return'].rolling(600).std()
    return df
```

According to Tsay's "Financial Time Series," there are interesting characteristics of intraday price changes, including a concentration on "no change" and discreteness. Let's investigate these characteristics step by step.

2.1 Concentration on "no change"

To examine the concentration of price changes around zero, we can calculate the frequency distribution of price changes at small time intervals (e.g., seconds or minutes).
By analyzing the distribution, we can determine if there is a significant number of instances where the price remains unchanged or experiences minimal fluctuations.

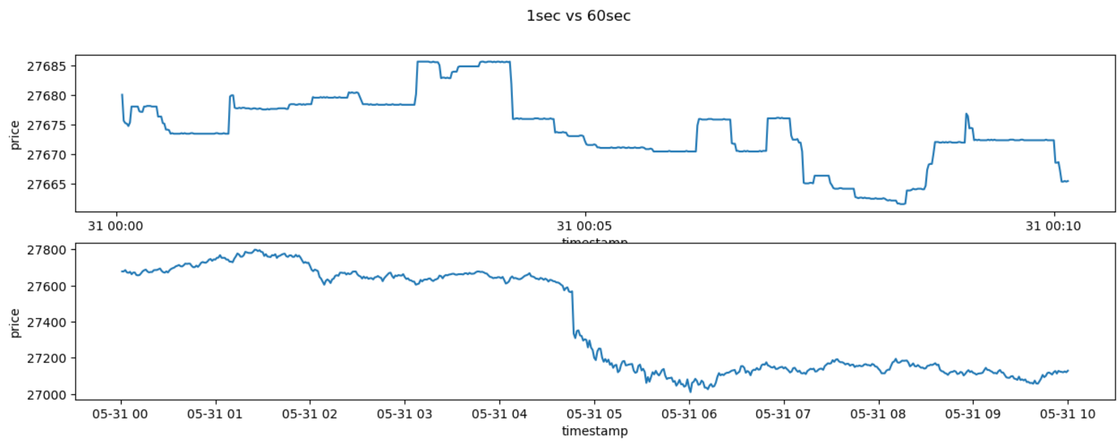
[7]:
```
one_sec = closed_time_series(df, 1)[:600]
one_min = closed_time_series(df, 60)[:600]

