```
import numpy as np
import pandas as pd
weather = pd.read_csv('/content/nyc_weather_2018.csv', parse_dates=['date'])
weather.head()
```

	attributes	datatype	date	station	value
0	,,N,	PRCP	2018-01-01	GHCND:US1CTFR0039	0.0
1	,,N,	PRCP	2018-01-01	GHCND:US1NJBG0015	0.0
2	,,N,	SNOW	2018-01-01	GHCND:US1NJBG0015	0.0
3	,,N,	PRCP	2018-01-01	GHCND:US1NJBG0017	0.0
4	,,N,	SNOW	2018-01-01	GHCND:US1NJBG0017	0.0

```
fb = pd.read_csv('/content/fb_2018.csv', index_col='date', parse_dates=True)

fb.head()
```

date	open	high	low	close	volume
2018-01-02	177.68	181.58	177.5500	181.42	18151903
2018-01-03	181.88	184.78	181.3300	184.67	16886563
2018-01-04	184.90	186.21	184.0996	184.33	13880896
2018-01-05	185.59	186.90	184.9300	186.85	13574535
2018-01-08	187.20	188.90	186.3300	188.28	17994726

```
fb.assign(
abs_z_score_volume=lambda x: x.volume.sub(x.volume.mean()).div(x.volume.std()).abs()
).query('abs_z_score_volume > 3')
```

date	open	high	low	close	volume	abs_z_score_volume
2018-03-19	177.01	177.17	170.06	172.56	88140060	3.145078
2018-03-20	167.47	170.20	161.95	168.15	129851768	5.315169
2018-03-21	164.80	173.40	163.30	169.39	106598834	4.105413
2018-03-26	160.82	161.10	149.02	160.06	126116634	5.120845
2018-07-26	174.89	180.13	173.75	176.26	169803668	7.393705

```
fb.assign(
volume_pct_change=fb.volume.pct_change(),
pct_change_rank=lambda x: x.volume_pct_change.abs().rank(
ascending=False
)
).nsmallest(5, 'pct_change_rank')
```

date	open	high	low	close	volume	volume_pct_change	pct_change_rank
2018-01-12	178.06	181.48	177.40	179.37	77551299	7.087876	1.0
2018-03-19	177.01	177.17	170.06	172.56	88140060	2.611789	2.0
2018-07-26	174.89	180.13	173.75	176.26	169803668	1.628841	3.0
2018-09-							

```
fb['2018-01-11':'2018-01-12']
```

date	open	high	low	close	volume
2018-01-11	188.40	188.40	187.38	187.77	9588587
2018-01-12	178.06	181.48	177.40	179.37	77551299

```
(fb > 215).any()
```

```
open       True
high       True
low       False
close      True
volume     True
dtype: bool
```

```
(fb > 215).all()
```

```
open      False
high      False
low       False
close     False
volume     True
dtype: bool
```

```
(fb.volume.value_counts() > 1).sum()
```

```
0
```

```
volume_binned = pd.cut(fb.volume, bins=3, labels=['low', 'med', 'high'])
volume_binned.value_counts()
```

```
low     240
med       8
high      3
Name: volume, dtype: int64
```

```
fb[volume_binned == 'high'].sort_values(
'volume', ascending=False
)
```

date	open	high	low	close	volume
2018-07-26	174.89	180.13	173.75	176.26	169803668
2018-03-20	167.47	170.20	161.95	168.15	129851768
2018-03-26	160.82	161.10	149.02	160.06	126116634

```
fb['2018-07-25':'2018-07-26']
```

