Coursebook: Reshaping and Visualization

- Part 3 of Data Analytics Specialization
- Course Length: 12 hours
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Background

Top-Down Approach

The coursebook is part of the **Data Analytics Specialization** offered by Algoritma. It takes a more accessible approach compared to Algoritma's core educational products, by getting participants to overcome the "how" barrier first, rather than a detailed breakdown of the "why".

This translates to an overall easier learning curve, one where the reader is prompted to write short snippets of code in frequent intervals, before being offered an explanation on the underlying theoretical frameworks. Instead of mastering the syntactic design of the Python programming language, then moving into data structures, and then the `pandas` library, and then the mathematical details in an imputation algorithm, and its code implementation; we would do the opposite: Implement the imputation, then a succinct explanation of why it works and applicational considerations (what to look out for, what are assumptions it made, when *not* to use it etc).

Training Objectives

This coursebook is intended for participants who have completed the preceding courses offered in the **Data Analytics Developer Specialization**. This is the third course, **Reshaping and Visualization**.

The coursebook focuses on:

- Stacking and Unstacking
- Working with MultiIndex DataFrames
- Reshaping your DataFrame with Melt
- Using Group By Effectively
- Visual Data Exploratory

At the end of this course is a Learn by Building section, where you are expected to apply all that you've learned on a new dataset, and attempt the given questions.

Reproducible Environment

There are some new packages we'll use in this material. Usually, we can use `pip install` / `conda install` to install new libraries to our environment. But for now, let's try on another approach on preparing libraries needed for a certain project.

Imagine you're working with your team on a collaborative project. You initialize the project with certain dependencies and versions on your computer and all goes well. Later on, you need to 'ship' that project to your team which requires them to set up the same environment as yours. What would you do then to make sure that program will also runs smoothly on their machine?

This is where you need to make your environment reproducible by creating a `requirements.txt` file.

If you browse on `/assets` directory on this repository, you'll find a file called `requirements.txt`. This file is used for specifying what python packages are required to run a certain project. If you open up the file, you will see something that looks similar to this:

```
-----------------
matplotlib==3.5.0
numpy==1.21.4
pandas==1.3.4
yfinance==0.1.67
-----------------
```

Notice we have a line for each package, then a version number. This is important because as you start developing your python applications, you will develop the application with specific versions of the packages in mind. In simple, `requirements.txt` helps to keep track of what version of each package you are using to prevent unexpected changes.

Importing Requirements

We have discussed what the requirement files is for but how do we use it? Since we don't want to manually install and track every package needed for a certain project, let's try to import the requirements with the following steps:

Step 1: Prepare your current new environment and activate it

```
conda activate <ENV_NAME>
```

Step 2: Navigate to the folder with your `requirements.txt`

```
cd <PATH_TO_REQUIREMENTS>
```

Step 3: Install the requirements

```
pip install -r requirements.txt
```

Exporting Requirements

The `pip install` command always installs the latest published version of a package, but sometimes, you may want to install a specific version that you know works on your project.

Requirement files allow you to specify exactly which packages and versions should be installed. You can follow these steps to generate your requirement files:

Step 1: Activate desired environment

```
conda activate <ENV_NAME>
```

Step 2: Navigate to the folder where you want to save the `requirements.txt`

```
cd <PATH_TO_REQUIREMENTS_FOLDER>
```

Step 3: Freeze the environment

```
pip freeze > requirements.txt
```

The `freeze` command dumps all the packages and their versions to a standardized output. You can save it by any name you want but the convention is to name it as requirements.txt.

Now that you've discovered how to make your environment reproducible, we can back to our main focus of this week material; data reshaping and visualisation with pandas!

Data Wrangling and Reshaping

In the previous two courses, we've got our hands on a few common techniques and learned how to explore data using `pandas` built-in methods. Specifically, we've in the first and second part of this series how to use the following inspection, diagnostic and exploratory tools:

Data Inspection

- `.head()` and `.tail()`
- `.describe()`
- `.shape` and `.size`
- `.axes`
- `.dtypes`
- Subsetting using `.loc`, `.iloc` and conditionals

Diagnostic and Exploratory

- Tables
- Cross-Tables and Aggregates
- Using `aggfunc` for aggregate functions
- Pivot Tables
- Working with DateTime
- Working with Categorical Data
- Duplicates and Missing Value Treatment

The first half of this course serves as an extension from the last. We'll pick up some new techniques to supplement our EDA toolset. Let us begin with reshaping techniques.

In [1]:
```
import pandas as pd
import yfinance as data
pd.set_option('display.float_format', lambda x: '%.2f' % x) #display setting purpose
```

In [2]:
```
symbol = ['AAPL', 'FB', 'GOOGL']
start_date = '2018-01-01'
end_date = '2022-01-01'
stock = data.download(symbol, start_date, end_date)
stock.columns.names = ['Attributes', 'Symbols']
stock.head()
```

```
[*********************100%***********************]  3 of 3 completed
```

Out[2]:

Attributes	Adj Close			Close			High			Low	
Symbols	AAPL	FB	GOOGL	AAPL	FB	GOOGL	AAPL	FB	GOOGL	AAPL	FB	GOOGL
Date												
2018-01-02	41.19	181.42	1073.21	43.06	181.42	1073.21	43.08	181.58	1075.98	42.31	177.55	1053.02
2018-01-03	41.18	184.67	1091.52	43.06	184.67	1091.52	43.64	184.78	1096.10	42.99	181.33	1073.43
2018-01-04	41.37	184.33	1095.76	43.26	184.33	1095.76	43.37	186.21	1104.08	43.02	184.10	1094.26
2018-01-05	41.84	186.85	1110.29	43.75	186.85	1110.29	43.84	186.90	1113.58	43.26	184.93	1101.80
2018-01-08	41.69	188.28	1114.21	43.59	188.28	1114.21	43.90	188.90	1119.16	43.48	186.33	1110.00

If you do not have the `pandas_datareader` module installed, or if you're following along this coursebook without an active connection, you can instead load it from the serialized object I stored in your `data_cache` folder.

Creating the DataFrame object by reading from `pickle`:

- `stock = pd.read_pickle('data_cache/stock')`

Serializing the DataFrame object to a byte stream using `pickle`:

- `stock.to_pickle('data_cache/stock')`

In [3]:
```
# write dataframe into pickle
# stock.to_pickle('data_cache/stock')
```

In [4]:
```
stock = pd.read_pickle('data_cache/stock')
stock.head()
```

Out[4]:

Attributes	Adj Close			Close			High			Low		
Symbols	AAPL	FB	GOOGL	AAPL	FB	GOOGL	AAPL	FB	GOOGL	AAPL	FB	GOOGL
Date												
2018-01-02	41.25	181.42	1073.21	43.06	181.42	1073.21	43.08	181.58	1075.98	42.31	177.55	1053.02
2018-01-03	41.24	184.67	1091.52	43.06	184.67	1091.52	43.64	184.78	1096.10	42.99	181.33	1073.43
2018-01-04	41.43	184.33	1095.76	43.26	184.33	1095.76	43.37	186.21	1104.08	43.02	184.10	1094.26
2018-01-05	41.90	186.85	1110.29	43.75	186.85	1110.29	43.84	186.90	1113.58	43.26	184.93	1101.80
2018-01-08	41.75	188.28	1114.21	43.59	188.28	1114.21	43.90	188.90	1119.16	43.48	186.33	1110.00

Notice how the data frame is a multi-index data frame. If you pay close attention, you can see a 2 levels of column axis: `Attributes` and `Symbols`. If you were to subset the data using square bracket, you will be accessing the highest level index:

In [5]:
```
# access attribute `High`
stock['High']

# Otherwise, this code will raise an error
# stock['AAPL']
```

Out[5]:

Symbols	AAPL	FB	GOOGL
Date			
2018-01-02	43.08	181.58	1075.98
2018-01-03	43.64	184.78	1096.10
2018-01-04	43.37	186.21	1104.08
2018-01-05	43.84	186.90	1113.58
2018-01-08	43.90	188.90	1119.16
...	...	...	...
2021-09-28	144.75	349.60	2781.93
2021-09-29	144.45	345.23	2743.02
2021-09-30	144.38	342.80	2710.85
2021-10-01	142.92	345.02	2738.21
2021-10-04	142.21	335.94	2719.21

946 rows × 3 columns

Subsetting the `Close` column from the data frame will leave us with a single index column from the `Symbols` level.

Dive Deeper:

Create a DataFrame by subsetting only the `Close` columns. Name it `closingprice`. Then, use `.isna().sum()` to count the number of missing values in each of the columns present in `closingprice`.

If there are any missing values, use the `.fillna(method='ffill')` method to fill those missing values:

In [6]:
```
## Write your solution code here
```

If you pay close attention to the index of `stock`, you may already realized by now that there are days where no records were present. 2018-01-01, 2018-01-06, and 2018-01-07 were absent from our DataFrame because they happen to fall on weekends.

While the trading hours of different stock markets differ (the NYSE for example open its market floor from 9.30am to 4pm five days a week), on weekends as well as federal holidays all stock exchanges are closed for business.

