03_normalize_tick_data

September 29, 2021

1 Analyze Order Book Data

1.1 Imports & Settings

[1]:
```
import pandas as pd
from pathlib import Path
import numpy as np
import seaborn as sns
import matplotlib as mpl
import matplotlib.pyplot as plt
from matplotlib.ticker import FuncFormatter
from math import pi
from bokeh.plotting import figure, show
from scipy.stats import normaltest
```

[2]:
```
%matplotlib inline
pd.set_option('display.float_format', lambda x: '%.2f' % x)
sns.set_style('whitegrid')
```

[3]:
```
data_path = Path('data')
itch_store = str(data_path / 'itch.h5')
order_book_store = str(data_path / 'order_book.h5')
stock = 'AAPL'
date = '20191030'
title = '{} | {}'.format(stock, pd.to_datetime(date).date())
```

1.2 Load system event data

[4]:
```
with pd.HDFStore(itch_store) as store:
    sys_events = store['S'].set_index('event_code').drop_duplicates()
    sys_events.timestamp = sys_events.timestamp.add(pd.to_datetime(date)).dt.
↪time
    market_open = sys_events.loc['Q', 'timestamp']
    market_close = sys_events.loc['M', 'timestamp']
```

1.3 Trade Summary

We will combine the messages that refer to actual trades to learn about the volumes for each asset.

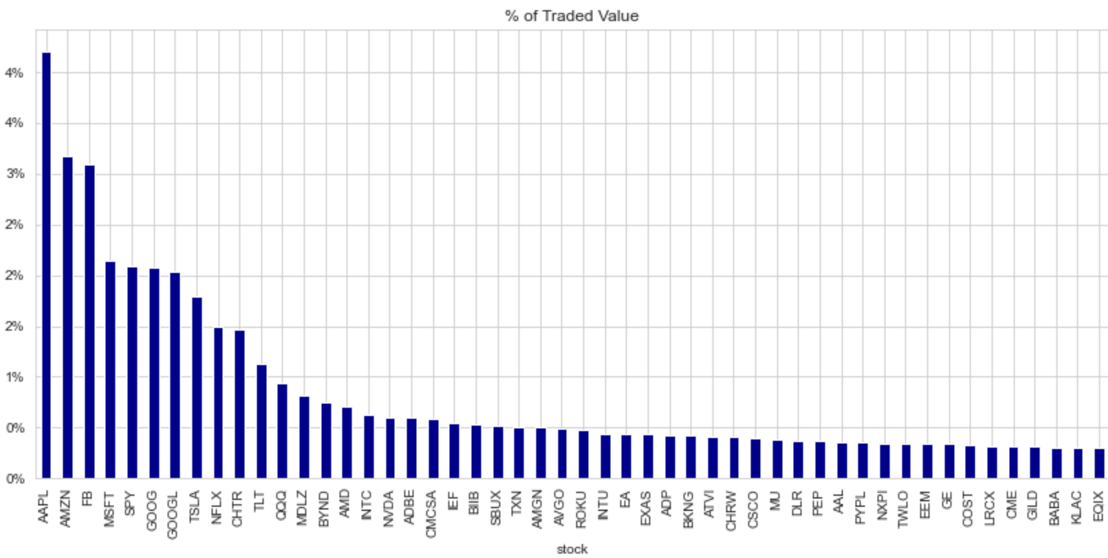
[5]:
```
with pd.HDFStore(itch_store) as store:
    stocks = store['R']
stocks.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 8887 entries, 0 to 8886
Data columns (total 17 columns):
 #   Column                        Non-Null Count  Dtype
---  ------                        --------------  -----
 0   stock_locate                  8887 non-null   int64
 1   tracking_number               8887 non-null   int64
 2   timestamp                     8887 non-null   timedelta64[ns]
 3   stock                         8887 non-null   object
 4   market_category               8887 non-null   object
 5   financial_status_indicator    8887 non-null   object
 6   round_lot_size                8887 non-null   int64
 7   round_lots_only               8887 non-null   object
 8   issue_classification          8887 non-null   object
 9   issue_sub_type                8887 non-null   object
 10  authenticity                  8887 non-null   object
 11  short_sale_threshold_indicator 8887 non-null   object
 12  ipo_flag                      8887 non-null   object
 13  luld_reference_price_tier     8887 non-null   object
 14  etp_flag                      8887 non-null   object
 15  etp_leverage_factor           8887 non-null   int64
 16  inverse_indicator             8887 non-null   object
dtypes: int64(4), object(12), timedelta64[ns](1)
memory usage: 1.2+ MB
```

