Data Science Tutorial

Contents:

Import Libraries

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

from subprocess import check_output
print(check_output(["ls", "../input"]).decode("utf8"))
```

In [3]:
```
data = pd.read_csv('../input/pokemon.csv')
data.head()
```

Out[3]:

	#	Name	Type 1	Type 2	HP	Attack	Defense	Sp. Atk	Sp. Def	Speed	Generation	Legendary
0	1	Bulbasaur	Grass	Poison	45	49	49	65	65	45	1	False
1	2	Ivysaur	Grass	Poison	60	62	63	80	80	60	1	False
2	3	Venusaur	Grass	Poison	80	82	83	100	100	80	1	False
3	4	Mega Venusaur	Grass	Poison	80	100	123	122	120	80	1	False
4	5	Charmander	Fire	NaN	39	52	43	60	50	65	1	False

In [4]:
```
data.info()
```

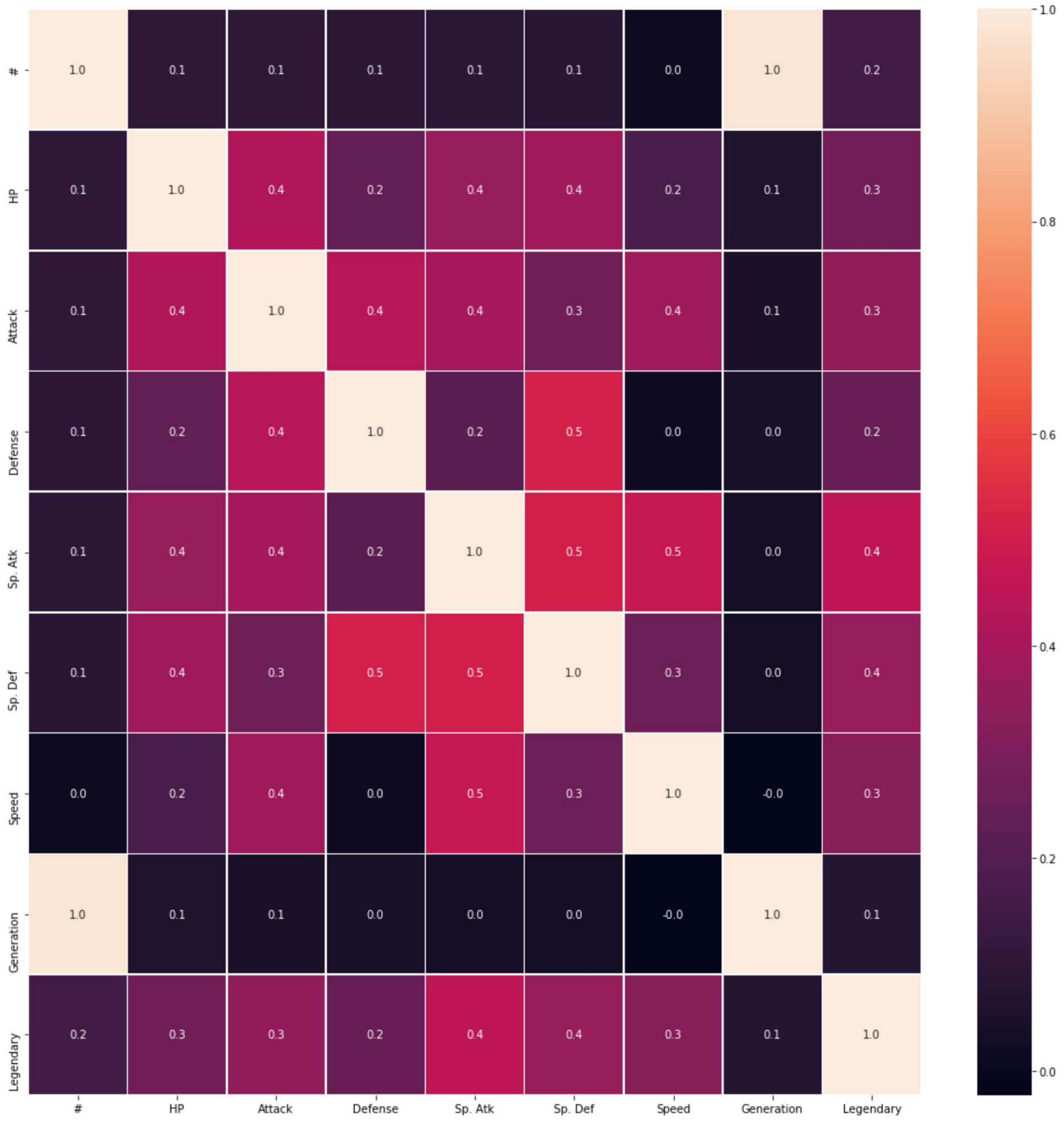
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 800 entries, 0 to 799
Data columns (total 12 columns):
#             800 non-null int64
Name          799 non-null object
Type 1        800 non-null object
Type 2        414 non-null object
HP            800 non-null int64
Attack        800 non-null int64
Defense       800 non-null int64
Sp. Atk       800 non-null int64
Sp. Def       800 non-null int64
Speed         800 non-null int64
Generation    800 non-null int64
Legendary     800 non-null bool
dtypes: bool(1), int64(8), object(3)
memory usage: 69.6+ KB
```

In [5]:
```
data.corr()
```

Out[5]:

	#	HP	Attack	Defense	Sp. Atk	Sp. Def	Speed	Generation	Legendary
#	1.000000	0.097712	0.102664	0.094691	0.089199	0.085596	0.012181	0.983428	0.154336
HP	0.097712	1.000000	0.422386	0.239622	0.362380	0.378718	0.175952	0.058683	0.273620
Attack	0.102664	0.422386	1.000000	0.438687	0.396362	0.263990	0.381240	0.051451	0.345408
Defense	0.094691	0.239622	0.438687	1.000000	0.223549	0.510747	0.015227	0.042419	0.246377
Sp. Atk	0.089199	0.362380	0.396362	0.223549	1.000000	0.506121	0.473018	0.036437	0.448907
Sp. Def	0.085596	0.378718	0.263990	0.510747	0.506121	1.000000	0.259133	0.028486	0.363937
Speed	0.012181	0.175952	0.381240	0.015227	0.473018	0.259133	1.000000	-0.023121	0.326715
Generation	0.983428	0.058683	0.051451	0.042419	0.036437	0.028486	-0.023121	1.000000	0.079794
Legendary	0.154336	0.273620	0.345408	0.246377	0.448907	0.363937	0.326715	0.079794	1.000000

In [6]:
```
#correlation map
f,ax = plt.subplots(figsize=(18, 18))
sns.heatmap(data.corr(), annot=True, linewidths=.5, fmt= '.1f',ax=ax)
plt.show()
```



In [7]:
```
data.head(10)
```

Out[7]:

	#	Name	Type 1	Type 2	HP	Attack	Defense	Sp. Atk	Sp. Def	Speed	Generation	Legendary
0	1	Bulbasaur	Grass	Poison	45	49	49	65	65	45	1	False
1	2	Ivysaur	Grass	Poison	60	62	63	80	80	60	1	False
2	3	Venusaur	Grass	Poison	80	82	83	100	100	80	1	False
3	4	Mega Venusaur	Grass	Poison	80	100	123	122	120	80	1	False
4	5	Charmander	Fire	NaN	39	52	43	60	50	65	1	False
5	6	Charmeleon	Fire	NaN	58	64	58	80	65	80	1	False
6	7	Charizard	Fire	Flying	78	84	78	109	85	100	1	False
7	8	Mega Charizard X	Fire	Dragon	78	130	111	130	85	100	1	False
8	9	Mega Charizard Y	Fire	Flying	78	104	78	159	115	100	1	False
9	10	Squirtle	Water	NaN	44	48	65	50	64	43	1	False

In [8]:
```
data.columns
```

Out[8]:
```
Index(['#', 'Name', 'Type 1', 'Type 2', 'HP', 'Attack', 'Defense', 'Sp. Atk',
       'Sp. Def', 'Speed', 'Generation', 'Legendary'],
      dtype='object')
```