We can create (or recreate) the index by passing in our own values. In the following cell we created a date range and create the index using that new date range:

In [7]:
```
pd.date_range(start="2019-01-01", end="2019-03-31")
```

Out[7]:
```
DatetimeIndex(['2019-01-01', '2019-01-02', '2019-01-03', '2019-01-04',
               '2019-01-05', '2019-01-06', '2019-01-07', '2019-01-08',
               '2019-01-09', '2019-01-10', '2019-01-11', '2019-01-12',
               '2019-01-13', '2019-01-14', '2019-01-15', '2019-01-16',
               '2019-01-17', '2019-01-18', '2019-01-19', '2019-01-20',
               '2019-01-21', '2019-01-22', '2019-01-23', '2019-01-24',
               '2019-01-25', '2019-01-26', '2019-01-27', '2019-01-28',
               '2019-01-29', '2019-01-30', '2019-01-31', '2019-02-01',
               '2019-02-02', '2019-02-03', '2019-02-04', '2019-02-05',
               '2019-02-06', '2019-02-07', '2019-02-08', '2019-02-09',
               '2019-02-10', '2019-02-11', '2019-02-12', '2019-02-13',
               '2019-02-14', '2019-02-15', '2019-02-16', '2019-02-17',
               '2019-02-18', '2019-02-19', '2019-02-20', '2019-02-21',
               '2019-02-22', '2019-02-23', '2019-02-24', '2019-02-25',
               '2019-02-26', '2019-02-27', '2019-02-28', '2019-03-01',
               '2019-03-02', '2019-03-03', '2019-03-04', '2019-03-05',
               '2019-03-06', '2019-03-07', '2019-03-08', '2019-03-09',
               '2019-03-10', '2019-03-11', '2019-03-12', '2019-03-13',
               '2019-03-14', '2019-03-15', '2019-03-16', '2019-03-17',
               '2019-03-18', '2019-03-19', '2019-03-20', '2019-03-21',
               '2019-03-22', '2019-03-23', '2019-03-24', '2019-03-25',
               '2019-03-26', '2019-03-27', '2019-03-28', '2019-03-29',
               '2019-03-30', '2019-03-31'],
              dtype='datetime64[ns]', freq='D')
```

In [8]:
```
closingprice = stock['Close']
quarter1 = pd.date_range(start="2019-01-01", end="2019-03-31")
closingprice = closingprice.reindex(quarter1)
closingprice
```

Out[8]:

Symbols	AAPL	FB	GOOGL
2019-01-01	NaN	NaN	NaN
2019-01-02	39.48	135.68	1054.68
2019-01-03	35.55	131.74	1025.47
2019-01-04	37.06	137.95	1078.07
2019-01-05	NaN	NaN	NaN
...	...	...	...
2019-03-27	47.12	165.87	1178.01
2019-03-28	47.18	165.55	1172.27
2019-03-29	47.49	166.69	1176.89
2019-03-30	NaN	NaN	NaN
2019-03-31	NaN	NaN	NaN

90 rows × 3 columns

Now use forward-fill to fill the `NA` values:

In [9]:
```
## Write your solution code here

closingprice.ffill()
```

Out[9]:

Symbols	AAPL	FB	GOOGL
2019-01-01	NaN	NaN	NaN
2019-01-02	39.48	135.68	1054.68
2019-01-03	35.55	131.74	1025.47
2019-01-04	37.06	137.95	1078.07
2019-01-05	37.06	137.95	1078.07
...	...	...	...
2019-03-27	47.12	165.87	1178.01
2019-03-28	47.18	165.55	1172.27
2019-03-29	47.49	166.69	1176.89
2019-03-30	47.49	166.69	1176.89
2019-03-31	47.49	166.69	1176.89

90 rows × 3 columns

`stack()` and `unstack()`

`stack()` stack the prescribed level(s) from columns to index and is particularly useful on DataFrames having a multi-level columns. It does so by "shifting" the columns to create new levels on its index.

This is easier understood when we just see an example. Notice that `stock` has a 2-level column (Attributes and Symbols) and 1-level index (Date):

In [10]:
```
stock.head(10)
```

Out[10]:

Attributes	Adj Close			Close			High			Low		
Symbols	AAPL	FB	GOOGL	AAPL	FB	GOOGL	AAPL	FB	GOOGL	AAPL	FB	GOOGL
Date												
2018-01-02	41.25	181.42	1073.21	43.06	181.42	1073.21	43.08	181.58	1075.98	42.31	177.55	1053.02
2018-01-03	41.24	184.67	1091.52	43.06	184.67	1091.52	43.64	184.78	1096.10	42.99	181.33	1073.43
2018-01-04	41.43	184.33	1095.76	43.26	184.33	1095.76	43.37	186.21	1104.08	43.02	184.10	1094.26
2018-01-05	41.90	186.85	1110.29	43.75	186.85	1110.29	43.84	186.90	1113.58	43.26	184.93	1101.80
2018-01-08	41.75	188.28	1114.21	43.59	188.28	1114.21	43.90	188.90	1119.16	43.48	186.33	1110.00
2018-01-09	41.74	187.87	1112.79	43.58	187.87	1112.79	43.76	188.80	1118.44	43.35	187.10	1108.20
2018-01-10	41.73	187.84	1110.14	43.57	187.84	1110.14	43.58	187.89	1112.78	43.25	185.63	1103.98
2018-01-11	41.97	187.77	1112.05	43.82	187.77	1112.05	43.87	188.40	1114.85	43.62	187.38	1106.48
2018-01-12	42.40	179.37	1130.65	44.27	179.37	1130.65	44.34	181.48	1131.30	43.91	177.40	1108.01
2018-01-16	42.19	178.39	1130.70	44.05	178.39	1130.70	44.85	181.75	1148.88	44.03	178.04	1126.66

When we stack the `stock` DataFrame, we shrink the number of levels on its column by one: `stock` now has 1-level column named `Attributes`:

In [11]:
```
stock.stack()
```

Out[11]:

	Attributes	Adj Close	Close	High	Low	Open	Volume
Date	Symbols						
2018-01-02	AAPL	41.25	43.06	43.08	42.31	42.54	102223600
	FB	181.42	181.42	181.58	177.55	177.68	18151900
	GOOGL	1073.21	1073.21	1075.98	1053.02	1053.02	1588300
2018-01-03	AAPL	41.24	43.06	43.64	42.99	43.13	118071600
	FB	184.67	184.67	184.78	181.33	181.88	16886600
...	...	...	...	...	...	...	...
2021-10-01	FB	343.01	343.01	345.02	338.64	341.61	14905300
	GOOGL	2730.86	2730.86	2738.21	2681.46	2688.95	1768000
2021-10-04	AAPL	139.14	139.14	142.21	138.27	141.76	98180300
	FB	326.23	326.23	335.94	322.70	335.53	42772900
	GOOGL	2673.19	2673.19	2719.21	2621.00	2719.21	2557900

2838 rows × 6 columns

`unstack()` does the opposite: it "shifts" the levels from index axis onto column axis. **Try and create a stack DataFrame, and then apply `unstack` on the new DataFrame to see it return to the original shape:**

In [12]:
```
## Write your code to try out .unstack() method here
```

Dive Deeper

Answer these following questions to ensure that you can continue for the next session:

1. How to swap the position (level) of Symbols and Attributes ?
2. Based on your knowledge, what company (symbol) worth invest on ? (You may look on its fluctuations, means, etc)

In [13]:
```
# Write your solution code here
```

Knowledge Check: Stack and Unstack

Which of the following statement is correct?

- [] `stack()` changes the DataFrame from wide to long
- [] `unstack()` changes the DataFrame from long to wide
- [] `unstack()` changes the DataFrame from wide to long

Melt

Speaking of reshaping a DataFrame from wide format to long, another method that should be in your toolset is `melt()`. Consider the following DataFrame, which is created from `pandas` MultiIndex Slicers method, `.xs()` (Abbreviation for 'Cross Section'):

In [14]:
```
aapl = stock.xs(key = 'GOOGL', level='Symbols', axis=1)
aapl.head()
```

Out[14]:

Attributes	Adj Close	Close	High	Low	Open	Volume
Date						
2018-01-02	1073.21	1073.21	1075.98	1053.02	1053.02	1588300
2018-01-03	1091.52	1091.52	1096.10	1073.43	1073.93	1565900
2018-01-04	1095.76	1095.76	1104.08	1094.26	1097.09	1302600
2018-01-05	1110.29	1110.29	1113.58	1101.80	1103.45	1512500
2018-01-08	1114.21	1114.21	1119.16	1110.00	1111.00	1232200

In [15]:
```
aapl.shape
```

Out[15]:
```
(946, 6)
```

The DataFrame above is wide: it has 329 rows and 6 columns. The `melt()` function gathers all the columns into one and store the value corresponding to each column such that the resulting DataFrame has 329 * 6 = 1,974 rows, along with the identifier and values columns:

In [16]:
```
aapl_melted = aapl.melt()
aapl_melted
```

Out[16]:

	Attributes	value
0	Adj Close	1073.21
1	Adj Close	1091.52
2	Adj Close	1095.76
3	Adj Close	1110.29
4	Adj Close	1114.21
...	...	...
5671	Volume	2288600.00
5672	Volume	1542400.00
5673	Volume	1899800.00
5674	Volume	1768000.00
5675	Volume	2557900.00

5676 rows × 2 columns

In [17]:
```
aapl_melted.shape
```

Out[17]:
```
(5676, 2)
```

Knowledge Check : What's the difference betweent melt and stack ?