As expected, a small number of the over 8,500 equity securities traded on this day account for most trades

[6]:
```
with pd.HDFStore(itch_store) as store:
    stocks = store['R'].loc[:, ['stock_locate', 'stock']]
    trades = store['P'].append(store['Q'].rename(columns={'cross_price':␣
 ↪'price'}), sort=False).merge(stocks)

trades['value'] = trades.shares.mul(trades.price)
trades['value_share'] = trades.value.div(trades.value.sum())
trade_summary = trades.groupby('stock').value_share.sum().
 ↪sort_values(ascending=False)
trade_summary.iloc[:50].plot.bar(figsize=(14, 6), color='darkblue', title='% of␣
 ↪Traded Value')
plt.gca().yaxis.set_major_formatter(FuncFormatter(lambda y, _: '{:.0%}'.
 ↪format(y)))
```



1.4 AAPL Trade Summary

[7]:
```
with pd.HDFStore(order_book_store) as store:
    trades = store['{}/trades'.format(stock)]
```

[8]:
```
trades.price = trades.price.mul(1e-4) # format price
trades = trades[trades.cross == 0]
trades = trades.between_time(market_open, market_close).drop('cross', axis=1)
trades.info()
```

```
<class 'pandas.core.frame.DataFrame'>
DatetimeIndex: 58713 entries, 2019-10-30 09:30:00.010384780 to 2019-10-30
15:59:59.979015439
Data columns (total 2 columns):
 #   Column  Non-Null Count  Dtype
---  ------  --------------  -----
 0   shares  58713 non-null  int64
 1   price   58713 non-null  float64
dtypes: float64(1), int64(1)
memory usage: 1.3 MB
```

1.5 Tick Bars

The trade data is indexed by nanoseconds and is very noisy. The bid-ask bounce, for instance, causes the price to oscillate between the bid and ask prices when trade initiation alternates between buy and sell market orders. To improve the noise-signal ratio and improve the statistical properties, we need to resample and regularize the tick data by aggregating the trading activity.

We typically collect the open (first), low, high, and closing (last) price for the aggregated period, alongside the volume-weighted average price (VWAP), the number of shares traded, and the timestamp associated with the data.

[9]:
```
tick_bars = trades.copy()
tick_bars.index = tick_bars.index.time
tick_bars.price.plot(figsize=(10, 5),
                     title='Tick Bars | {} | {}'.format(stock, pd.
 ↪to_datetime(date).date()), lw=1)
plt.xlabel('')
plt.tight_layout();
```

1.5.1 Test for Normality of tick returns

[10]:
```
normaltest(tick_bars.price.pct_change().dropna())
```

[10]:
```
NormaltestResult(statistic=20684.40456159484, pvalue=0.0)
```

1.6 Regularizing Tick Data

1.6.1 Price-Volume Chart

We will use the `price_volume` function to compare the price-volume relation for various regularization methods.