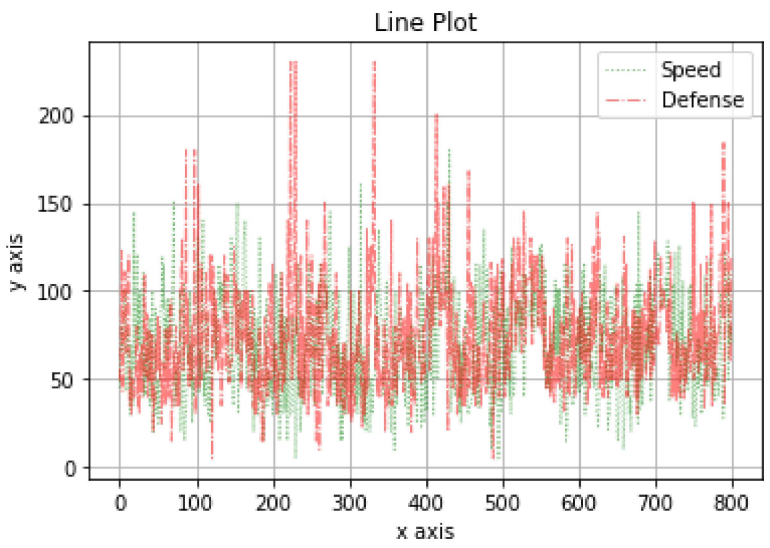
Introduction to Python

Matplotlib is a Python library that helps us plot data. The easiest and most basic types of plots it offers are line plots, scatter plots, and histograms.

A line plot is preferable when the x-axis represents time. A scatter plot is more suitable when there is a correlation between two variables. A histogram is more effective when visualizing the distribution of numerical data.

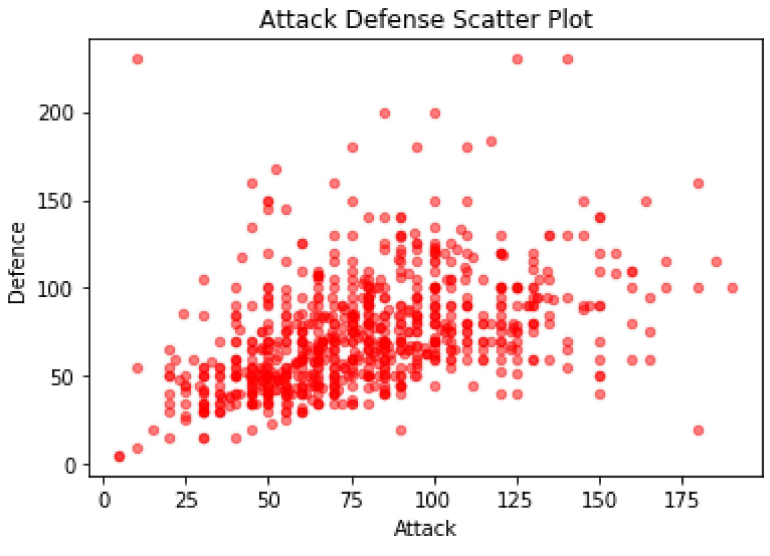
Customization options include colors, labels, line thickness, titles, opacity, grid display, figure size, axis ticks, and line styles.

In [9]:
```
# Line Plot
# color = color, label = label, linewidth = width of line, alpha = opacity, grid = grid, linestyle = sytle of line
data.Speed.plot(kind = 'line', color = 'g',label = 'Speed',linewidth=1,alpha = 0.5,grid = True,linestyle = ':')
data.Defense.plot(color = 'r',label = 'Defense',linewidth=1, alpha = 0.5,grid = True,linestyle = '-.')
plt.legend(loc='upper right')     # legend = puts label into plot
plt.xlabel('x axis')              # label = name of label
plt.ylabel('y axis')
plt.title('Line Plot')            # title = title of plot
plt.show()
```

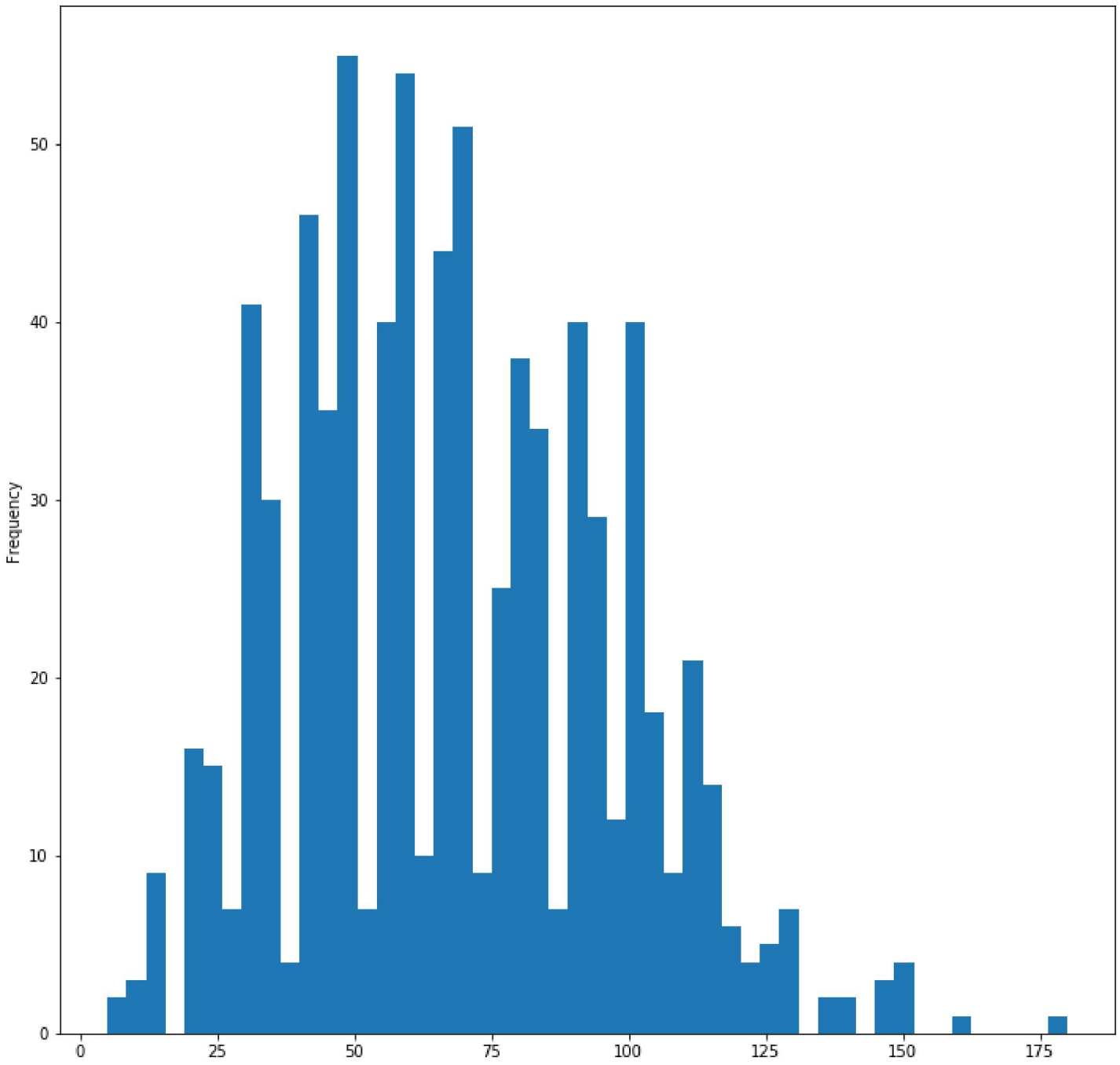


In [10]:
```
# Scatter Plot
# x = attack, y = defense
data.plot(kind='scatter', x='Attack', y='Defense',alpha = 0.5,color = 'red')
plt.xlabel('Attack')              # label = name of label
plt.ylabel('Defence')
plt.title('Attack Defense Scatter Plot')            # title = title of plot
```

Out[10]:
```
Text(0.5,1,'Attack Defense Scatter Plot')
```



In [11]:
```
# Histogram
# bins = number of bar in figure
data.Speed.plot(kind = 'hist',bins = 50,figsize = (12,12))
plt.show()
```



In [12]:
```
# clf() = cleans it up again you can start a fresh
data.Speed.plot(kind = 'hist',bins = 50)
plt.clf()
# We cannot see plot due to clf()
```

```
<Figure size 432x288 with 0 Axes>
```

Dictionaries

Why do we need dictionary?