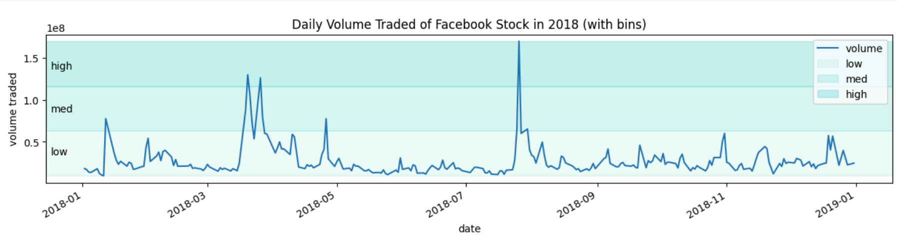
date	open	high	low	close	volume
2018-07-25	215.715	218.62	214.27	217.50	64592585
2018-07-26	174.890	180.13	173.75	176.26	169803668

```
fb['2018-03-16':'2018-03-20']
```

date	open	high	low	close	volume
2018-03-16	184.49	185.33	183.41	185.09	24403438
2018-03-19	177.01	177.17	170.06	172.56	88140060
2018-03-20	167.47	170.20	161.95	168.15	129851768

```
import matplotlib.pyplot as plt
```

```
fb.plot(y='volume', figsize=(15, 3), title='Daily Volume Traded of Facebook Stock in 2018 (with bins)')

for bin_name, alpha, bounds in zip(
    ['low', 'med', 'high'], [0.1, 0.2, 0.3], pd.cut(fb.volume, bins=3).unique().categories.values
):
    plt.axhspan(bounds.left, bounds.right, alpha=alpha, label=bin_name, color='mediumturquoise')
    plt.annotate(bin_name, xy=('2017-12-17', (bounds.left + bounds.right)/2.1))

plt.ylabel('volume traded')
plt.legend()
plt.show()
```

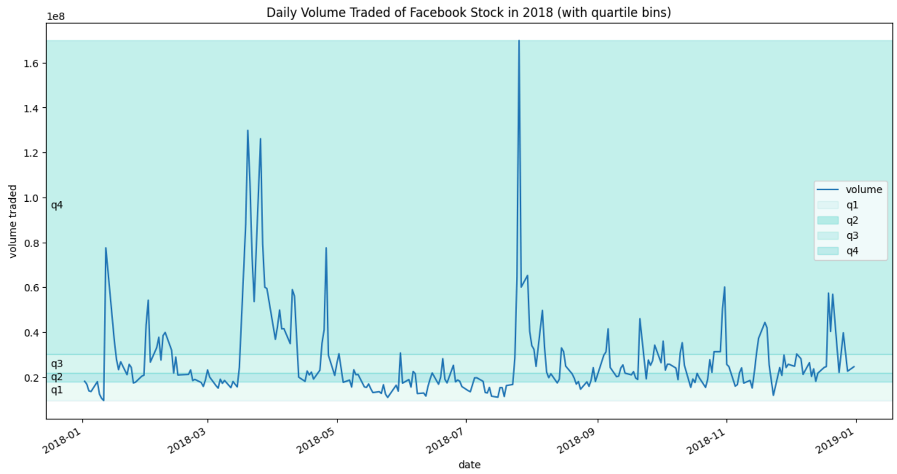



```
volume_qbinned = pd.qcut(fb.volume, q=4, labels=['q1', 'q2', 'q3', 'q4'])
volume_qbinned.value_counts()
```

```
q1    63
q2    63
q4    63
q3    62
Name: volume, dtype: int64
```

```
fb.plot(y='volume', figsize=(15, 8), title='Daily Volume Traded of Facebook Stock in 2018 (with quartile bins)')

for bin_name, alpha, bounds in zip(
    ['q1', 'q2', 'q3', 'q4'], [0.1, 0.35, 0.2, 0.3], pd.qcut(fb.volume, q=4).unique().categories.values
):
    plt.axhspan(bounds.left, bounds.right, alpha=alpha, label=bin_name, color='mediumturquoise')
    plt.annotate(bin_name, xy=('2017-12-17', (bounds.left + bounds.right)/2.1))
```

```
plt.ylabel('volume traded')
plt.legend()
plt.show()
```




```
central_park_weather = weather.query(
   'station == "GHCND:USW00094728"'
).pivot(index='date', columns='datatype', values='value')
```

```
central_park_weather.SNOW.clip(0, 1).value_counts()
```

```
0.0    354
1.0     11
Name: SNOW, dtype: int64
```

```
oct_weather_z_scores = central_park_weather.loc[
'2018-10', ['TMIN', 'TMAX', 'PRCP']
].apply(lambda x: x.sub(x.mean()).div(x.std()))
oct_weather_z_scores.describe().T
```

