

```
In [1]: #===== Importing the dataset=====
import pandas as pd

dataset = pd.read_csv("QueryResults.csv", header = 0)
print(dataset)
```

	m	TagName	Unnamed: 2
0	2008-07-01 00:00:00	c#	3
1	2008-08-01 00:00:00	assembly	8
2	2008-08-01 00:00:00	javascript	162
3	2008-08-01 00:00:00	c	85
4	2008-08-01 00:00:00	python	124
...
1986	2020-07-01 00:00:00	r	5694
1987	2020-07-01 00:00:00	go	743
1988	2020-07-01 00:00:00	ruby	775
1989	2020-07-01 00:00:00	perl	182
1990	2020-07-01 00:00:00	swift	3607

[1991 rows x 3 columns]

```
In [2]: #=====checking the columns and the nature of the columns=====
# Renaming the columns

dataset.rename(columns={"m": "Date",
                        "TagName": "Tag",
                        "Unnamed: 2": "POSTS"},
               inplace=True)

print(dataset)
# Checking the type of columns
print(dataset.dtypes)

# Need to change the date to datetime module
dataset["Date"] = pd.to_datetime(dataset["Date"])
```

	Date	Tag	POSTS
0	2008-07-01 00:00:00	c#	3
1	2008-08-01 00:00:00	assembly	8
2	2008-08-01 00:00:00	javascript	162
3	2008-08-01 00:00:00	c	85
4	2008-08-01 00:00:00	python	124
...
1986	2020-07-01 00:00:00	r	5694
1987	2020-07-01 00:00:00	go	743
1988	2020-07-01 00:00:00	ruby	775
1989	2020-07-01 00:00:00	perl	182
1990	2020-07-01 00:00:00	swift	3607

[1991 rows x 3 columns]

```
Date      object
Tag        object
POSTS      int64
dtype: object
```

```
In [3]: #=====Explore the dataset=====
# Top 5 and Last 5
dataset.head(5)
dataset.tail(5)
```

```

    #Shape of the dataset
dataset.shape
dataset.columns

    # Count the number of entries in each column
print(dataset.count())
    # Counts the number of non 0 values.

    # Get the number of N/A Values
dataset.isna().sum()
    # Point: No need to do listwise or partial deletions

```

```

Date      1991
Tag       1991
POSTS     1991
dtype: int64

```

```

Out[3]: Date      0
        Tag       0
        POSTS    0
        dtype: int64

```

```

In [20]: #=====Challenge 1=====
#Challenge 1: The TAG is the name of the programming language.
# So for example in July 2008, there were 3 posts tagged with the Language C#.
# Given that the TAG serves as our category column.
# Can you figure out how to count the number of posts per language?
# Which programming language had the most number of posts since the creation of

#Also, some languages are older like C and other languages are newer (like Swift
##The dataset starts in July 2008, so some languages will not have any posts for
###Can you count how many months of posts exist for each programming language?

    # Posts per Language
number_posts_per_language = dataset.groupby("Tag")["POSTS"].sum()

    # Sorting the values by highest post.
number_posts_per_language.sort_values( ascending = False)
print(number_posts_per_language)

    # Number of days posted
months_posted = dataset.groupby("Tag").count()
months_posted.sort_values(by = "POSTS", ascending = False )
print(months_posted[["POSTS"]])

```

Tag	
assembly	34852
c	336042
c#	1423530
c++	684210
delphi	46212
go	47499
java	1696403
javascript	2056510
perl	65286
php	1361988
python	1496210
r	356799
ruby	214582
swift	273055

Name: POSTS, dtype: int64

	POSTS
Tag	
assembly	144
c	144
c#	145
c++	144
delphi	144
go	129
java	144
javascript	144
perl	144
php	144
python	144
r	142
ruby	144
swift	135

```
In [ ]: #=====Use of pivot table=====
pivoted_dataset = dataset.pivot(index = "Date", columns = "Tag", values="POSTS")
print(pivoted_dataset)

# Assessing the pivot table
pivoted_dataset.shape
pivoted_dataset.columns
pivoted_dataset.count()
```