- It has 'key' and 'value'
- Faster than lists

  What is key and value. Example:
- dictionary = {'spain' : 'madrid'}
- Key is spain.
- Values is madrid.

It's that easy.

Lets practice some other properties like keys(), values(), update, add, check, remove key, remove all entries and remove dicrionary.

In [13]:
```
#create dictionary and look its keys and values
dictionary = {'spain' : 'madrid','usa' : 'vegas'}
print(dictionary.keys())
print(dictionary.values())
```

```
dict_keys(['spain', 'usa'])
dict_values(['madrid', 'vegas'])
```

In [14]:
```
# Keys have to be immutable objects like string, boolean, float, integer or tubles
# List is not immutable
# Keys are unique
dictionary['spain'] = "barcelona"    # update existing entry
print(dictionary)
dictionary['france'] = "paris"       # Add new entry
print(dictionary)
del dictionary['spain']              # remove entry with key 'spain'
print(dictionary)
print('france' in dictionary)        # check include or not
dictionary.clear()                   # remove all entries in dict
print(dictionary)
```

```
{'spain': 'barcelona', 'usa': 'vegas'}
{'spain': 'barcelona', 'usa': 'vegas', 'france': 'paris'}
{'usa': 'vegas', 'france': 'paris'}
True
{}
```

In [15]:
```
# In order to run all code you need to take comment this line
#del dictionary         # delete entire dictionary
print(dictionary)       # it gives error because dictionary is deleted
```

```
{}
```

Pandas

What do we need to know about pandas?

- CSV: comma - separated values

In [16]:
```
data = pd.read_csv('../input/pokemon.csv')
```

In [17]:
```
series = data['Defense']        # data['Defense'] = series
print(type(series))
data_frame = data[['Defense']]  # data[['Defense']] = data frame
print(type(data_frame))
```

```
<class 'pandas.core.series.Series'>
<class 'pandas.core.frame.DataFrame'>
```

Before continuing with pandas, we need to learn **logic, control flow** and **filtering.**
Comparison operator: ==, <, >, <=
Boolean operators: and, or ,not
Filtering pandas

In [18]:
```
# Comparison operator
print(3 > 2)
print(3!=2)
# Boolean operators
print(True and False)
print(True or False)
```

```
True
True
False
True
```

In [19]:
```
# 1 - Filtering Pandas data frame
x = data['Defense']>200     # There are only 3 pokemons who have higher defense value than 200
data[x]
```

Out[19]:

	#	Name	Type 1	Type 2	HP	Attack	Defense	Sp. Atk	Sp. Def	Speed	Generation	Legendary
224	225	Mega Steelix	Steel	Ground	75	125	230	55	95	30	2	False
230	231	Shuckle	Bug	Rock	20	10	230	10	230	5	2	False
333	334	Mega Aggron	Steel	NaN	70	140	230	60	80	50	3	False

In [20]:
```
# 2 - Filtering pandas with logical_and
# There are only 2 pokemons who have higher defence value than 2oo and higher attack value than 100
data[np.logical_and(data['Defense']>200, data['Attack']>100 )]
```

Out[20]:

	#	Name	Type 1	Type 2	HP	Attack	Defense	Sp. Atk	Sp. Def	Speed	Generation	Legendary
224	225	Mega Steelix	Steel	Ground	75	125	230	55	95	30	2	False
333	334	Mega Aggron	Steel	NaN	70	140	230	60	80	50	3	False

In [21]:
```
# This is also same with previous code line. Therefore we can also use '&' for filtering.
data[(data['Defense']>200) & (data['Attack']>100)]
```

Out[21]:

	#	Name	Type 1	Type 2	HP	Attack	Defense	Sp. Atk	Sp. Def	Speed	Generation	Legendary
224	225	Mega Steelix	Steel	Ground	75	125	230	55	95	30	2	False
333	334	Mega Aggron	Steel	NaN	70	140	230	60	80	50	3	False

While and For Loops

We will learn the most basic while and for loops

In [22]:
```
# Stay in loop if condition( i is not equal 5) is true
i = 0
while i != 5 :
    print('i is: ',i)
    i +=1
print(i,' is equal to 5')
```

```
i is:  0
i is:  1
i is:  2
i is:  3
i is:  4
5  is equal to 5
```

In [23]:
```
# Stay in loop if condition( i is not equal 5) is true
lis = [1,2,3,4,5]
for i in lis:
    print('i is: ',i)
print('')

# Enumerate index and value of list
# index : value = 0:1, 1:2, 2:3, 3:4, 4:5
for index, value in enumerate(lis):
    print(index," : ",value)
print('')

# For dictionaries
# We can use for loop to achive key and value of dictionary. We learnt key and value at dictionary part.
dictionary = {'spain':'madrid','france':'paris'}
for key,value in dictionary.items():
    print(key," : ",value)
print('')

# For pandas we can achieve index and value
for index,value in data[['Attack']][0:1].iterrows():
    print(index," : ",value)
```

```
i is:  1
i is:  2
i is:  3
i is:  4
i is:  5

0  :  1
1  :  2
2  :  3
3  :  4
4  :  5

spain  :  madrid
france  :  paris

0  :  Attack    49
Name: 0, dtype: int64
```

In this part, you learn:

- how to import csv file
- plotting line,scatter and histogram
- basic dictionary features
- basic pandas features like filtering
- While and for loops

Python Data Science Toolbox

USER DEFINED FUNCTION

What do we need to know about functions:

- docstrings: documentation for functions. Example:
  for f():
  """This is docstring for documentation of function f"""
- tuple: sequence of immutable python objects.
  cant modify values
  tuple uses paranthesis like tuble = (1,2,3)
  unpack tuple into several variables like a,b,c = tuple

In [24]:
```
# example of what we learn above
def tuple_ex():
    """ return defined t tuple"""
    t = (1,2,3)
    return t
a,b,c = tuple_ex()
print(a,b,c)
```

```
1 2 3
```

SCOPE

What we need to know about scope:

- global: defined main body in script
- local: defined in a function
- built in scope: names in predefined built in scope module such as print, len

  Lets make some basic examples

In [25]:
```
# guess prints what
x = 2
```

```
def f():
    x = 3
    return x
print(x)      # x = 2 global scope
print(f())    # x = 3 local scope
```

```
2
3
```

In [26]:
```
# What if there is no local scope
x = 5
def f():
    y = 2*x        # there is no local scope x
    return y
print(f())         # it uses global scope x
# First local scope searched, then global scope searched, if two of them cannot be found lastly built in scope searched
```

```
10
```

In [27]:
```
# How can we learn what is built in scope
import builtins
dir(builtins)
```

Out[27]:
```
['ArithmeticError',
 'AssertionError',
 'AttributeError',
 'BaseException',
 'BlockingIOError',
 'BrokenPipeError',
 'BufferError',
 'BytesWarning',
 'ChildProcessError',
 'ConnectionAbortedError',
 'ConnectionError',
 'ConnectionRefusedError',
 'ConnectionResetError',
 'DeprecationWarning',
 'EOFError',
 'Ellipsis',
 'EnvironmentError',
 'Exception',
 'False',
 'FileExistsError',
 'FileNotFoundError',
 'FloatingPointError',
 'FutureWarning',
 'GeneratorExit',
 'IOError',
 'ImportError',
 'ImportWarning',
 'IndentationError',
 'IndexError',
 'InterruptedError',
 'IsADirectoryError',
 'KeyError',
 'KeyboardInterrupt',
 'LookupError',
 'MemoryError',
 'ModuleNotFoundError',
 'NameError',
 'None',
 'NotADirectoryError',
 'NotImplemented',
 'NotImplementedError',
 'OSError',
 'OverflowError',
 'PendingDeprecationWarning',
 'PermissionError',
 'ProcessLookupError',
 'RecursionError',
 'ReferenceError',
 'ResourceWarning',
 'RuntimeError',
 'RuntimeWarning',
 'StopAsyncIteration',
 'StopIteration',
 'SyntaxError',
 'SyntaxWarning',
 'SystemError',
 'SystemExit',
 'TabError',
 'TimeoutError',
 'True',
 'TypeError',
 'UnboundLocalError',
 'UnicodeDecodeError',
 'UnicodeEncodeError',
 'UnicodeError',
 'UnicodeTranslateError',
 'UnicodeWarning',
 'UserWarning',
 'ValueError',
 'Warning',
 'ZeroDivisionError',
 '__IPYTHON__',
 '__build_class__',
 '__debug__',
 '__doc__',
 '__import__',
 '__loader__',
 '__name__',
 '__package__',
 '__pybind11_internals_v1__',
 '__spec__',
 'abs',
 'all',
 'any',
 'ascii',
 'bin',
 'bool',
 'bytearray',
 'bytes',
 'callable',
 'chr',
 'classmethod',
 'compile',
 'complex',
 'copyright',
```

```
'credits',
'delattr',
'dict',
'dir',
'display',
'divmod',
'enumerate',
'eval',
'exec',
'filter',
'float',
'format',
'frozenset',
'get_ipython',
'getattr',
'globals',
'hasattr',
'hash',
'help',
'hex',
'id',
'input',
'int',
'isinstance',
'issubclass',
'iter',
'len',
'license',
'list',
'locals',
'map',
'max',
'memoryview',
'min',
'next',
'object',
'oct',
'open',
'ord',
'pow',
'print',
'property',
'range',
'repr',
'reversed',
'round',
'set',
'setattr',
'slice',
'sorted',
'staticmethod',
'str',
'sum',
'super',
'tuple',
'type',
'vars',
'zip']
```