We can optionally specify one or more columns to be identifier variables (`id_vars`), which treat all other columns as value variables (`value_vars`):

In [18]:
```
aapl.reset_index().melt(id_vars=['Date'])
```

Out[18]:

	Date	Attributes	value
0	2018-01-02	Adj Close	1073.21
1	2018-01-03	Adj Close	1091.52
2	2018-01-04	Adj Close	1095.76
3	2018-01-05	Adj Close	1110.29
4	2018-01-08	Adj Close	1114.21
...	...	...	...
5671	2021-09-28	Volume	2288600.00
5672	2021-09-29	Volume	1542400.00
5673	2021-09-30	Volume	1899800.00
5674	2021-10-01	Volume	1768000.00
5675	2021-10-04	Volume	2557900.00

5676 rows × 3 columns

In [19]:
```
aapl.reset_index().melt(value_vars=['High', 'Low'])
```

Out[19]:

	Attributes	value
0	High	1075.98
1	High	1096.10
2	High	1104.08
3	High	1113.58
4	High	1119.16
...	...	...
1887	Low	2707.20
1888	Low	2677.30
1889	Low	2671.12
1890	Low	2681.46
1891	Low	2621.00

1892 rows × 2 columns

Knowledge Check: Missing Values

Given a data below, fill the missing values in `aapl` using appropriate method:

In [20]:
```
march = pd.date_range(start="2018-03-01", end="2019-03-31")
aapl = stock.xs('AAPL', level='Symbols', axis=1)
aapl = aapl.reindex(march)
aapl
```

Out[20]:

Attributes	Adj Close	Close	High	Low	Open	Volume
2018-03-01	42.08	43.75	44.94	43.17	44.63	195208000.00
2018-03-02	42.37	44.05	44.08	43.11	43.20	153816000.00
2018-03-03	NaN	NaN	NaN	NaN	NaN	NaN
2018-03-04	NaN	NaN	NaN	NaN	NaN	NaN
2018-03-05	42.51	44.21	44.44	43.63	43.80	113605600.00
...	...	...	...	...	...	...
2019-03-27	46.00	47.12	47.44	46.64	47.19	119393600.00
2019-03-28	46.06	47.18	47.39	46.88	47.24	83121600.00
2019-03-29	46.37	47.49	47.52	47.13	47.46	94256000.00
2019-03-30	NaN	NaN	NaN	NaN	NaN	NaN
2019-03-31	NaN	NaN	NaN	NaN	NaN	NaN

396 rows × 6 columns

In [21]:
```
## Write your code to fill the missing values in `aapl`
```

Pandas and Matplotlib

Surely this is the point where a data analyst whip up some flashy charts using the popular `matplotlib` library?

Well - yes. Even better, we're going to use the `DataFrame.plot()` method, built-into `pandas` which in turn calls `matplotlib` plotting functions under-the-hood. Notice that we added `matplotlib.pyplot` as an import, even though our code will not explicitly call `matplotlib` but rely on `pandas` implementation.

Now let's take a look at apple stock data frame:

In [22]:
```
aapl.head()
```

Out[22]:

Attributes	Adj Close	Close	High	Low	Open	Volume
2018-03-01	42.08	43.75	44.94	43.17	44.63	195208000.00
2018-03-02	42.37	44.05	44.08	43.11	43.20	153816000.00
2018-03-03	NaN	NaN	NaN	NaN	NaN	NaN
2018-03-04	NaN	NaN	NaN	NaN	NaN	NaN
2018-03-05	42.51	44.21	44.44	43.63	43.80	113605600.00

The best way to demonstrate the efficiency gains of `DataFrame.plot()` is to see it in action. We will call `.plot()` directly on our `DataFrame` - `pandas` take care of the matplotlib code that, by matplotlib's own admission, *can be daunting to many new users*.

In [23]:
```
stock
```

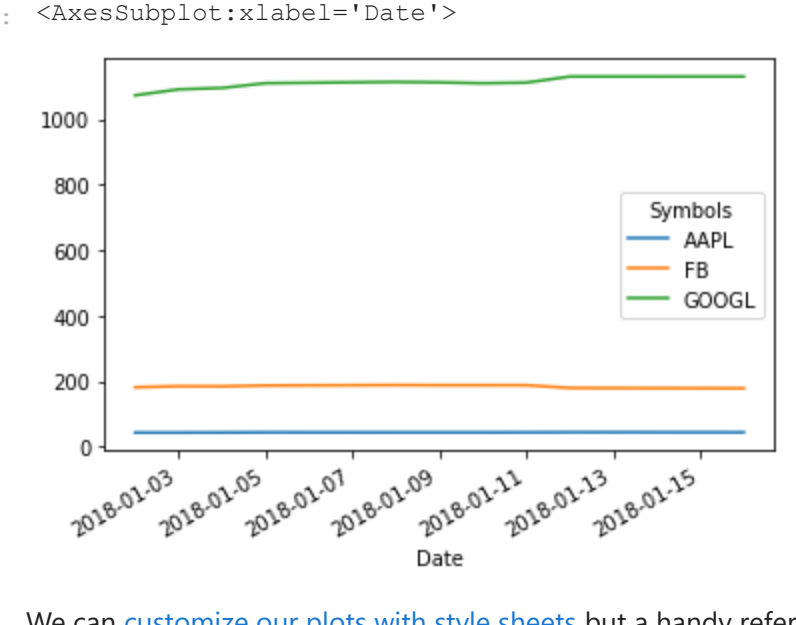
Out[23]:

Attributes	Adj Close			Close			High			Low		
Symbols	AAPL	FB	GOOGL	AAPL	FB	GOOGL	AAPL	FB	GOOGL	AAPL	FB	GOOGL
Date												
2018-01-02	41.25	181.42	1073.21	43.06	181.42	1073.21	43.08	181.58	1075.98	42.31	177.55	1053.02
2018-01-03	41.24	184.67	1091.52	43.06	184.67	1091.52	43.64	184.78	1096.10	42.99	181.33	1073.43
2018-01-04	41.43	184.33	1095.76	43.26	184.33	1095.76	43.37	186.21	1104.08	43.02	184.10	1094.26
2018-01-05	41.90	186.85	1110.29	43.75	186.85	1110.29	43.84	186.90	1113.58	43.26	184.93	1101.80
2018-01-08	41.75	188.28	1114.21	43.59	188.28	1114.21	43.90	188.90	1119.16	43.48	186.33	1110.00
...	...	...	...	...	...	...	...	...	...	...	...	...
2021-09-28	141.91	340.65	2716.60	141.91	340.65	2716.60	144.75	349.60	2781.93	141.69	338.92	2707.20
2021-09-29	142.83	339.61	2687.07	142.83	339.61	2687.07	144.45	345.23	2743.02	142.03	338.88	2677.30
2021-09-30	141.50	339.39	2673.52	141.50	339.39	2673.52	144.38	342.80	2710.85	141.28	338.15	2671.12
2021-10-01	142.65	343.01	2730.86	142.65	343.01	2730.86	142.92	345.02	2738.21	139.11	338.64	2681.46
2021-10-04	139.14	326.23	2673.19	139.14	326.23	2673.19	142.21	335.94	2719.21	138.27	322.70	2621.00

946 rows × 18 columns

In [24]:
```
stock['Close'].head(10).plot()
```

Out[24]:
```
<AxesSubplot:xlabel='Date'>
```



We can customize our plots with style sheets but a handy reference is within reach. You can substitute 'default' for any one of the styles available and re-run the plotting code to see the styles being applied.

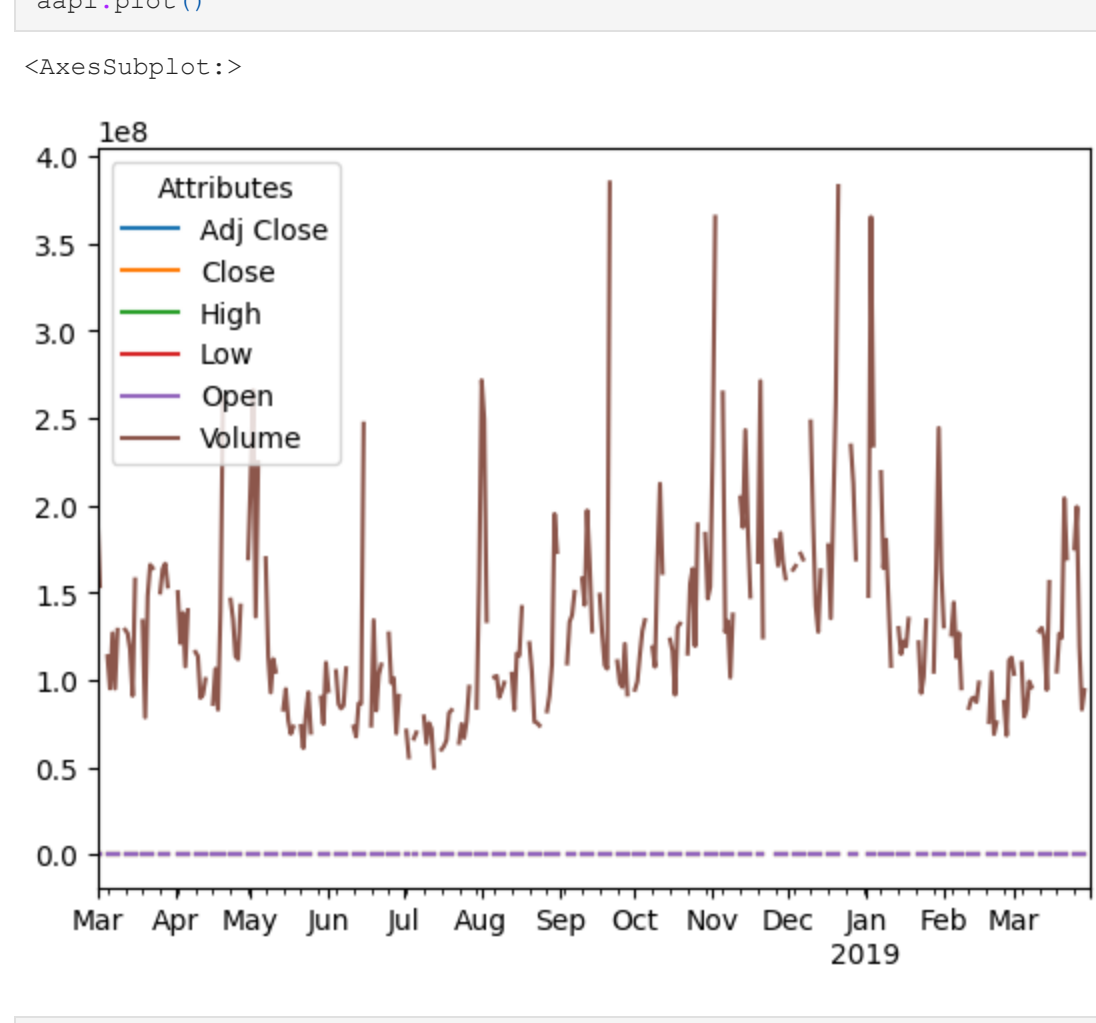
In [25]:
```
import matplotlib.pyplot as plt
print(plt.style.available)
plt.style.use('default')
```

```
['Solarize_Light2', '_classic_test_patch', '_mpl-gallery', '_mpl-gallery-nogrid', 'bmh', 'classic', 'dark_background', 'fast', 'fivethirtyeight', 'ggplot', 'grayscale', 'seaborn', 'seaborn-bright', 'seaborn-colorblind', 'seaborn-dark', 'seaborn-dark-palette', 'seaborn-darkgrid', 'seaborn-deep', 'seaborn-muted', 'seaborn-notebook', 'seaborn-paper', 'seaborn-pastel', 'seaborn-poster', 'seaborn-talk', 'seaborn-ticks', 'seaborn-white', 'seaborn-whitegrid', 'tableau-colorblind10']
```