	count	mean	std	min	25%	50%	75%	max
datatype								
TMIN	31.0	-1.790682e-16	1.0	-1.339112	-0.751019	-0.474269	1.065152	1.843511
TMAX	31.0	1.951844e-16	1.0	-1.305582	-0.870013	-0.138258	1.011643	1.604016
PRCP	31.0	4.655774e-17	1.0	-0.394438	-0.394438	-0.394438	-0.240253	3.936167

```
oct_weather_z_scores.query('PRCP > 3')
```

datatype	TMIN	TMAX	PRCP
date			
2018-10-27	-0.751019	-1.201045	3.936167

```
central_park_weather.loc['2018-10', 'PRCP'].describe()
```

```
count    31.000000
mean      2.941935
std       7.458542
min       0.000000
25%       0.000000
50%       0.000000
75%       1.150000
max      32.300000
Name: PRCP, dtype: float64
```

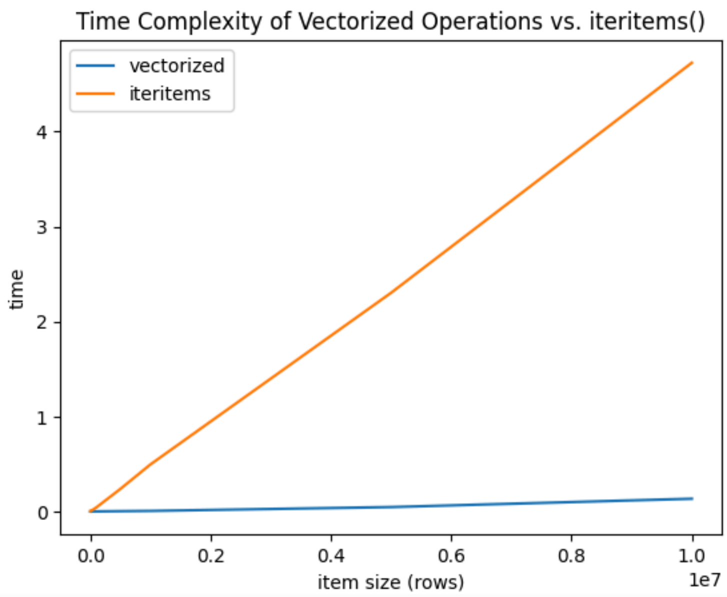
```
import numpy as np
fb.apply(
lambda x: np.vectorize(lambda y: len(str(np.ceil(y))))(x)
).astype('int64').equals(
fb.applymap(lambda x: len(str(np.ceil(x))))
)
```

```
True
```

```
import time
import matplotlib.pyplot as plt
import numpy as np
import pandas as pd
```

```
np.random.seed(0)
vectorized_results = {}
iteritems_results = {}

for size in [10, 100, 1000, 10000, 100000, 500000, 1000000, 5000000, 10000000]:
    test = pd.Series(np.random.uniform(size=size))

    start = time.time()
    x = test + 10
    end = time.time()
    vectorized_results[size] = end - start

    start = time.time()
    x = []
    for i, v in test.iteritems():
        x.append(v + 10)
    x = pd.Series(x)
    end = time.time()
    iteritems_results[size] = end - start

pd.DataFrame(
    [pd.Series(vectorized_results, name='vectorized'), pd.Series(iteritems_results, name='iteritems')]
).T.plot(title='Time Complexity of Vectorized Operations vs. iteritems()')

plt.xlabel('item size (rows)')
plt.ylabel('time')
plt.show()
```

```
<ipython-input-28-f1a67f4a94a1>:20: FutureWarning: iteritems is deprecated and will be r
  for i, v in test.iteritems():
```




```
central_park_weather['2018-10'].assign(
rolling_PRCP=lambda x: x.PRCP.rolling('3D').sum()
)[['PRCP', 'rolling_PRCP']].head(7).T
```

```
<ipython-input-29-289d253875a5>:1: FutureWarning: Indexing a DataFrame with a datetimeli
  central_park_weather['2018-10'].assign(
```