NESTED FUNCTION

- function inside function.
- There is a LEGB rule that is search local scope, enclosing function, global and built in scopes, respectively.

In [28]:
```
#nested function
def square():
    """ return square of value """
    def add():
        """ add two local variable """
        x = 2
        y = 3
        z = x + y
        return z
    return add()**2
print(square())
```

```
25
```

DEFAULT and FLEXIBLE ARGUMENTS

- Default argument example:

  def f(a, b=1):
    """ b = 1 is default argument"""
- Flexible argument example:

  def f(*args):
   """ *args can be one or more"""

  def f(** kwargs)
   """ **kwargs is a dictionary"""

lets write some code to practice

In [29]:
```
# default arguments
def f(a, b = 1, c = 2):
    y = a + b + c
    return y
print(f(5))
# what if we want to change default arguments
print(f(5,4,3))
```

```
8
12
```

In [30]:
```
# flexible arguments *args
def f(*args):
    for i in args:
        print(i)
f(1)
print("")
f(1,2,3,4)
# flexible arguments **kwargs that is dictionary
def f(**kwargs):
    """ print key and value of dictionary"""
    for key, value in kwargs.items():               # If you do not understand this part turn for loop part and look at
        print(key, " ", value)
f(country = 'spain', capital = 'madrid', population = 123456)
```

```
1

1
2
3
4
country   spain
capital   madrid
population   123456
```

LAMBDA FUNCTION

Faster way of writing function

In [31]:
```
# lambda function
square = lambda x: x**2     # where x is name of argument
print(square(4))
tot = lambda x,y,z: x+y+z   # where x,y,z are names of arguments
print(tot(1,2,3))
```

```
16
6
```

ANONYMOUS FUNCTİON

Like lambda function but it can take more than one arguments.

- map(func,seq) : applies a function to all the items in a list

In [32]:
```
number_list = [1,2,3]
y = map(lambda x:x**2,number_list)
print(list(y))
```

```
[1, 4, 9]
```

ITERATORS

- iterable is an object that can return an iterator
- iterable: an object with an associated iter() method
  example: list, strings and dictionaries
- iterator: produces next value with next() method

In [33]:
```
# iteration example
name = "ronaldo"
it = iter(name)
print(next(it))    # print next iteration
print(*it)         # print remaining iteration
```

```
r
o n a l d o
```

zip(): zip lists

In [34]:
```
# zip example
list1 = [1,2,3,4]
list2 = [5,6,7,8]
z = zip(list1,list2)
print(z)
z_list = list(z)
print(z_list)
```

```
<zip object at 0x7e9f80ba3bc8>
[(1, 5), (2, 6), (3, 7), (4, 8)]
```

In [35]:
```
un_zip = zip(*z_list)
un_list1,un_list2 = list(un_zip) # unzip returns tuple
print(un_list1)
print(un_list2)
print(type(un_list2))
```

```
(1, 2, 3, 4)
(5, 6, 7, 8)
<class 'tuple'>
```

LIST COMPREHENSİON

One of the most important topic of this kernel

We use list comprehension for data analysis often.

list comprehension: collapse for loops for building lists into a single line

Ex: num1 = [1,2,3] and we want to make it num2 = [2,3,4]. This can be done with for loop. However it is unnecessarily long. We can make it one line code that is list comprehension.

In [36]:
```
# Example of list comprehension
num1 = [1,2,3]
num2 = [i + 1 for i in num1 ]
print(num2)
```

```
[2, 3, 4]
```

[i + 1 for i in num1]: list of comprehension

i +1: list comprehension syntax

for i in num1: for loop syntax

i: iterator

num1: iterable object

In [37]:
```
# Conditionals on iterable
num1 = [5,10,15]
num2 = [i**2 if i == 10 else i-5 if i < 7 else i+5 for i in num1]
print(num2)
```

```
[0, 100, 20]
```

In [38]:
```
# lets return pokemon csv and make one more list comprehension example
# lets classify pokemons whether they have high or low speed. Our threshold is average speed.
threshold = sum(data.Speed)/len(data.Speed)
data["speed_level"] = ["high" if i > threshold else "low" for i in data.Speed]
data.loc[:10,["speed_level","Speed"]] # we will learn loc more detailed later
```

Out[38]:

	speed_level	Speed
0	low	45
1	low	60
2	high	80
3	high	80
4	low	65
5	high	80
6	high	100
7	high	100
8	high	100
9	low	43
10	low	58

Up to now, you learn

- User defined function
- Scope
- Nested function
- Default and flexible arguments
- Lambda function
- Anonymous function
- Iterators

- List comprehension

Clearning Data

DIAGNOSE DATA for CLEANING

We need to diagnose and clean data before exploring.
Unclean data:

- Column name inconsistency like upper-lower case letter or space between words
- missing data
- different language

We will use head, tail, columns, shape and info methods to diagnose data

In [39]:
```
data = pd.read_csv('../input/pokemon.csv')
data.head()  # head shows first 5 rows
```

Out[39]:

	#	Name	Type 1	Type 2	HP	Attack	Defense	Sp. Atk	Sp. Def	Speed	Generation	Legendary
0	1	Bulbasaur	Grass	Poison	45	49	49	65	65	45	1	False
1	2	Ivysaur	Grass	Poison	60	62	63	80	80	60	1	False
2	3	Venusaur	Grass	Poison	80	82	83	100	100	80	1	False
3	4	Mega Venusaur	Grass	Poison	80	100	123	122	120	80	1	False
4	5	Charmander	Fire	NaN	39	52	43	60	50	65	1	False

In [40]:
```
# tail shows last 5 rows
data.tail()
```

Out[40]:

	#	Name	Type 1	Type 2	HP	Attack	Defense	Sp. Atk	Sp. Def	Speed	Generation	Legendary
795	796	Diancie	Rock	Fairy	50	100	150	100	150	50	6	True
796	797	Mega Diancie	Rock	Fairy	50	160	110	160	110	110	6	True
797	798	Hoopa Confined	Psychic	Ghost	80	110	60	150	130	70	6	True
798	799	Hoopa Unbound	Psychic	Dark	80	160	60	170	130	80	6	True
799	800	Volcanion	Fire	Water	80	110	120	130	90	70	6	True

In [41]:
```
# columns gives column names of features
data.columns
```

Out[41]:
```
Index(['#', 'Name', 'Type 1', 'Type 2', 'HP', 'Attack', 'Defense', 'Sp. Atk',
       'Sp. Def', 'Speed', 'Generation', 'Legendary'],
      dtype='object')
```

In [42]:
```
# shape gives number of rows and columns in a tuble
data.shape
```

Out[42]:
```
(800, 12)
```

In [43]:
```
# info gives data type like dataframe, number of sample or row, number of feature or column, feature types and memory us
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 800 entries, 0 to 799
Data columns (total 12 columns):
#             800 non-null int64
Name          799 non-null object
Type 1        800 non-null object
Type 2        414 non-null object
HP            800 non-null int64
Attack        800 non-null int64
Defense       800 non-null int64
Sp. Atk       800 non-null int64
Sp. Def       800 non-null int64
Speed         800 non-null int64
Generation    800 non-null int64
Legendary     800 non-null bool
dtypes: bool(1), int64(8), object(3)
memory usage: 69.6+ KB
```

EXPLORATORY DATA ANALYSIS

value_counts(): Frequency counts
outliers: the value that is considerably higher or lower from rest of the data

- Lets say value at 75% is Q3 and value at 25% is Q1.