[11]:
```
def price_volume(df, price='vwap', vol='vol', suptitle=title, fname=None):

    fig, axes = plt.subplots(nrows=2, sharex=True, figsize=(15,8))
    axes[0].plot(df.index, df[price])
    axes[1].bar(df.index, df[vol], width=1/(5*len(df.index)), color='r')
```

```python
    # formatting
    xfmt = mpl.dates.DateFormatter('%H:%M')
    axes[1].xaxis.set_major_locator(mpl.dates.HourLocator(interval=3))
    axes[1].xaxis.set_major_formatter(xfmt)
    axes[1].get_xaxis().set_tick_params(which='major', pad=25)
    axes[0].set_title('Price', fontsize=14)
    axes[1].set_title('Volume', fontsize=14)
    fig.autofmt_xdate()
    fig.suptitle(suptitle)
    fig.tight_layout()
    plt.subplots_adjust(top=0.9);
```

1.6.2 Time Bars

Time bars involve trade aggregation by period.

[12]:
```python
def get_bar_stats(agg_trades):
    vwap = agg_trades.apply(lambda x: np.average(x.price, weights=x.shares)).
 ↪to_frame('vwap')
    ohlc = agg_trades.price.ohlc()
    vol = agg_trades.shares.sum().to_frame('vol')
    txn = agg_trades.shares.size().to_frame('txn')
    return pd.concat([ohlc, vwap, vol, txn], axis=1)
```

We create time bars using the `.resample()` method with the desired period.

[13]:
```python
resampled = trades.groupby(pd.Grouper(freq='1Min'))
time_bars = get_bar_stats(resampled)
normaltest(time_bars.vwap.pct_change().dropna())
```

[13]:
```
NormaltestResult(statistic=65.70387182967823, pvalue=5.402384769537968e-15)
```

[14]:
```python
price_volume(time_bars,
             suptitle=f'Time Bars | {stock} | {pd.to_datetime(date).date()}',
             fname='time_bars')
```

1.6.3 Bokeh Candlestick Chart

Alternative visualization using the the bokeh library:

[15]:
```
resampled = trades.groupby(pd.Grouper(freq='5Min')) # 5 Min bars for better␣
↪print
df = get_bar_stats(resampled)

increase = df.close > df.open
decrease = df.open > df.close
w = 2.5 * 60 * 1000 # 2.5 min in ms

WIDGETS = "pan, wheel_zoom, box_zoom, reset, save"

p = figure(x_axis_type='datetime', tools=WIDGETS, plot_width=1500, title =␣
↪"AAPL Candlestick")
p.xaxis.major_label_orientation = pi/4
p.grid.grid_line_alpha=0.4

p.segment(df.index, df.high, df.index, df.low, color="black")
p.vbar(df.index[increase], w, df.open[increase], df.close[increase],␣
↪fill_color="#D5E1DD", line_color="black")
p.vbar(df.index[decrease], w, df.open[decrease], df.close[decrease],␣
↪fill_color="#F2583E", line_color="black")
show(p)
```

1.6.4 Volume Bars

Time bars smooth some of the noise contained in the raw tick data but may fail to account for the fragmentation of orders. Execution-focused algorithmic trading may aim to match the volume weighted average price (VWAP) over a given period, and will divide a single order into multiple trades and place orders according to historical patterns. Time bars would treat the same order differently, even though no new information has arrived in the market.

Volume bars offer an alternative by aggregating trade data according to volume. We can accomplish this as follows:

[16]:
```
with pd.HDFStore(order_book_store) as store:
    trades = store['{}/trades'.format(stock)]

trades.price = trades.price.mul(1e-4)
trades = trades[trades.cross == 0]
trades = trades.between_time(market_open, market_close).drop('cross', axis=1)
trades.info()
```

```
<class 'pandas.core.frame.DataFrame'>
DatetimeIndex: 58713 entries, 2019-10-30 09:30:00.010384780 to 2019-10-30
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 1   price   58713 non-null  float64
dtypes: float64(1), int64(1)
memory usage: 1.3 MB
```

[17]:
```
trades_per_min = trades.shares.sum()/(60*7.5) # min per trading day
trades['cumul_vol'] = trades.shares.cumsum()
```