date	2018-10-01	2018-10-02	2018-10-03	2018-10-04	2018-10-05	2018-10-06	2018-10-07
datatype							
PRCP	0.0	17.5	0.0	1.0	0.0	0.0	0.0
rolling_PRCP	0.0	17.5	17.5	18.5	1.0	1.0	0.0

```
central_park_weather['2018-10'].rolling('3D').mean().head(7).iloc[:,:6]
```

```
<ipython-input-30-2abb37634d3b>:1: FutureWarning: Indexing a DataFrame with a datetimeli
  central_park_weather['2018-10'].rolling('3D').mean().head(7).iloc[:,:6]
```

datatype	AWND	PRCP	SNOW	SNWD	TMAX	TMIN
date						
2018-10-01	0.900000	0.000000	0.0	0.0	24.400000	17.200000
2018-10-02	0.900000	8.750000	0.0	0.0	24.700000	17.750000
2018-10-03	0.966667	5.833333	0.0	0.0	24.233333	17.566667
2018-10-04	0.800000	6.166667	0.0	0.0	24.233333	17.200000
2018-10-05	1.033333	0.333333	0.0	0.0	23.133333	16.300000
2018-10-06	0.833333	0.333333	0.0	0.0	22.033333	16.300000
2018-10-07	1.066667	0.000000	0.0	0.0	22.600000	17.400000

```
central_park_weather['2018-10-01':'2018-10-07'].rolling('3D').agg(
{'TMAX': 'max', 'TMIN': 'min', 'AWND': 'mean', 'PRCP': 'sum'}
).join( # join with original data for comparison
central_park_weather[['TMAX', 'TMIN', 'AWND', 'PRCP']],
lsuffix='_rolling'
```

```
).sort_index(axis=1) # sort columns so rolling calcs are next to originals
```

datatype date	AWND	AWND_rolling	PRCP	PRCP_rolling	TMAX	TMAX_rolling	TMIN	TMIN_rolling
2018-10-01	0.9	0.900000	0.0	0.0	24.4	24.4	17.2	17.2
2018-10-02	0.9	0.900000	17.5	17.5	25.0	25.0	18.3	17.2
2018-10-03	1.1	0.966667	0.0	17.5	23.3	25.0	17.2	17.2
2018-10-04	0.4	0.800000	1.0	18.5	24.4	25.0	16.1	16.1

```
central_park_weather.PRCP.expanding().sum().equals(central_park_weather.PRCP.cumsum())
```

```
False
```

```
central_park_weather['2018-10-01':'2018-10-07'].expanding().agg(
{'TMAX': np.max, 'TMIN': np.min, 'AWND': np.mean, 'PRCP': np.sum}
).join(
central_park_weather[['TMAX', 'TMIN', 'AWND', 'PRCP']],
lsuffix='_expanding'
).sort_index(axis=1)
```

datatype date	AWND	AWND_expanding	PRCP	PRCP_expanding	TMAX	TMAX_expanding	TMIN	TMIN_e
2018-10-01	0.9	0.900000	0.0	0.0	24.4	24.4	17.2	
2018-10-02	0.9	0.900000	17.5	17.5	25.0	25.0	18.3	
2018-10-03	1.1	0.966667	0.0	17.5	23.3	25.0	17.2	
2018-10-04	0.4	0.825000	1.0	18.5	24.4	25.0	16.1	

```
fb.assign(
close_ewma=lambda x: x.close.ewm(span=5).mean()
).tail(10)[['close', 'close_ewma']]
```