Because the `.plot()` method is called on a DataFrame object, we can have an indexed DataFrame with multiple columns and `plot` will handle these using its default options:

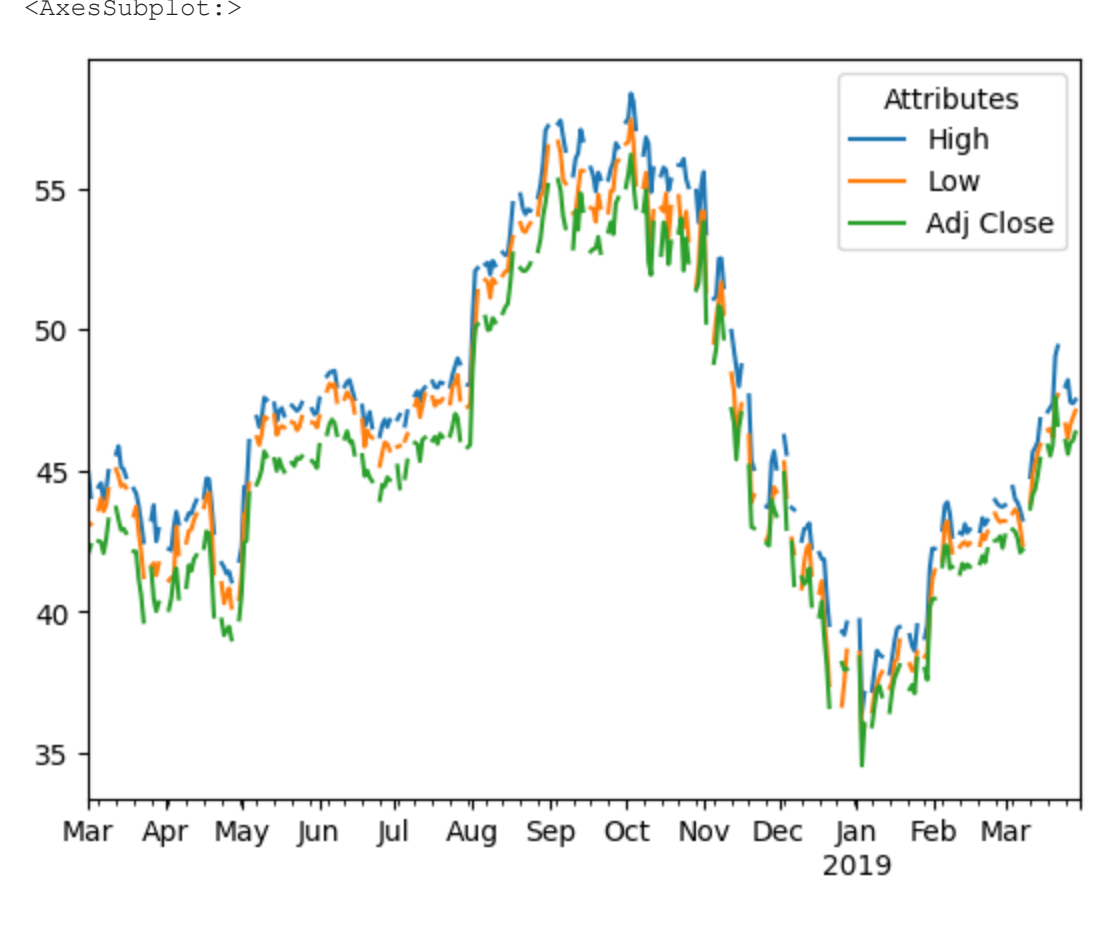
In [26]:
```
aapl.plot()
```

Out[26]:
```
<AxesSubplot:>
```



In [27]:
```
aapl.loc[:, ['High', 'Low', 'Adj Close']].plot()
```

Out[27]:
```
<AxesSubplot:>
```



Other Visualization

one column visualization:

- `.plot.bar()` or `.plot.barh()` for bar plots
- `.plot.hist()` for histogram
- `.plot.box()` or `.boxplot()` for boxplot
- `.plot.kde()` or `.plot.density()` for density plots
- `.plot.area()` for area plots
- `.plot.pie()` for pie plots

two column visualization:

- `.plot.scatter()` for scatter plots
- `.plot.hexbin()` for hexagonal bin plots

Group By

Reshaping data is an important component of any data wrangling toolkit as it allows the analyst to "massage" the data into the desired shape for further processing.

Another equally important technique is the group by operation. Analysts having some experience with SQL or other data analysis toolsets (R's `tidyverse` for example) will find the group by operation a familiar strategy in many analysis-heavy workflow.

Consider the following DataFrame:

In [28]:
```
stock_adj = stock.stack()
stock_adj['Volume USD'] = stock_adj['Volume'] * stock_adj['Adj Close']
stock_adj = stock_adj.unstack()
```

In [29]:
```
volume = stock_adj.xs('Volume USD', level='Attributes', axis=1)
```

```
volume = volume.round(2)
volume
```

Out[29]:

Symbols	AAPL	FB	GOOGL
Date			
2018-01-02	4216548021.56	3293117664.76	1704579380.96
2018-01-03	4869402249.11	3118448391.08	1709211198.58
2018-01-04	3718099512.82	2558666322.42	1427336988.72
2018-01-05	3965830237.73	2536395407.85	1679313684.08
2018-01-08	3434719032.89	3388042094.03	1372929513.87
...	...	...	...
2021-09-28	15464259492.07	7395613562.49	6217210983.50
2021-09-29	10655403796.60	4908111430.30	4144536873.44
2021-09-30	12584189300.00	5615920511.39	5079153333.11
2021-10-01	13500338362.37	5112667098.56	4828160669.92
2021-10-04	13660806882.08	13953803636.92	6837752551.12

946 rows × 3 columns

Notice how the data frame shows amount of daily volume transaction, say we would like to compare the average daily transaction for AAPL, FB, and GOOGL. Let's perform a melting function:

In [30]:
```
volume_melted = volume.melt()
volume_melted
```

Out[30]:

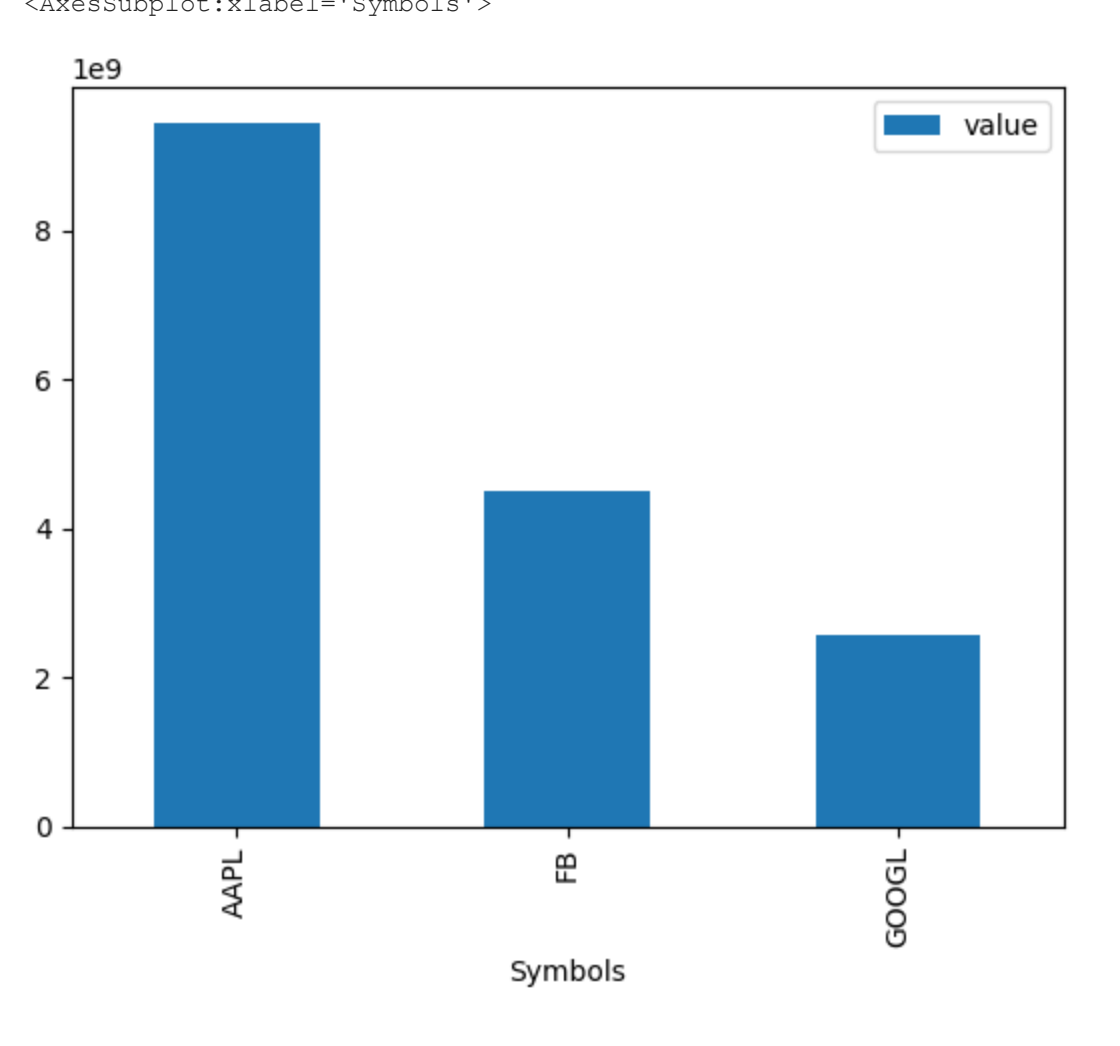
	Symbols	value
0	AAPL	4216548021.56
1	AAPL	4869402249.11
2	AAPL	3718099512.82
3	AAPL	3965830237.73
4	AAPL	3434719032.89
...	...	...
2833	GOOGL	6217210983.50
2834	GOOGL	4144536873.44
2835	GOOGL	5079153333.11
2836	GOOGL	4828160669.92
2837	GOOGL	6837752551.12