Tag	assembly	c	c#	c++	delphi	go	java \
Date							
2008-07-01	NaN	NaN	3.0	NaN	NaN	NaN	NaN
2008-08-01	8.0	85.0	511.0	164.0	14.0	NaN	222.0
2008-09-01	28.0	321.0	1649.0	755.0	105.0	NaN	1137.0
2008-10-01	15.0	303.0	1989.0	811.0	112.0	NaN	1153.0
2008-11-01	17.0	259.0	1730.0	735.0	141.0	NaN	958.0
...
2020-03-01	317.0	2670.0	8954.0	5107.0	181.0	719.0	13253.0
2020-04-01	406.0	3472.0	10042.0	6820.0	250.0	887.0	15377.0
2020-05-01	386.0	3602.0	9923.0	7063.0	221.0	826.0	14711.0
2020-06-01	363.0	2757.0	9064.0	6161.0	214.0	765.0	13015.0
2020-07-01	298.0	2294.0	9145.0	5756.0	212.0	743.0	12723.0

Tag	javascript	perl	php	python	r	ruby	swift
Date							
2008-07-01	NaN	NaN	NaN	NaN	NaN	NaN	NaN
2008-08-01	162.0	28.0	161.0	124.0	NaN	73.0	NaN
2008-09-01	640.0	131.0	482.0	542.0	6.0	290.0	NaN
2008-10-01	725.0	127.0	617.0	510.0	NaN	249.0	NaN
2008-11-01	579.0	97.0	504.0	452.0	1.0	160.0	NaN
...
2020-03-01	20483.0	215.0	6672.0	26673.0	5761.0	780.0	3434.0
2020-04-01	24634.0	240.0	8060.0	32605.0	7047.0	860.0	4015.0
2020-05-01	25196.0	228.0	7917.0	34478.0	6833.0	774.0	4066.0
2020-06-01	23360.0	203.0	7188.0	31817.0	6249.0	670.0	3733.0
2020-07-01	23802.0	182.0	7334.0	31261.0	5694.0	775.0	3607.0

[145 rows x 14 columns]

```
Out[ ]: Tag
assembly      144
c              144
c#            145
c++           144
delphi        144
go            129
java          144
javascript    144
perl          144
php           144
python        144
r             142
ruby          144
swift         135
dtype: int64
```

```
In [ ]: #=====Filling in missing values=====
        # We dont want to drop the missing values. Therefore use fillna
        pivoted_dataset.fillna("0")

        # Cecking if there are any missing vlaues
        pivoted_dataset.isna().values.any()
```

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Out[ ]: np.True_
```

```
In [ ]: #=====Building charts in matplotlib Lib=====
import matplotlib.pyplot as plt