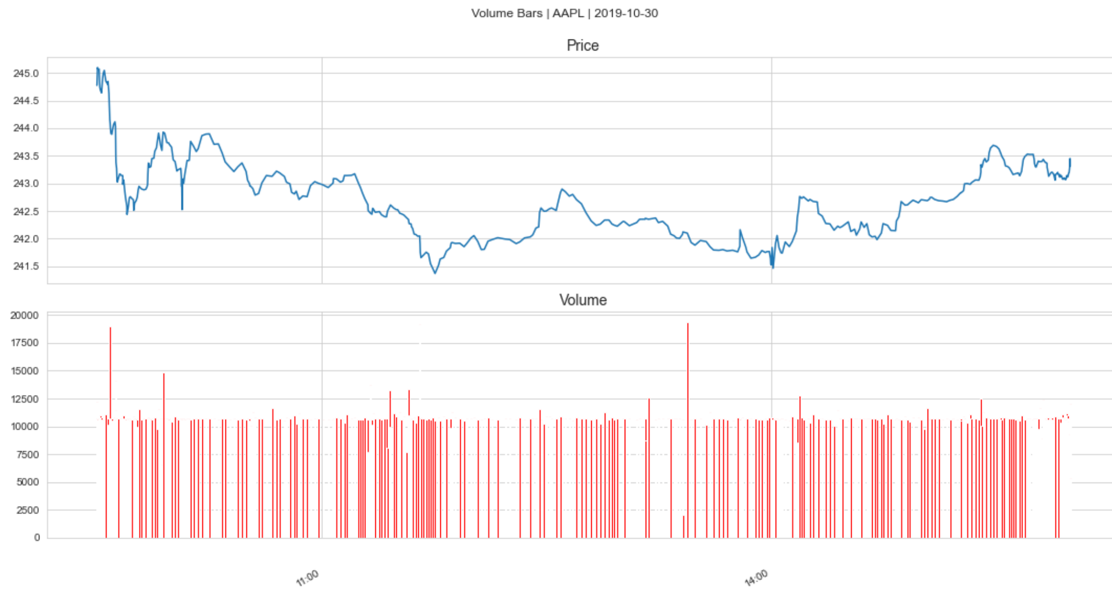
[18]:
```
df = trades.reset_index()
by_vol = df.groupby(df.cumul_vol.div(trades_per_min).round().astype(int))
vol_bars = pd.concat([by_vol.timestamp.last().to_frame('timestamp'),␣
↪get_bar_stats(by_vol)], axis=1)
vol_bars.head()
```

[18]:
```
                              timestamp   open   high    low  close   vwap  \
cumul_vol
0         2019-10-30 09:30:01.658183871 244.83 244.94 244.72 244.82 244.77
1         2019-10-30 09:30:02.124784227 244.82 244.85 244.76 244.77 244.79
2         2019-10-30 09:30:04.690393971 244.77 244.97 244.66 244.97 244.80
3         2019-10-30 09:30:13.816494419 244.98 245.00 244.88 245.00 244.98
4         2019-10-30 09:30:17.522394656 245.00 245.25 245.00 245.10 245.10

             vol  txn
cumul_vol
```

```
0            5317   57
1            9127   44
2           12257   76
3           10675  124
4           10679  118
```

[19]:
```
price_volume(vol_bars.set_index('timestamp'),
             suptitle=f'Volume Bars | {stock} | {pd.to_datetime(date).date()}',
             fname='volume_bars')
```



[20]:
```
normaltest(vol_bars.vwap.dropna())
```

[20]: NormaltestResult(statistic=26.54669921949387, pvalue=1.7197190736584466e-06)

1.6.5 Dollar Bars

[21]:
```
with pd.HDFStore(order_book_store) as store:
    trades = store['{}/trades'.format(stock)]

trades.price = trades.price.mul(1e-4)
trades = trades[trades.cross == 0]
trades = trades.between_time(market_open, market_close).drop('cross', axis=1)
trades.info()
```

```
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Data columns (total 2 columns):
```

```
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 1   price   58713 non-null  float64
dtypes: float64(1), int64(1)
memory usage: 1.3 MB
```