2838 rows × 2 columns

Supposed we would like to compare the average volume transaction between each stock price. On average, which of the 3 stocks has the highest average daily transaction volume?

In [31]:
```
volume_melted.groupby(['Symbols']).mean().plot.bar()
```

Out[31]: <AxesSubplot:xlabel='Symbols'>

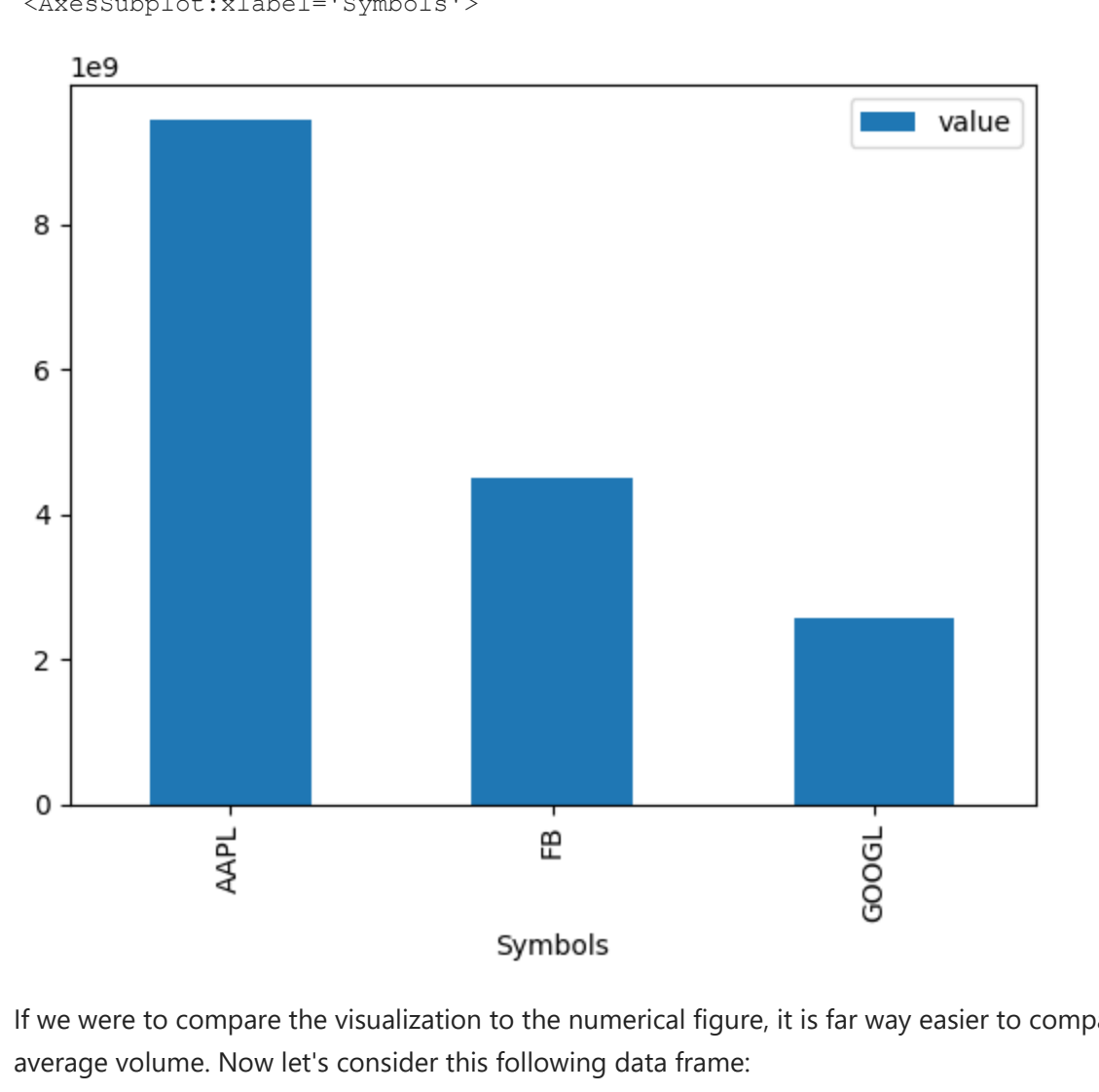


Visualizing Barchart for Comparison

Say we would like to compare the average daily volume sold from the companies. To do that, we will need to extract volume attribute from our dataframe, and perform a melt function:

In [32]:
```
volume_melted.groupby('Symbols').mean().plot.bar()
```

Out[32]: <AxesSubplot:xlabel='Symbols'>



If we were to compare the visualization to the numerical figure, it is far way easier to compare each stock's average volume. Now let's consider this following data frame:

In [33]:
```
aapl = stock.xs('AAPL', level='Symbols', axis=1)
aapl = aapl.round(2)
aapl['Close_Diff'] = aapl['Close'].diff()
aapl['Weekday'] = aapl.index.day_name()
aapl['Month'] = aapl.index.month_name()
aapl
```

Out[33]:

Attributes	Adj Close	Close	High	Low	Open	Volume	Close_Diff	Weekday	Month
Date									
2018-01-02	41.25	43.06	43.08	42.31	42.54	102223600	NaN	Tuesday	January
2018-01-03	41.24	43.06	43.64	42.99	43.13	118071600	0.00	Wednesday	January
2018-01-04	41.43	43.26	43.37	43.02	43.13	89738400	0.20	Thursday	January
2018-01-05	41.90	43.75	43.84	43.26	43.36	94640000	0.49	Friday	January
2018-01-08	41.75	43.59	43.90	43.48	43.59	82271200	-0.16	Monday	January
...	...	...	...	...	...	...	...	...	...
2021-09-28	141.91	141.91	144.75	141.69	143.25	108972300	-3.46	Tuesday	September
2021-09-29	142.83	142.83	144.45	142.03	142.47	74602000	0.92	Wednesday	September
2021-09-30	141.50	141.50	144.38	141.28	143.66	88934200	-1.33	Thursday	September
2021-10-01	142.65	142.65	142.92	139.11	141.90	94639600	1.15	Friday	October
2021-10-04	139.14	139.14	142.21	138.27	141.76	98180300	-3.51	Monday	October

946 rows × 9 columns

Pay special attention to how the Close_Diff column was created. It's the difference between the Close value of a stock price on a given day and the following day.

Supposed we want to compare the Close_Diff between each Weekday; On average, does Tuesday record a higher difference between the Close price of Apple stock compared to a Thursday?