- Outlier are smaller than Q1 - 1.5(Q3-Q1) and bigger than Q3 + 1.5(Q3-Q1). (Q3-Q1) = IQR
  We will use describe() method. Describe method includes:
- count: number of entries
- mean: average of entries
- std: standart deviation
- min: minimum entry
- 25%: first quantile
- 50%: median or second quantile
- 75%: third quantile
- max: maximum entry

What is quantile?

- 1,4,5,6,8,9,11,12,13,14,15,16,17
- The median is the number that is in **middle** of the sequence. In this case it would be 11.
- The lower quartile is the median in between the smallest number and the median i.e. in between 1 and 11, which is 6.
- The upper quartile, you find the median between the median and the largest number i.e. between 11 and 17, which will be 14 according to the question above.

In [44]:
```
# For example lets look frequency of pokemom types
print(data['Type 1'].value_counts(dropna =False))  # if there are nan values that also be counted
# As it can be seen below there are 112 water pokemon or 70 grass pokemon
```

```
Water       112
Normal       98
Grass        70
Bug          69
Psychic      57
Fire         52
Electric     44
Rock         44
Ghost        32
Dragon       32
Ground       32
Dark         31
Poison       28
Fighting     27
Steel        27
Ice          24
Fairy        17
Flying        4
Name: Type 1, dtype: int64
```

In [45]:
```
1,2,3,4,200
```

Out[45]:
```
(1, 2, 3, 4, 200)
```

In [46]:
```
# For example max HP is 255 or min defense is 5
data.describe() #ignore null entries
```

Out[46]:

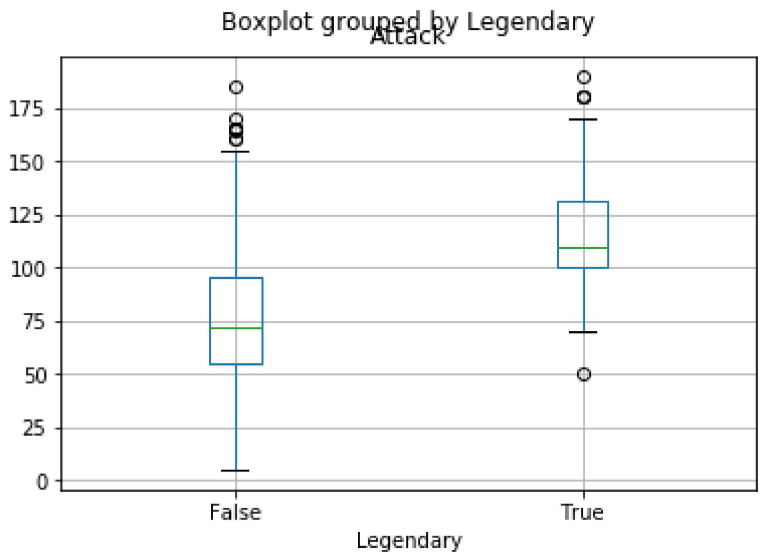
	#	HP	Attack	Defense	Sp. Atk	Sp. Def	Speed	Generation
count	800.0000	800.000000	800.000000	800.000000	800.000000	800.000000	800.000000	800.00000
mean	400.5000	69.258750	79.001250	73.842500	72.820000	71.902500	68.277500	3.32375
std	231.0844	25.534669	32.457366	31.183501	32.722294	27.828916	29.060474	1.66129
min	1.0000	1.000000	5.000000	5.000000	10.000000	20.000000	5.000000	1.00000
25%	200.7500	50.000000	55.000000	50.000000	49.750000	50.000000	45.000000	2.00000
50%	400.5000	65.000000	75.000000	70.000000	65.000000	70.000000	65.000000	3.00000
75%	600.2500	80.000000	100.000000	90.000000	95.000000	90.000000	90.000000	5.00000
max	800.0000	255.000000	190.000000	230.000000	194.000000	230.000000	180.000000	6.00000

VISUAL EXPLORATORY DATA ANALYSIS

- Box plots: visualize basic statistics like outliers, min/max or quantiles

In [47]:
```
# For example: compare attack of pokemons that are legendary  or not
# Black line at top is max
# Blue line at top is 75%
# Green line is median (50%)
# Blue line at bottom is 25%
# Black line at bottom is min
# There are no outliers
data.boxplot(column='Attack',by = 'Legendary')
```