fig, axs = plt.subplots(1, 2, figsize=(15, 5))
fig.suptitle('1sec vs 60sec')
sns.histplot(data=one_sec, x='return', bins=100, ax=axs[0], kde=True)
sns.histplot(data=one_min, x='return', bins=100, ax=axs[1], kde=True)
axs[0].set_ylabel('frequency')
axs[1].set_ylabel('frequency')
plt.show()
```



2.2 Discreteness

The discreteness refers to the occurrence of discrete jumps or sudden changes in prices rather than continuous movements. This can be observed by plotting the intraday price series and examining whether there are frequent instances where prices exhibit sharp discontinuities or large jumps within short time intervals.

[9]:
```
fig, axs = plt.subplots(2, 1, figsize=(15, 5))
# one_min_slice = one_min[:600]
# one_sec_slice = one_sec[:600]
fig.suptitle('1sec vs 60sec')
sns.lineplot(data=one_sec, x=one_sec.index, y='price', ax=axs[0])
sns.lineplot(data=one_min, x=one_min.index, y='price', ax=axs[1])
plt.show()
```



2.3 Exception Case : BTC/TUSD with zero trading fee

Recently, Binance initiated a zero trading fee promotion for the BTC/TUSD spot pair. This is an excellent opportunity for both regular traders and market makers as they can trade without incurring any fees. However, this has led to some interesting phenomena. In very short time durations, there are numerous price movements which are continuous.

This might be due to the increase in 'noise traders' who operate on incomplete information and typically have shorter trading durations. The absence of trading fees may encourage more noise traders to participate, leading to more frequent and continuous price movements.

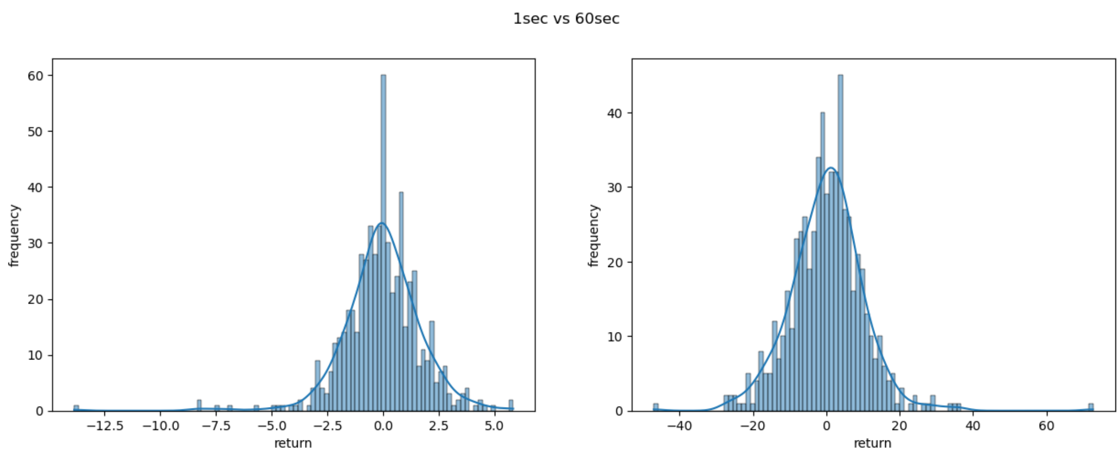
However, a comprehensive understanding of these phenomena would require expertise in market microstructure theory.

[10]:
```
header = ['number','price','quantity','start trade','end␣
↪trade','timestamp','s','is_buyer_maker']
df = pd.read_csv('./BTCTUSD-aggTrades-2023-06-27.csv',header=0 , names = header)
df.head()
```

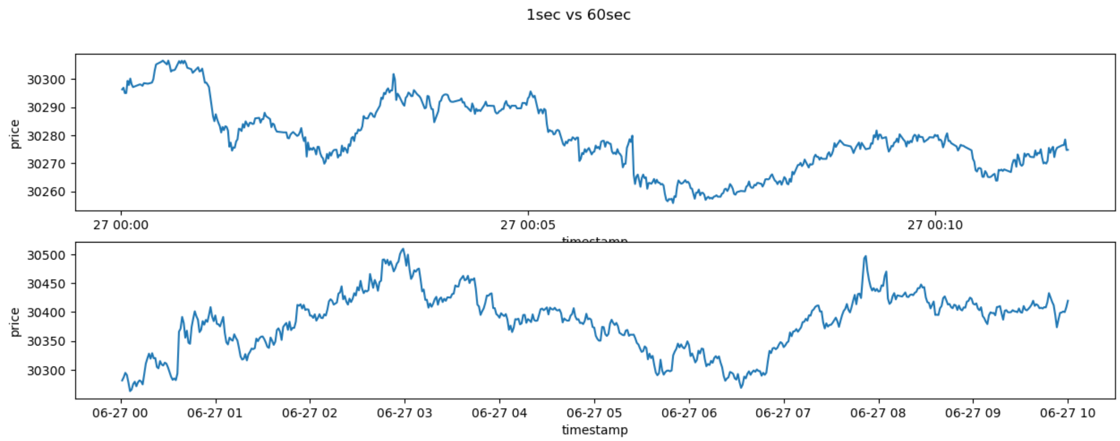
[10]:
```
      number     price  quantity  start trade  end trade      timestamp     s  \
0  173017437  30295.75   0.00181    215415073  215415073  1687824000301  True
1  173017438  30295.75   0.00472    215415074  215415074  1687824000308  True
```

```
2  173017439  30295.72   0.00128    215415075  215415075  1687824000308  True
3  173017440  30295.64   0.00132    215415076  215415076  1687824000308  True
4  173017441  30295.60   0.00400    215415077  215415078  1687824000308  True

   is_buyer_maker
0            True
1            True
2            True
3            True
4            True
```

[11]:
```python
one_sec = closed_time_series(df, 1)[:600]
one_min = closed_time_series(df, 60)[:600]

fig, axs = plt.subplots(1, 2, figsize=(15, 5))
fig.suptitle('1sec vs 60sec')
sns.histplot(data=one_sec, x='return', bins=100, ax=axs[0], kde=True)
sns.histplot(data=one_min, x='return', bins=100, ax=axs[1], kde=True)
axs[0].set_ylabel('frequency')
axs[1].set_ylabel('frequency')
plt.show()
```



[12]:
```python
fig, axs = plt.subplots(2, 1, figsize=(15, 5))
# one_min_slice = one_min[:600]
# one_sec_slice = one_sec[:600]
fig.suptitle('1sec vs 60sec')
sns.lineplot(data=one_sec, x=one_sec.index, y='price', ax=axs[0])
sns.lineplot(data=one_min, x=one_min.index, y='price', ax=axs[1])
plt.show()
```


1sec vs 60sec
price
30300
30290
30280
30270
30260
27 00:00
27 00:05
27 00:10
price
30500
30450
30400
30350
30300
06-27 00
06-27 01
06-27 02
06-27 03
06-27 04
06-27 05
06-27 06
06-27 07
06-27 08
06-27 09
06-27 10
timestamp