In [34]:
```
aapl.groupby('Weekday').mean()
```

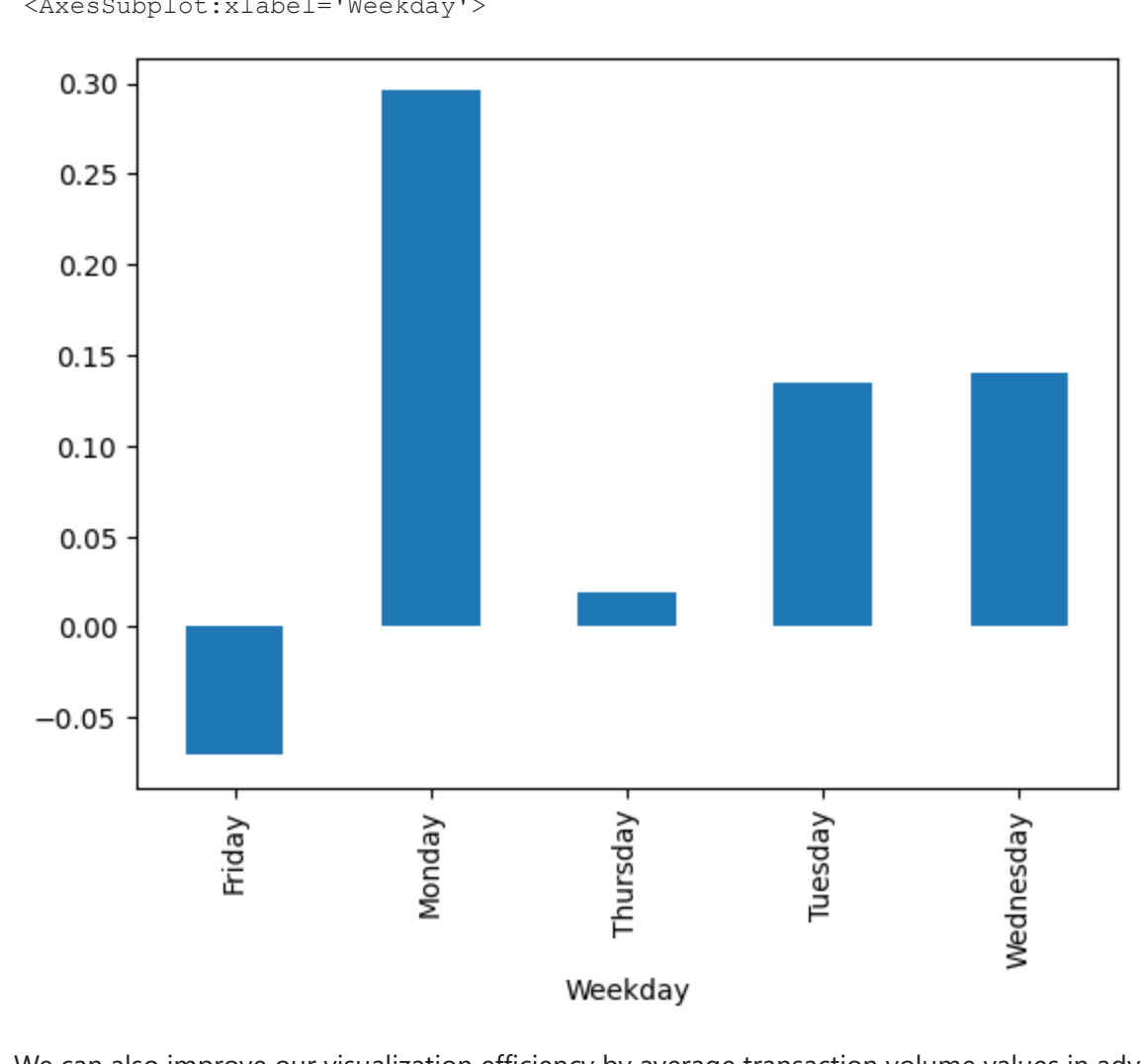
Out[34]:

Attributes	Adj Close	Close	High	Low	Open	Volume	Close_Diff
Weekday							
Friday	77.56	78.51	79.33	77.56	78.52	138210821.69	-0.07
Monday	77.92	78.86	79.66	77.70	78.58	127570146.93	0.30
Thursday	78.27	79.23	80.12	78.40	79.24	122426524.48	0.02
Tuesday	78.34	79.30	80.20	78.41	79.32	123647604.12	0.13
Wednesday	78.49	79.44	80.29	78.64	79.47	120455407.29	0.14

Now to create the same bar chart using `plot` function:

In [35]:
```
aapl.groupby('Weekday').mean()['Close_Diff'].plot.bar()
```

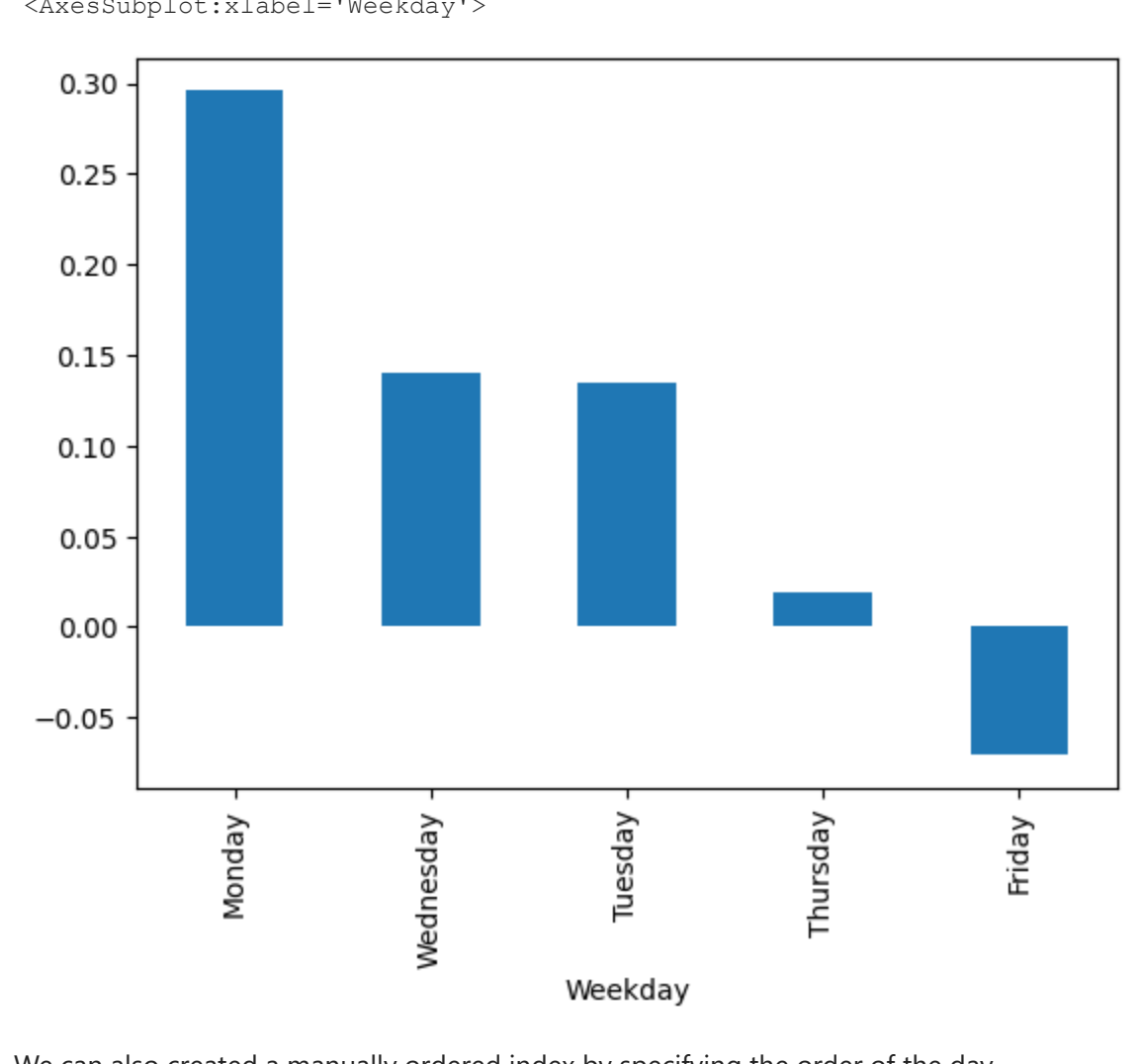
Out[35]: <AxesSubplot:xlabel='Weekday'>



We can also improve our visualization efficiency by average transaction volume values in advance, so then the bars from our plot will be arranged based on the value, rather than the weekday's alphabetical order.

In [36]:
```
# aapl.groupby('Weekday').mean()['Close_Diff'].plot.bar()
aapl.groupby('Weekday').mean()['Close_Diff'].sort_values(ascending=False).plot.bar()
```

Out[36]: <AxesSubplot:xlabel='Weekday'>



We can also created a manually ordered index by specifying the order of the day.

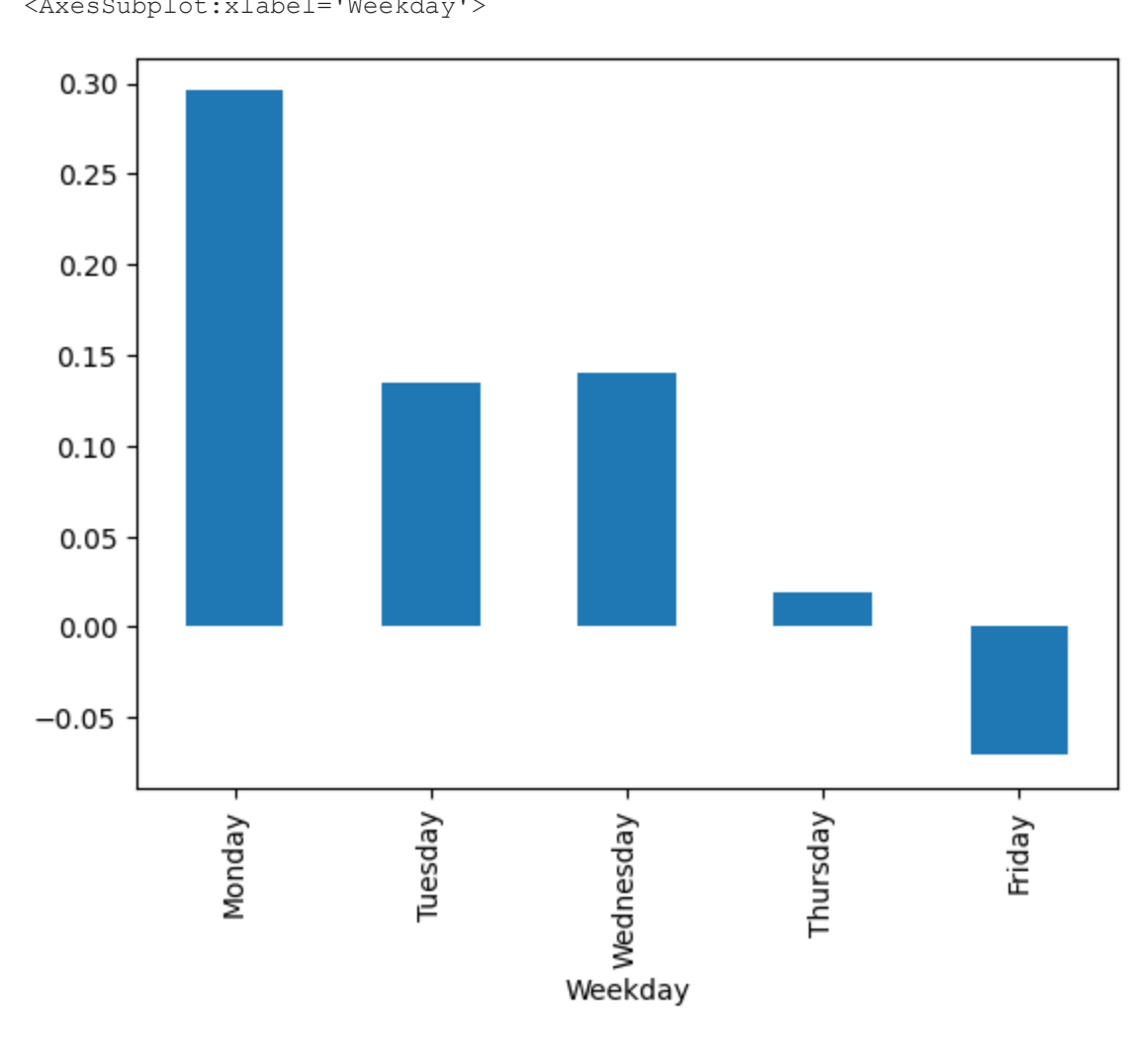
In [37]:
```
wday = ["Monday", "Tuesday", "Wednesday", "Thursday", "Friday"]

aapl_wday = aapl.groupby('Weekday').mean()['Close_Diff']
```