date	close	close_ewma
2018-12-17	140.19	142.235433
2018-12-18	143.66	142.710289
2018-12-19	133.24	139.553526
2018-12-20	133.40	137.502350
2018-12-21	124.95	133.318234
2018-12-24	124.06	130.232156
2018-12-26	134.18	131.548104
2018-12-27	134.52	132.538736
2018-12-28	133.20	132.759157
2018-12-31	131.09	132.202772

```
def get_info(df):
    return '%d rows and %d columns and max closing z-score was %d' % (*df.shape, df.close.max())

fb['2018-Q1'].apply(lambda x: (x - x.mean())/x.std()).pipe(get_info)\
    == get_info(fb['2018-Q1'].apply(lambda x: (x - x.mean())/x.std()))
```

```
<ipython-input-39-f3245a45e137>:4: FutureWarning: Indexing a DataFrame with a datetimelike index using a single string to slice the rows
  fb['2018-Q1'].apply(lambda x: (x - x.mean())/x.std()).pipe(get_info)\
<ipython-input-39-f3245a45e137>:5: FutureWarning: Indexing a DataFrame with a datetimelike index using a single string to slice the rows
  == get_info(fb['2018-Q1'].apply(lambda x: (x - x.mean())/x.std()))
True
```

```
fb.pipe(pd.DataFrame.rolling, '20D').mean().equals(fb.rolling('20D').mean())
```

```
True
```

```
pd.DataFrame.rolling(fb, '20D').mean().equals(fb.rolling('20D').mean())
```

```
True
```

```
def window_calc(df, func, agg_dict, *args, **kwargs):
    """
    Run a window calculation of your choice on a DataFrame.

    Parameters:
        - df: The DataFrame to run the calculation on.
        - func: The window calculation method that takes df
              as the first argument.
        - agg_dict: Information to pass to `agg()`, could be a
                  dictionary mapping the columns to the aggregation
                  function to use, a string name for the function,
                  or the function itself.
        - args: Positional arguments to pass to `func`.
        - kwargs: Keyword arguments to pass to `func`.

    Returns:
        - A new DataFrame object.
    """
    return df.pipe(func, *args, **kwargs).agg(agg_dict)
```

```
window_calc(fb, pd.DataFrame.expanding, np.median).head()
```

date	open	high	low	close	volume
2018-01-02	177.68	181.580	177.5500	181.420	18151903.0
2018-01-03	179.78	183.180	179.4400	183.045	17519233.0
2018-01-04	181.88	184.780	181.3300	184.330	16886563.0
2018-01-05	183.39	185.495	182.7148	184.500	15383729.5
2018-01-08	184.90	186.210	184.0996	184.670	16886563.0

```
window_calc(fb, pd.DataFrame.ewm, 'mean', span=3).head()
```

date	open	high	low	close	volume
2018-01-02	177.680000	181.580000	177.550000	181.420000	1.815190e+07
2018-01-03	180.480000	183.713333	180.070000	183.586667	1.730834e+07
2018-01-04	183.005714	185.140000	182.372629	184.011429	1.534980e+07
2018-01-05	184.384000	186.078667	183.736560	185.525333	1.440299e+07
2018-01-08	185.837419	187.534839	185.075110	186.947097	1.625679e+07

```
window_calc(
central_park_weather['2018-10'],
pd.DataFrame.rolling,
{'TMAX': 'max', 'TMIN': 'min', 'AWND': 'mean', 'PRCP': 'sum'},
'3D'
).head()
```

```
<ipython-input-50-31ab72cfb87f>:2: FutureWarning: Indexing a DataFrame with a datetimeli
  central_park_weather['2018-10'],
```

datatype / date	TMAX	TMIN	AWND	PRCP
2018-10-01	24.4	17.2	0.900000	0.0
2018-10-02	25.0	17.2	0.900000	17.5
2018-10-03	25.0	17.2	0.966667	17.5
2018-10-04	25.0	16.1	0.800000	18.5
2018-10-05	24.4	15.6	1.033333	1.0

Comments

Covering a wide range of DataFrame operations, this document presents the versatility of pandas in performing arithmetic, statistics, binning, and more. Using Facebook's stock price and NYC weather data as examples, it demonstrates how to apply mathematical and statistical operations directly on DataFrames. These operations form the basis for more complex data analysis and manipulation tasks.

Conclusion

My takeaways is the use of the z-score for identifying outliers in Facebook's trading volume, showcasing the practical application of statistical methods in financial analysis. Similarly, the document's discussion on binning and thresholds offers insights into categorizing data, a useful technique for segmenting datasets into meaningful groups or ranges. These operations underscore the analytical power of pandas, enabling detailed exploratory data analysis and preprocessing for modeling.