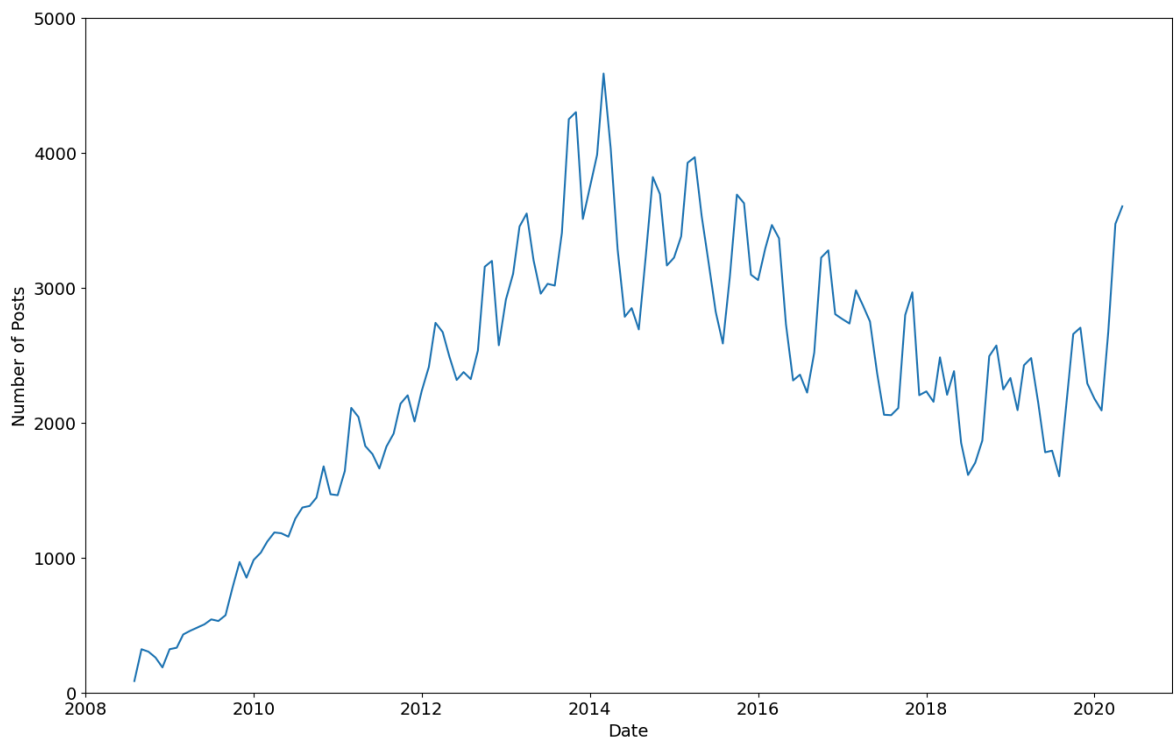
#Sizing of the chart
```

```
plt.figure(figsize =(16, 10))

plt.xticks(fontsize = 14)
plt.yticks(fontsize = 14)
plt.xlabel("Date", fontsize= 14)
plt.ylabel("Number of Posts", fontsize= 14)
plt.ylim(0, 5000)

# Plot functions
plt.plot(pivoted_dataset.index[: -2], pivoted_dataset["c"][: -2])
```

Out[]: [

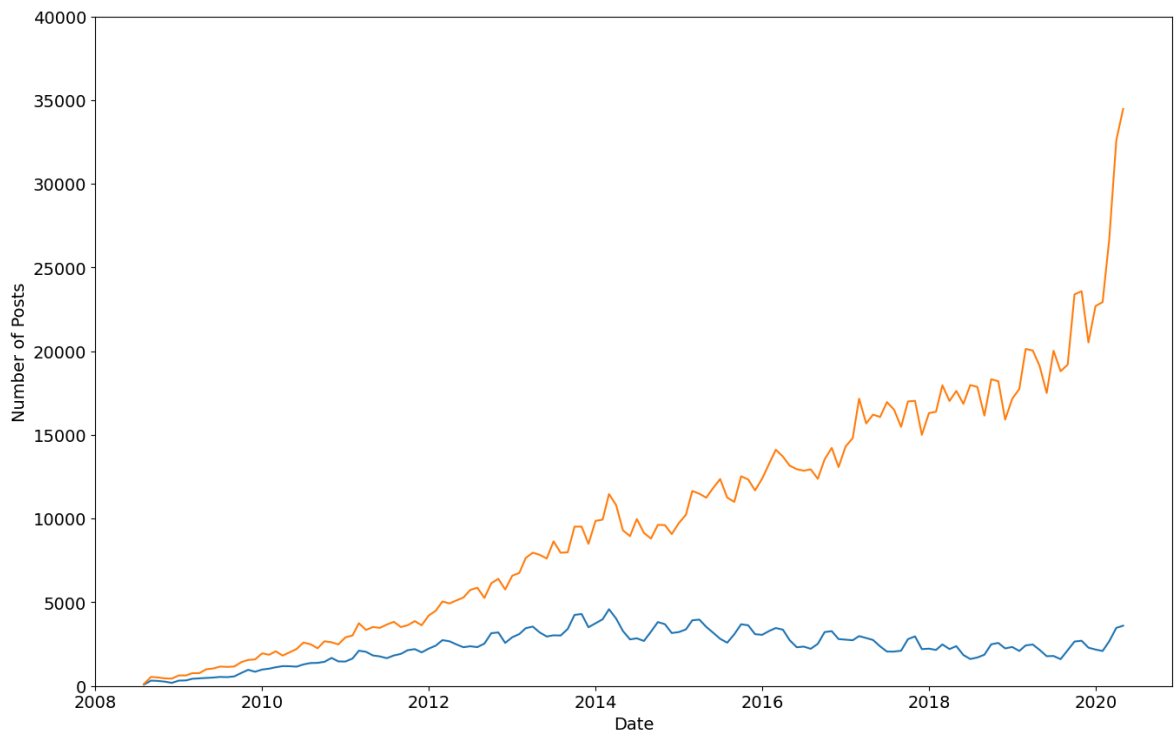


```
In [ ]: #=====Multiple Plots=====
#Sizing of the chart
plt.figure(figsize =(16, 10))

plt.xticks(fontsize = 14)
plt.yticks(fontsize = 14)
plt.xlabel("Date", fontsize= 14)
plt.ylabel("Number of Posts", fontsize= 14)
plt.ylim(0, 40000)