In [38]:
```
aapl_wday.index = pd.CategoricalIndex(aapl_wday.index,\
                                      categories=wday,\
                                      ordered=True)
```

In [39]:
```
aapl_wday.sort_index().plot.bar()
```

Out[39]: <AxesSubplot:xlabel='Weekday'>



Using Grouped Barchart

Using `closingprice`, we can try to visualize using a grouped barchart to compare each month's closing price for the first quarter of 2019 and compare it for the 3 stocks.

First, take a look at `closingprice` and make sure that the data has no missing values. If it has, fill it using appropriate method

In [40]:
```
closingprice.head()
```

Out[40]:

Symbols	AAPL	FB	GOOGL
2019-01-01	NaN	NaN	NaN
2019-01-02	39.48	135.68	1054.68
2019-01-03	35.55	131.74	1025.47
2019-01-04	37.06	137.95	1078.07
2019-01-05	NaN	NaN	NaN

In [41]:
```
## Write your solution code here

# Fill missing value if any
closingprice = closingprice.ffill().bfill()

# Create new column called 'Month', denoting the month name of the date
closingprice['Month'] = closingprice.index.month_name()
```

In [42]:
```
closingprice
```

Out[42]:

Symbols	AAPL	FB	GOOGL	Month
2019-01-01	39.48	135.68	1054.68	January
2019-01-02	39.48	135.68	1054.68	January
2019-01-03	35.55	131.74	1025.47	January
2019-01-04	37.06	137.95	1078.07	January
2019-01-05	37.06	137.95	1078.07	January
...	...	...	...	...
2019-03-27	47.12	165.87	1178.01	March
2019-03-28	47.18	165.55	1172.27	March
2019-03-29	47.49	166.69	1176.89	March
2019-03-30	47.49	166.69	1176.89	March
2019-03-31	47.49	166.69	1176.89	March

90 rows × 4 columns

After we have the `Month` columns, let's group it by Month and see the resulting DataFrame

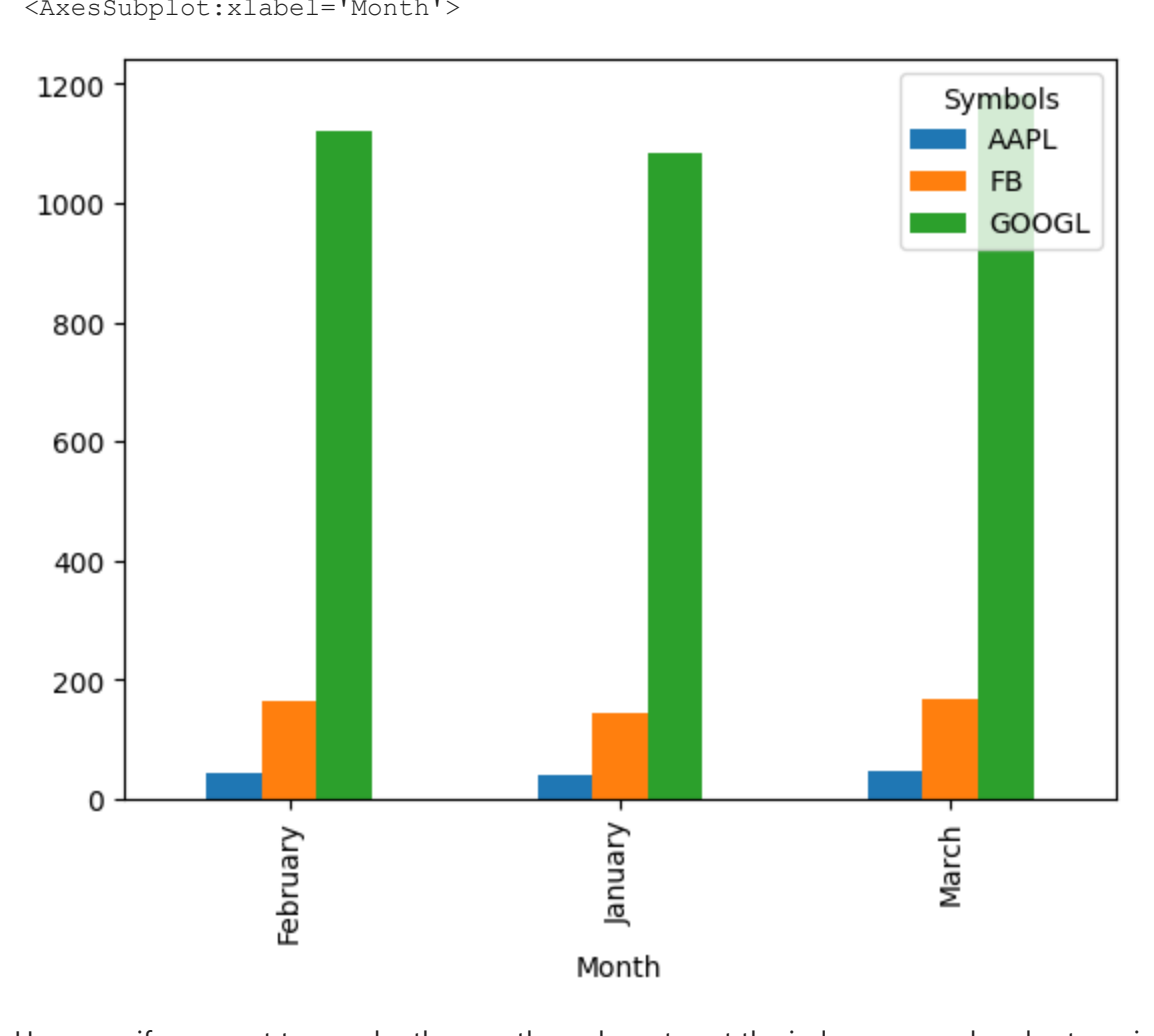
In [43]:
```
average_closing = closingprice.groupby('Month').mean()
average_closing
```

Out[43]:

Symbols	AAPL	FB	GOOGL
Month			
February	42.80	164.60	1119.32
January	38.57	145.20	1082.76
March	45.80	166.88	1181.21

In [44]:
```
average_closing.sort_index().plot.bar()
```

Out[44]: <AxesSubplot:xlabel='Month'>



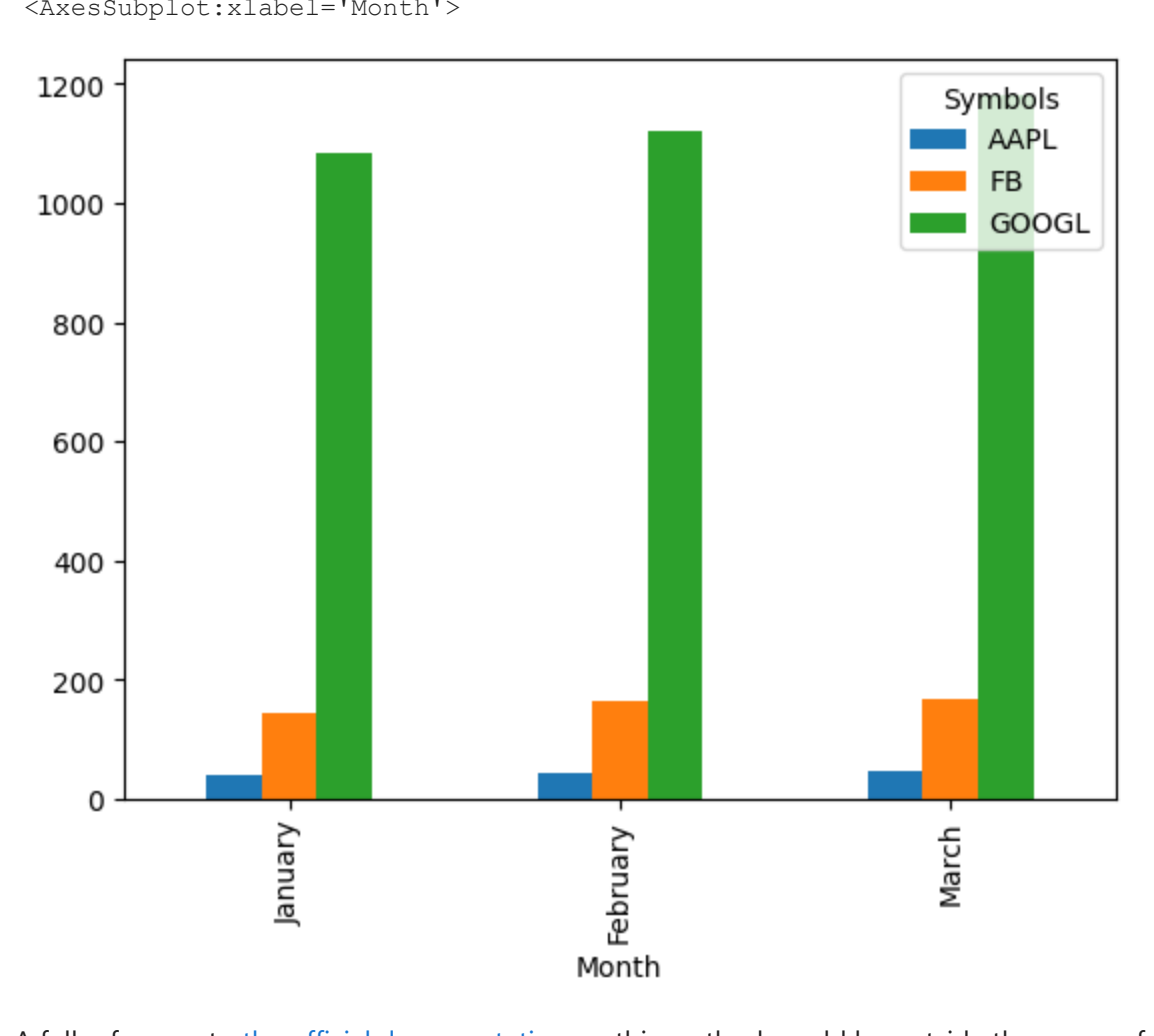
However, if you want to reorder the month, we have to set the index as an ordered categorical values (See Exploratory Data Analysis materials if you need to recall).