Out[47]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x7e9f80bb52e8>
```



TIDY DATA

We tidy data with melt(). Describing melt is confusing. Therefore lets make example to understand it.

In [48]:
```
# Firstly I create new data from pokemons data to explain melt nore easily.
data_new = data.head()    # I only take 5 rows into new data
data_new
```

Out[48]:

	#	Name	Type 1	Type 2	HP	Attack	Defense	Sp. Atk	Sp. Def	Speed	Generation	Legendary
0	1	Bulbasaur	Grass	Poison	45	49	49	65	65	45	1	False
1	2	Ivysaur	Grass	Poison	60	62	63	80	80	60	1	False
2	3	Venusaur	Grass	Poison	80	82	83	100	100	80	1	False
3	4	Mega Venusaur	Grass	Poison	80	100	123	122	120	80	1	False
4	5	Charmander	Fire	NaN	39	52	43	60	50	65	1	False

In [49]:
```
# lets melt
# id_vars = what we do not wish to melt
# value_vars = what we want to melt
melted = pd.melt(frame=data_new,id_vars = 'Name', value_vars= ['Attack','Defense'])
melted
```

Out[49]:

	Name	variable	value
0	Bulbasaur	Attack	49
1	Ivysaur	Attack	62
2	Venusaur	Attack	82
3	Mega Venusaur	Attack	100
4	Charmander	Attack	52
5	Bulbasaur	Defense	49
6	Ivysaur	Defense	63
7	Venusaur	Defense	83
8	Mega Venusaur	Defense	123
9	Charmander	Defense	43

PIVOTING DATA

Reverse of melting.

In [50]:
```
# Index is name
# I want to make that columns are variable
# Finally values in columns are value
melted.pivot(index = 'Name', columns = 'variable',values='value')
```

Out[50]:

variable	Attack	Defense
Name		
Bulbasaur	49	49
Charmander	52	43
Ivysaur	62	63
Mega Venusaur	100	123
Venusaur	82	83

CONCATENATING DATA

We can concatenate two dataframe

In [51]:
```
# Firstly lets create 2 data frame
data1 = data.head()
data2= data.tail()
conc_data_row = pd.concat([data1,data2],axis =0,ignore_index =True) # axis = 0 : adds dataframes in row
conc_data_row
```

Out[51]:

	#	Name	Type 1	Type 2	HP	Attack	Defense	Sp. Atk	Sp. Def	Speed	Generation	Legendary
0	1	Bulbasaur	Grass	Poison	45	49	49	65	65	45	1	False
1	2	Ivysaur	Grass	Poison	60	62	63	80	80	60	1	False
2	3	Venusaur	Grass	Poison	80	82	83	100	100	80	1	False
3	4	Mega Venusaur	Grass	Poison	80	100	123	122	120	80	1	False
4	5	Charmander	Fire	NaN	39	52	43	60	50	65	1	False
5	796	Diancie	Rock	Fairy	50	100	150	100	150	50	6	True
6	797	Mega Diancie	Rock	Fairy	50	160	110	160	110	110	6	True
7	798	Hoopa Confined	Psychic	Ghost	80	110	60	150	130	70	6	True
8	799	Hoopa Unbound	Psychic	Dark	80	160	60	170	130	80	6	True
9	800	Volcanion	Fire	Water	80	110	120	130	90	70	6	True

In [52]:
```
data1 = data['Attack'].head()
data2= data['Defense'].head()
conc_data_col = pd.concat([data1,data2],axis =1) # axis = 1 : adds dataframes in column
conc_data_col
```

Out[52]:

	Attack	Defense
0	49	49
1	62	63
2	82	83
3	100	123
4	52	43

DATA TYPES

There are 5 basic data types: object(string),boolean, integer, float and categorical.
We can make conversion data types like from str to categorical or from int to float
Why is category important:

- make dataframe smaller in memory
- can be utilized for anlaysis especially for sklearn(we will learn later)

In [53]:
```
data.dtypes
```

Out[53]:
```
#              int64
Name          object
Type 1        object
Type 2        object
HP             int64
Attack         int64
Defense        int64
Sp. Atk        int64
Sp. Def        int64
Speed          int64
Generation     int64
Legendary       bool
dtype: object
```

In [54]:
```
# lets convert object(str) to categorical and int to float.
data['Type 1'] = data['Type 1'].astype('category')
data['Speed'] = data['Speed'].astype('float')
```

In [55]:
```
# As you can see Type 1 is converted from object to categorical
# And Speed ,s converted from int to float
data.dtypes
```

Out[55]:
```
#               int64
Name           object
Type 1       category
Type 2         object
HP              int64
Attack          int64
Defense         int64
Sp. Atk         int64
Sp. Def         int64
Speed         float64
Generation      int64
Legendary        bool
dtype: object
```

MISSING DATA and TESTING WITH ASSERT

If we encounter with missing data, what we can do:

- leave as is
- drop them with dropna()
- fill missing value with fillna()
- fill missing values with test statistics like mean
  Assert statement: check that you can turn on or turn off when you are done with your testing of the program

In [56]:
```
# Lets look at does pokemon data have nan value
# As you can see there are 800 entries. However Type 2 has 414 non-null object so it has 386 null object.
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 800 entries, 0 to 799
Data columns (total 12 columns):
#             800 non-null int64
Name          799 non-null object
Type 1        800 non-null category
Type 2        414 non-null object
HP            800 non-null int64
Attack        800 non-null int64
Defense       800 non-null int64
Sp. Atk       800 non-null int64
Sp. Def       800 non-null int64
Speed         800 non-null float64
Generation    800 non-null int64
Legendary     800 non-null bool
dtypes: bool(1), category(1), float64(1), int64(7), object(2)
memory usage: 64.9+ KB
```

In [57]:
```
# Lets chech Type 2
data["Type 2"].value_counts(dropna =False)
# As you can see, there are 386 NAN value
```

Out[57]:
```
NaN         386
Flying       97
Ground       35
Poison       34
Psychic      33
Fighting     26
Grass        25
Fairy        23
Steel        22
Dark         20
Dragon       18
Ghost        14
Rock         14
Water        14
Ice          14
Fire         12
Electric      6
Normal        4
Bug           3
Name: Type 2, dtype: int64
```

In [58]:
```
# Lets drop nan values
data1=data   # also we will use data to fill missing value so I assign it to data1 variable
data1["Type 2"].dropna(inplace = True)  # inplace = True means we do not assign it to new variable. Changes automatical
# So does it work ?
```

In [59]:
```
#  Lets check with assert statement
# Assert statement:
assert 1==1 # return nothing because it is true
```

In [60]:
```
# In order to run all code, we need to make this line comment
# assert 1==2 # return error because it is false
```

In [61]:
```
assert  data['Type 2'].notnull().all() # returns nothing because we drop nan values
```

In [62]:
```
data["Type 2"].fillna('empty',inplace = True)
```

In [63]:
```
assert  data['Type 2'].notnull().all() # returns nothing because we do not have nan values
```

In [64]:
```
# # With assert statement we can check a lot of thing. For example
# assert data.columns[1] == 'Name'
# assert data.Speed.dtypes == np.int
```

In this part, you learn:

- Diagnose data for cleaning
- Exploratory data analysis
- Visual exploratory data analysis
- Tidy data
- Pivoting data
- Concatenating data
- Data types
- Missing data and testing with assert

Pandas Foundation

REVİEW of PANDAS

As you notice, I do not give all idea in a same time. Although, we learn some basics of pandas, we will go deeper in pandas.

- single column = series
- NaN = not a number
- dataframe.values = numpy

BUILDING DATA FRAMES FROM SCRATCH

- We can build data frames from csv as we did earlier.
- Also we can build dataframe from dictionaries
  - zip() method: This function returns a list of tuples, where the i-th tuple contains the i-th element from each of the argument sequences or iterables.
- Adding new column
- Broadcasting: Create new column and assign a value to entire column

In [65]:
```
# data frames from dictionary
country = ["Spain","France"]
population = ["11","12"]
list_label = ["country","population"]
list_col = [country,population]
zipped = list(zip(list_label,list_col))
data_dict = dict(zipped)
df = pd.DataFrame(data_dict)
df
```

Out[65]:

	country	population
0	Spain	11
1	France	12

In [66]:
```
# Add new columns
df["capital"] = ["madrid","paris"]
df
```

Out[66]:

	country	population	capital
0	Spain	11	madrid
1	France	12	paris

In [67]:
```
# Broadcasting
df["income"] = 0 #Broadcasting entire column
df
```

Out[67]:

	country	population	capital	income
0	Spain	11	madrid	0
1	France	12	paris	0

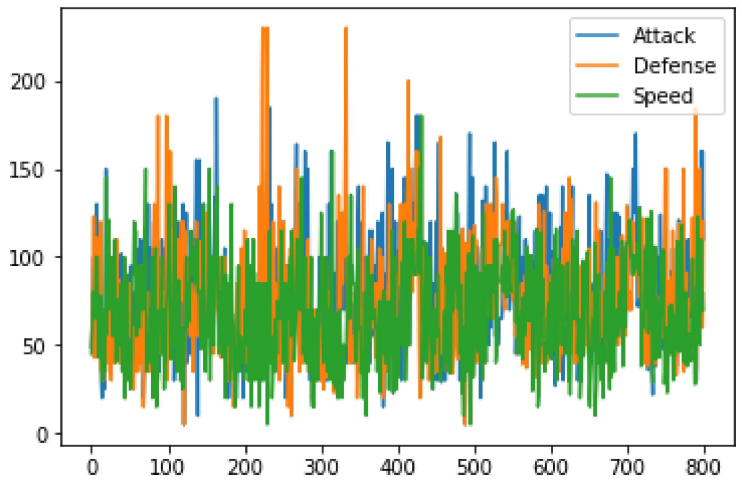
VISUAL EXPLORATORY DATA ANALYSIS

- Plot
- Subplot

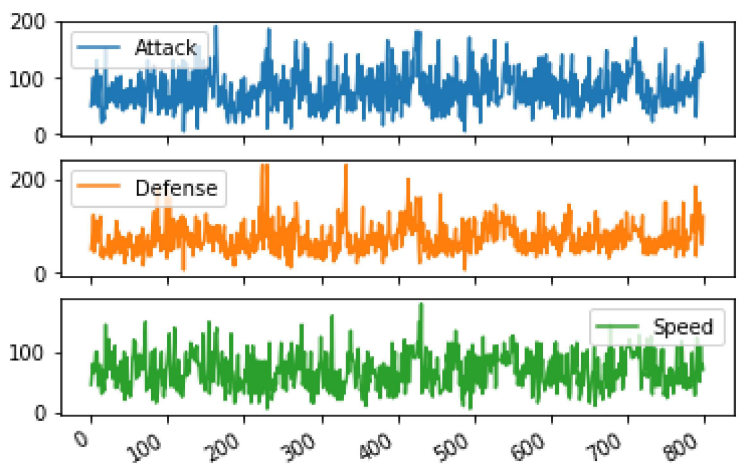
- Histogram:
  - bins: number of bins
  - range(tuble): min and max values of bins
  - normed(boolean): normalize or not
  - cumulative(boolean): compute cumulative distribution

In [68]:
```
# Plotting all data
data1 = data.loc[:,["Attack","Defense","Speed"]]
data1.plot()
# it is confusing
```

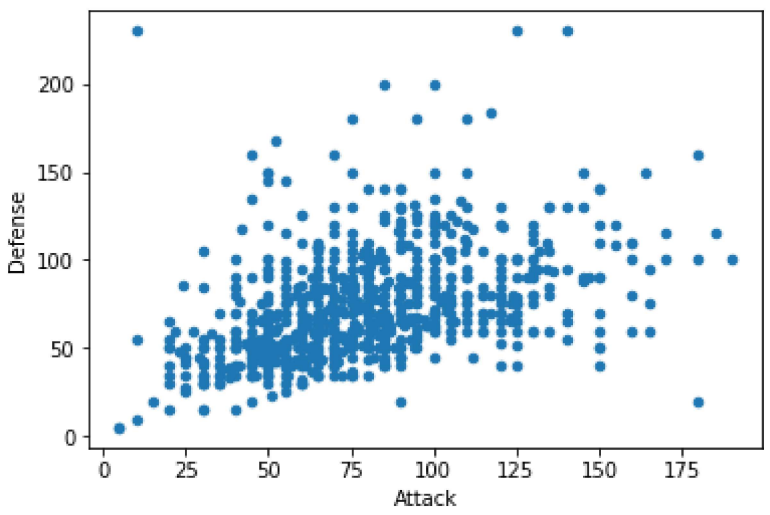
Out[68]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x7e9f80b6ceb8>
```