# Plot functions
plt.plot(pivoted_dataset.index[: -2], pivoted_dataset["c"][: -2])
plt.plot(pivoted_dataset.index[: -2], pivoted_dataset["python"][: -2])
```

Out[]: [

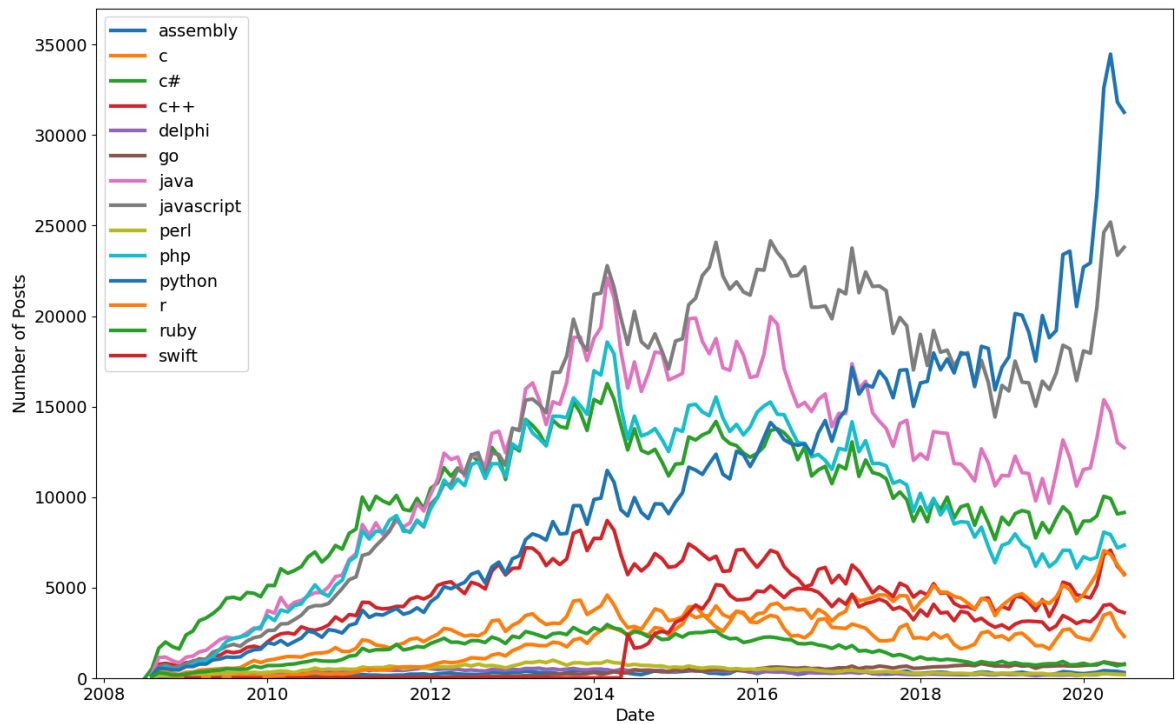


```
In [ ]: #=====Plotting the entire table=====
#Sizing of the chart
plt.figure(figsize =(16, 10))

plt.xticks(fontsize = 14)
plt.yticks(fontsize = 14)
plt.xlabel("Date", fontsize= 14)
plt.ylabel("Number of Posts", fontsize= 14)
plt.ylim(0, 37000)

# Plots
for columns in pivoted_dataset:
    plt.plot( pivoted_dataset.index,
              pivoted_dataset[columns],
              linewidth=3,
              label=pivoted_dataset[columns].name)
# Legend:
plt.legend( fontsize = 14)
```

```
Out[ ]: <matplotlib.legend.Legend at 0x1b63dab4050>
```



```
In [ ]: #=====Smooth out the results using the rolling mean=====
rolled_dataset = pivoted_dataset.rolling(window = 6).mean()

#Sizing of the chart
plt.figure(figsize =(16, 10))

plt.xticks(fontsize = 14)
plt.yticks(fontsize = 14)
plt.xlabel("Date", fontsize= 14)
plt.ylabel("Number of Posts", fontsize= 14)
plt.ylim(0, 37000)

# Plots
for columns in pivoted_dataset:
    plt.plot( pivoted_dataset.index,
              pivoted_dataset[columns],
              linewidth=3,
              label=pivoted_dataset[columns].name)

# Legend:
plt.legend( fontsize = 14)
```

```
Out[ ]: <matplotlib.legend.Legend at 0x1b63a5265d0>
```