In [45]:
```
months= ['January', 'February', 'March', 'April', 'May', 'June', 'July', 'August', 'Se
```

In [46]:
```
average_closing.index = pd.CategoricalIndex(average_closing.index,\
                                            categories=months,\
                                            ordered=True)

average_closing.sort_index().plot.bar()
```

Out[46]: <AxesSubplot:xlabel='Month'>



A full reference to the official documentation on this method would be outside the scope of this coursebook, but is worth a read.

Combining `agg` and `groupby`

So far, we have explored several pandas aggregational toolkit, such as:

- `pd.crosstab()`
- `pd.pivot_table()`

In this chapter, we'll explore another pandas' aggregating tools:

- `groupby` aggregation.

Disucission:

(`pivot_table` & `pd.crosstab` equivalency)

The `pivot_table` method and the `crosstab` function can both produce the exact same results with the same shape. They both share the parameters; `index`, `columns`, `values`, and `aggfunc`.

The major difference on the surface is that `crosstab` is a function and not a DataFrame method. This forces you to use columns as Series and not string names for the parameters.

1. Suppose you want to compare the number of total transactions over Weekdays of each quarter period. Create a `pivot_table` that solve the problem!

1. Try to reproduce the same result by using `crosstab`

1. What if, instead of compare the total transactions, you want to compare the total revenue from the same period? Use both `pivot_table` and `crosstab` as the solution. Discuss with your friend, which method is more relevant in this case?

Pay attention to the following group by operation:

In [47]:
```
stock.stack().reset_index().groupby('Symbols').mean()
```

Out[47]:

Attributes	Adj Close	Close	High	Low	Open	Volume
Symbols						
AAPL	78.12	79.07	79.93	78.15	79.03	126403665.64
FB	220.42	220.42	223.09	217.56	220.31	21194322.41
GOOGL	1483.25	1483.25	1497.46	1467.55	1482.35	1788145.14

In [48]:
```
stock.stack().reset_index().groupby('Symbols').agg({
    'Close': 'mean',
    'High': 'max',
    'Low': 'min'
})
```

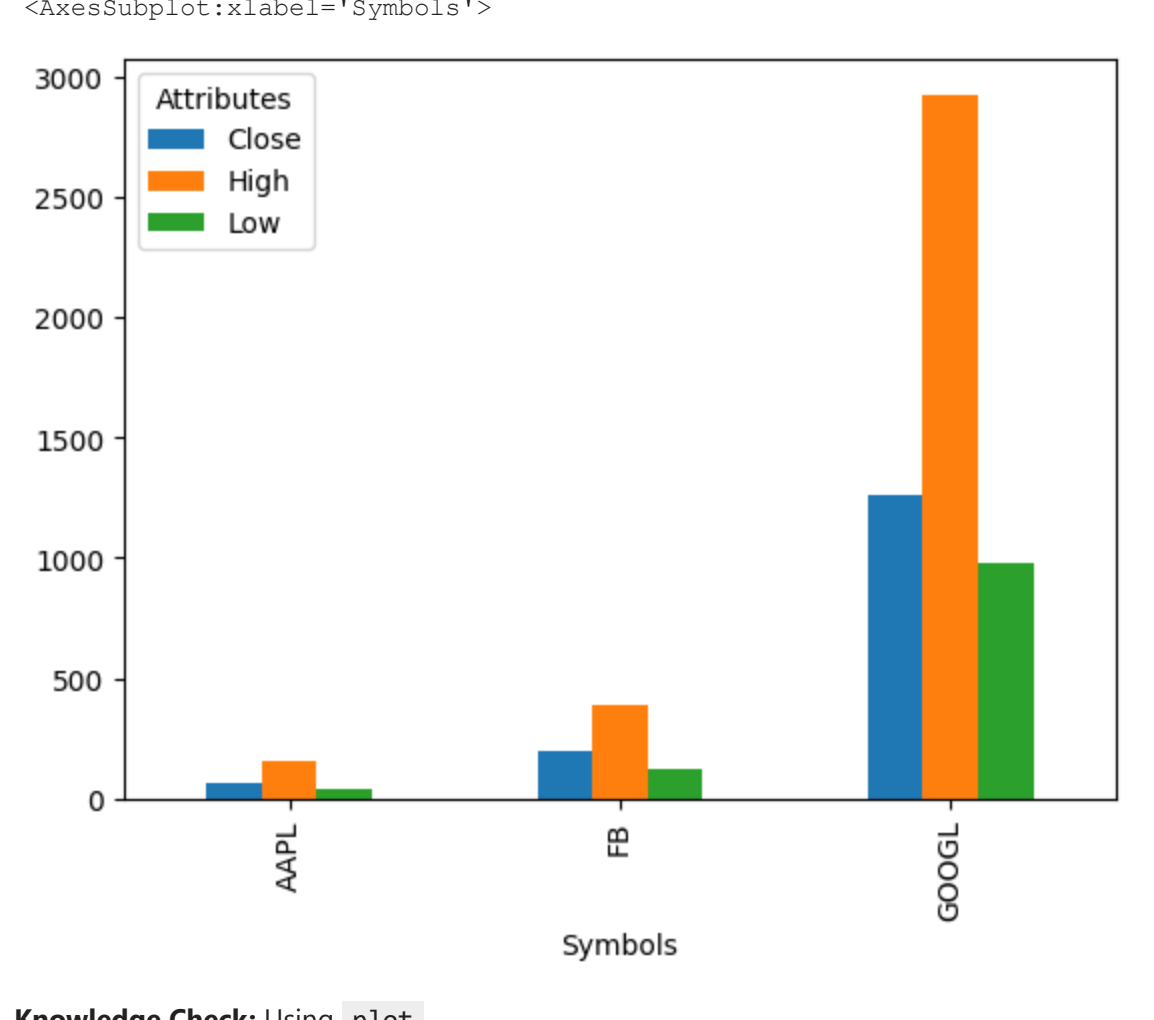
Out[48]:

Attributes	Close	High	Low
Symbols			
AAPL	79.07	157.26	35.50
FB	220.42	384.33	123.02
GOOGL	1483.25	2925.08	977.66

Say we would like to know a glimpse of the maximum stock price, minimum stock price, and the average of closing price from the 3 companies. To do that, we'll need to combine `groupby` with `agg` and map each column with its designated of the aggregation function.

In [49]:
```
stock.stack().reset_index().groupby('Symbols').agg({
    'Close': 'median',
    'High': 'max',
    'Low': 'min'
}).plot.bar()
```

Out[49]: <AxesSubplot:xlabel='Symbols'>



Knowledge Check: Using `plot`

Consider the following data frame:

In [50]:
```
import datetime

stock['YearMonth'] = pd.to_datetime(stock.index.date).to_period('M')
monthly_closing = stock.groupby('YearMonth').mean().loc[:,['Close','Low', 'High']]
monthly_closing.head()
```

Out[50]:

Attributes	Close			Low			High		
Symbols	AAPL	FB	GOOGL	AAPL	FB	GOOGL	AAPL	FB	GOOGL
YearMonth									
2018-01	43.50	184.96	1139.39	43.20	182.92	1129.20	43.80	186.21	1144.58
2018-02	41.91	180.27	1091.88	41.37	177.76	1078.15	42.47	183.13	1107.95
2018-03	43.62	173.49	1093.77	43.27	170.51	1078.95	44.20	176.15	1110.95
2018-04	42.46	163.81	1039.95	42.07	161.55	1028.28	42.91	166.09	1054.32
2018-05	46.38	182.93	1074.85	45.97	180.95	1063.68	46.62	183.87	1082.16

Which of the following will be appropriate plot to use?

- [ ] Line plot -> .plot()
- [ ] Scatter plot -> .plot.scatter(x=? , y=?)
- [ ] Bar plot -> .plot.bar()
- [ ] Box plot -> .plot.box()

In [51]:
```
## Your code below
```