In [69]:
```
# subplots
data1.plot(subplots = True)
plt.show()
```



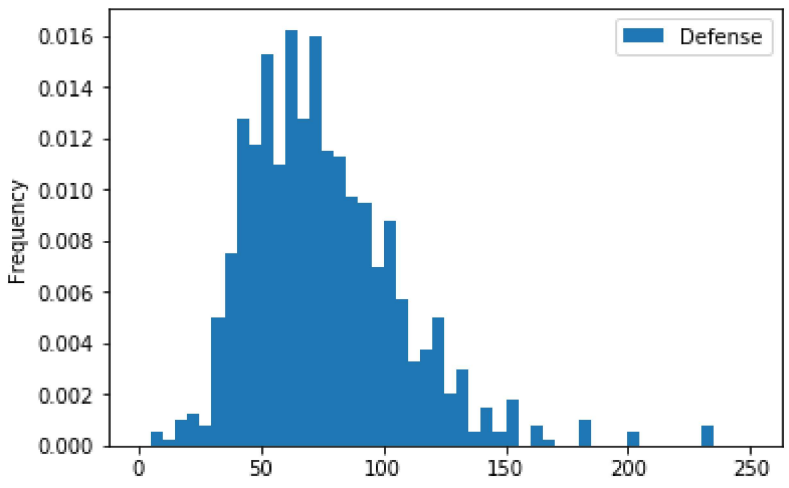
In [70]:
```
# scatter plot
data1.plot(kind = "scatter",x="Attack",y = "Defense")
plt.show()
```



In [71]:
```
# hist plot
data1.plot(kind = "hist",y = "Defense",bins = 50,range= (0,250),normed = True)
```

```
/opt/conda/lib/python3.6/site-packages/matplotlib/axes/_axes.py:6571: UserWarning: The 'normed' kwarg is deprecated, and has been replaced by the 'density' kwarg.
  warnings.warn("The 'normed' kwarg is deprecated, and has been "
```

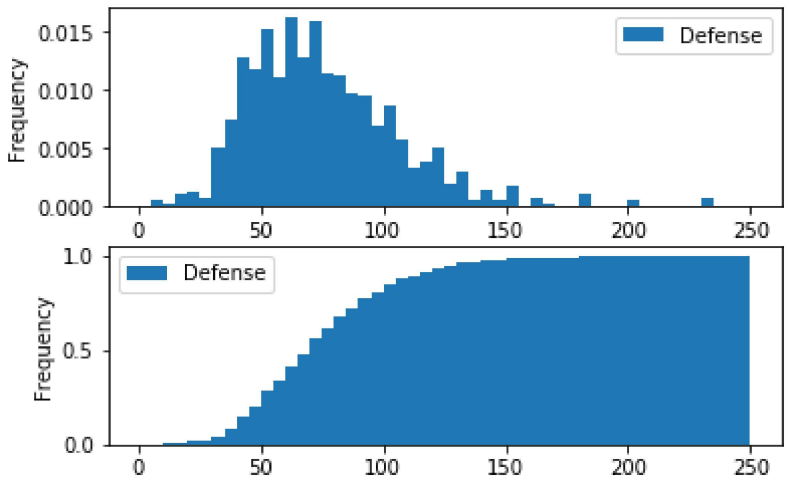
Out[71]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x7e9f80908f98>
```



In [72]:
```
# histogram subplot with non cumulative and cumulative
fig, axes = plt.subplots(nrows=2,ncols=1)
data1.plot(kind = "hist",y = "Defense",bins = 50,range= (0,250),normed = True,ax = axes[0])
data1.plot(kind = "hist",y = "Defense",bins = 50,range= (0,250),normed = True,ax = axes[1],cumulative = True)
plt.savefig('graph.png')
plt
```

```
/opt/conda/lib/python3.6/site-packages/matplotlib/axes/_axes.py:6571: UserWarning: The 'normed' kwarg is deprecated, an
d has been replaced by the 'density' kwarg.
  warnings.warn("The 'normed' kwarg is deprecated, and has been "
```

Out[72]:
```
<module 'matplotlib.pyplot' from '/opt/conda/lib/python3.6/site-packages/matplotlib/pyplot.py'>
```



STATISTICAL EXPLORATORY DATA ANALYSIS

- count: number of entries
- mean: average of entries
- std: standart deviation
- min: minimum entry
- 25%: first quantile
- 50%: median or second quantile
- 75%: third quantile
- max: maximum entry

In [73]:
```
data.describe()
```

Out[73]:

	#	HP	Attack	Defense	Sp. Atk	Sp. Def	Speed	Generation
count	800.0000	800.000000	800.000000	800.000000	800.000000	800.000000	800.000000	800.00000
mean	400.5000	69.258750	79.001250	73.842500	72.820000	71.902500	68.277500	3.32375
std	231.0844	25.534669	32.457366	31.183501	32.722294	27.828916	29.060474	1.66129
min	1.0000	1.000000	5.000000	5.000000	10.000000	20.000000	5.000000	1.00000
25%	200.7500	50.000000	55.000000	50.000000	49.750000	50.000000	45.000000	2.00000
50%	400.5000	65.000000	75.000000	70.000000	65.000000	70.000000	65.000000	3.00000
75%	600.2500	80.000000	100.000000	90.000000	95.000000	90.000000	90.000000	5.00000
max	800.0000	255.000000	190.000000	230.000000	194.000000	230.000000	180.000000	6.00000

INDEXING PANDAS TIME SERIES

- datetime = object
- parse_dates(boolean): Transform date to ISO 8601 (yyyy-mm-dd hh:mm:ss) format

In [74]:
```
time_list = ["1992-03-08","1992-04-12"]
print(type(time_list[1])) # As you can see date is string
# however we want it to be datetime object
datetime_object = pd.to_datetime(time_list)
print(type(datetime_object))
```

```
<class 'str'>
<class 'pandas.core.indexes.datetimes.DatetimeIndex'>
```

In [75]:
```
# close warning
import warnings
warnings.filterwarnings("ignore")
# In order to practice lets take head of pokemon data and add it a time list
data2 = data.head()
date_list = ["1992-01-10","1992-02-10","1992-03-10","1993-03-15","1993-03-16"]
datetime_object = pd.to_datetime(date_list)
data2["date"] = datetime_object
# lets make date as index
data2= data2.set_index("date")
data2
```

Out[75]:

date	#	Name	Type 1	Type 2	HP	Attack	Defense	Sp. Atk	Sp. Def	Speed	Generation	Legendary
1992-01-10	1	Bulbasaur	Grass	Poison	45	49	49	65	65	45.0	1	False
1992-02-10	2	Ivysaur	Grass	Poison	60	62	63	80	80	60.0	1	False
1992-03-10	3	Venusaur	Grass	Poison	80	82	83	100	100	80.0	1	False
1993-03-15	4	Mega Venusaur	Grass	Poison	80	100	123	122	120	80.0	1	False
1993-03-16	5	Charmander	Fire	NaN	39	52	43	60	50	65.0	1	False

In [76]:
```
# Now we can select according to our date index
print(data2.loc["1993-03-16"])
print(data2.loc["1992-03-10":"1993-03-16"])
```

```
#                    5
Name           Charmander
Type 1               Fire
Type 2                NaN
HP                     39
Attack                 52
Defense                43
Sp. Atk                60
Sp. Def                50
Speed                  65
Generation              1
Legendary           False
Name: 1993-03-16 00:00:00, dtype: object
            #           Name Type 1    ...     Speed  Generation  Legendary
date                                   ...
1992-03-10  3       Venusaur  Grass    ...      80.0           1      False
1993-03-15  4  Mega Venusaur  Grass    ...      80.0           1      False
1993-03-16  5     Charmander   Fire    ...      65.0           1      False