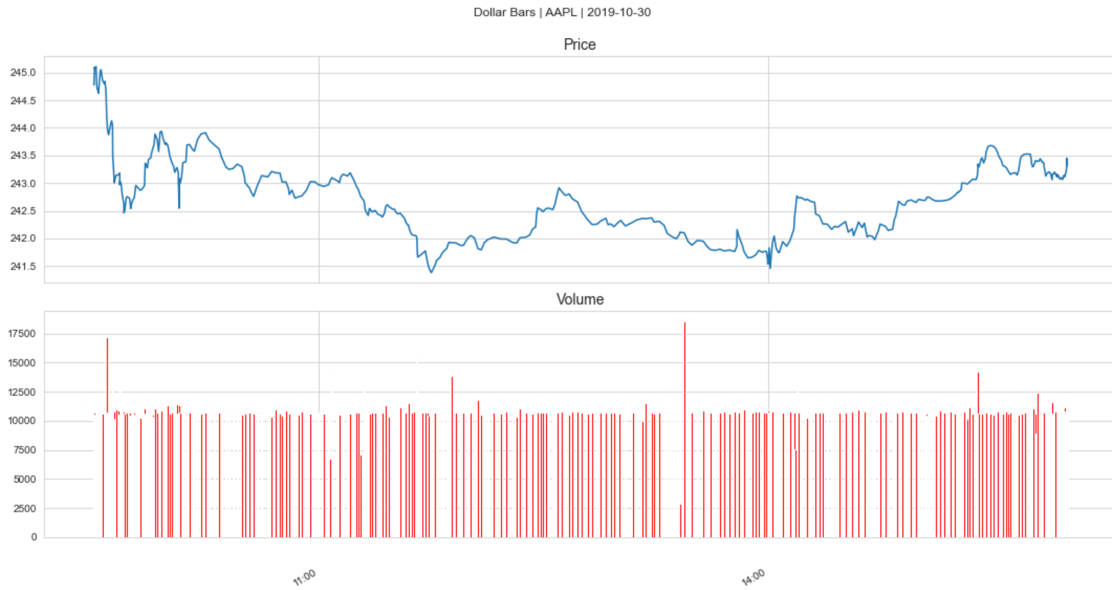
[22]:
```
value_per_min = trades.shares.mul(trades.price).sum()/(60*7.5) # min per␣
↪trading day
trades['cumul_val'] = trades.shares.mul(trades.price).cumsum()
```

[23]:
```
df = trades.reset_index()
by_value = df.groupby(df.cumul_val.div(value_per_min).round().astype(int))
dollar_bars = pd.concat([by_value.timestamp.last().to_frame('timestamp'),␣
↪get_bar_stats(by_value)], axis=1)
dollar_bars.head()
```

[23]:
```
                              timestamp    open    high     low   close    vwap  \
cumul_val
0         2019-10-30 09:30:01.658171058 244.83 244.94 244.72 244.82 244.77
1         2019-10-30 09:30:02.124784227 244.82 244.85 244.76 244.77 244.79
2         2019-10-30 09:30:04.095544194 244.77 244.96 244.66 244.87 244.80
3         2019-10-30 09:30:13.816494419 244.87 245.00 244.87 245.00 244.98
4         2019-10-30 09:30:17.522098123 245.00 245.25 245.00 245.13 245.09

             vol  txn
cumul_val
0           5287   56
1           9157   45
2          12047   71
3          10474  127
4          10690  116
```

[24]:
```
price_volume(dollar_bars.set_index('timestamp'),
             suptitle=f'Dollar Bars | {stock} | {pd.to_datetime(date).date()}',
             fname='dollar_bars')
```


Dollar Bars | AAPL | 2019-10-30
Price
245.0
244.5
244.0
243.5
243.0
242.5
242.0
241.5
Volume
17500
15000
12500
10000
7500
5000
2500
0
11:00
14:00