[3 rows x 12 columns]
```

RESAMPLING PANDAS TIME SERIES

- Resampling: statistical method over different time intervals
  - Needs string to specify frequency like "M" = month or "A" = year
- Downsampling: reduce date time rows to slower frequency like from daily to weekly
- Upsampling: increase date time rows to faster frequency like from daily to hourly
- Interpolate: Interpolate values according to different methods like 'linear', 'time' or index'
  - https://pandas.pydata.org/pandas-docs/stable/generated/pandas.Series.interpolate.html

In [77]:
```
# We will use data2 that we create at previous part
data2.resample("A").mean()
```

Out[77]:

date	#	HP	Attack	Defense	Sp. Atk	Sp. Def	Speed	Generation	Legendary
1992-12-31	2.0	61.666667	64.333333	65.0	81.666667	81.666667	61.666667	1.0	False
1993-12-31	4.5	59.500000	76.000000	83.0	91.000000	85.000000	72.500000	1.0	False

In [78]:
```
# Lets resample with month
data2.resample("M").mean()
# As you can see there are a lot of nan because data2 does not include all months
```

Out[78]:

date	#	HP	Attack	Defense	Sp. Atk	Sp. Def	Speed	Generation	Legendary
1992-01-31	1.0	45.0	49.0	49.0	65.0	65.0	45.0	1.0	0.0
1992-02-29	2.0	60.0	62.0	63.0	80.0	80.0	60.0	1.0	0.0
1992-03-31	3.0	80.0	82.0	83.0	100.0	100.0	80.0	1.0	0.0
1992-04-30	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
1992-05-31	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
1992-06-30	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
1992-07-31	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
1992-08-31	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
1992-09-30	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
1992-10-31	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
1992-11-30	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
1992-12-31	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
1993-01-31	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
1993-02-28	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
1993-03-31	4.5	59.5	76.0	83.0	91.0	85.0	72.5	1.0	0.0

In [79]:
```
# In real life (data is real. Not created from us like data2) we can solve this problem with interpolate
# We can interpolete from first value
data2.resample("M").first().interpolate("linear")
```

Out[79]:

date	#	Name	Type 1	Type 2	HP	Attack	Defense	Sp. Atk	Sp. Def	Speed	Generation	Legendary
1992-01-31	1.000000	Bulbasaur	Grass	Poison	45.0	49.0	49.000000	65.000000	65.000000	45.0	1.0	False
1992-02-29	2.000000	Ivysaur	Grass	Poison	60.0	62.0	63.000000	80.000000	80.000000	60.0	1.0	False
1992-03-31	3.000000	Venusaur	Grass	Poison	80.0	82.0	83.000000	100.000000	100.000000	80.0	1.0	False
1992-04-30	3.083333	NaN	NaN	NaN	80.0	83.5	86.333333	101.833333	101.666667	80.0	1.0	NaN
1992-05-31	3.166667	NaN	NaN	NaN	80.0	85.0	89.666667	103.666667	103.333333	80.0	1.0	NaN
1992-06-30	3.250000	NaN	NaN	NaN	80.0	86.5	93.000000	105.500000	105.000000	80.0	1.0	NaN
1992-07-31	3.333333	NaN	NaN	NaN	80.0	88.0	96.333333	107.333333	106.666667	80.0	1.0	NaN
1992-08-31	3.416667	NaN	NaN	NaN	80.0	89.5	99.666667	109.166667	108.333333	80.0	1.0	NaN
1992-09-30	3.500000	NaN	NaN	NaN	80.0	91.0	103.000000	111.000000	110.000000	80.0	1.0	NaN
1992-10-31	3.583333	NaN	NaN	NaN	80.0	92.5	106.333333	112.833333	111.666667	80.0	1.0	NaN
1992-11-30	3.666667	NaN	NaN	NaN	80.0	94.0	109.666667	114.666667	113.333333	80.0	1.0	NaN
1992-12-31	3.750000	NaN	NaN	NaN	80.0	95.5	113.000000	116.500000	115.000000	80.0	1.0	NaN
1993-01-31	3.833333	NaN	NaN	NaN	80.0	97.0	116.333333	118.333333	116.666667	80.0	1.0	NaN
1993-02-28	3.916667	NaN	NaN	NaN	80.0	98.5	119.666667	120.166667	118.333333	80.0	1.0	NaN
1993-03-31	4.000000	Mega Venusaur	Grass	Poison	80.0	100.0	123.000000	122.000000	120.000000	80.0	1.0	False

In [80]:
```
# Or we can interpolate with mean()
data2.resample("M").mean().interpolate("linear")
```

Out[80]:

date	#	HP	Attack	Defense	Sp. Atk	Sp. Def	Speed	Generation	Legendary
1992-01-31	1.000	45.000000	49.0	49.0	65.00	65.00	45.000	1.0	0.0
1992-02-29	2.000	60.000000	62.0	63.0	80.00	80.00	60.000	1.0	0.0
1992-03-31	3.000	80.000000	82.0	83.0	100.00	100.00	80.000	1.0	0.0
1992-04-30	3.125	78.291667	81.5	83.0	99.25	98.75	79.375	1.0	0.0
1992-05-31	3.250	76.583333	81.0	83.0	98.50	97.50	78.750	1.0	0.0
1992-06-30	3.375	74.875000	80.5	83.0	97.75	96.25	78.125	1.0	0.0
1992-07-31	3.500	73.166667	80.0	83.0	97.00	95.00	77.500	1.0	0.0
1992-08-31	3.625	71.458333	79.5	83.0	96.25	93.75	76.875	1.0	0.0
1992-09-30	3.750	69.750000	79.0	83.0	95.50	92.50	76.250	1.0	0.0
1992-10-31	3.875	68.041667	78.5	83.0	94.75	91.25	75.625	1.0	0.0
1992-11-30	4.000	66.333333	78.0	83.0	94.00	90.00	75.000	1.0	0.0
1992-12-31	4.125	64.625000	77.5	83.0	93.25	88.75	74.375	1.0	0.0
1993-01-31	4.250	62.916667	77.0	83.0	92.50	87.50	73.750	1.0	0.0
1993-02-28	4.375	61.208333	76.5	83.0	91.75	86.25	73.125	1.0	0.0
1993-03-31	4.500	59.500000	76.0	83.0	91.00	85.00	72.500	1.0	0.0

Manipulating Data Frames with Pandas

INDEXING DATA FRAMES

- Indexing using square brackets
- Using column attribute and row label
- Using loc accessor
- Selecting only some columns

In [81]:
```
# read data
data = pd.read_csv('../input/pokemon.csv')
data= data.set_index("#")
data.head()
```

Out[81]:

#	Name	Type 1	Type 2	HP	Attack	Defense	Sp. Atk	Sp. Def	Speed	Generation	Legendary
1	Bulbasaur	Grass	Poison	45	49	49	65	65	45	1	False
2	Ivysaur	Grass	Poison	60	62	63	80	80	60	1	False
3	Venusaur	Grass	Poison	80	82	83	100	100	80	1	False
4	Mega Venusaur	Grass	Poison	80	100	123	122	120	80	1	False
5	Charmander	Fire	NaN	39	52	43	60	50	65	1	False

In [82]:
```
# indexing using square brackets
data["HP"][1]
```

Out[82]:
```
45
```

In [83]:
```
# using column attribute and row label
data.HP[1]
```

Out[83]:
```
45
```

In [84]:
```
# using loc accessor
data.loc[1,["HP"]]
```

Out[84]:
```
HP    45
Name: 1, dtype: object
```

In [85]:
```
# Selecting only some columns
data[["HP","Attack"]]
```

Out[85]:

#	HP	Attack
1	45	49
2	60	62
3	80	82
4	80	100
5	39	52
6	58	64
7	78	84
8	78	130
9	78	104
10	44	48
11	59	63
12	79	83
13	79	103
14	45	30
15	50	20
16	60	45
17	40	35
18	45	25
19	65	90
20	65	150
21	40	45
22	63	60
23	83	80
24	83	80
25	30	56
26	55	81
27	40	60
28	65	90
29	35	60
30	60	85
...	...	...
771	95	65
772	78	92
773	67	58
774	50	50
775	45	50
776	68	75
777	90	100
778	57	80
779	43	70
780	85	110
781	49	66
782	44	66
783	54	66
784	59	66
785	65	90
786	55	85
787	75	95
788	85	100
789	55	69
790	95	117
791	40	30
792	85	70

#	HP	Attack
793	126	131
794	126	131
795	108	100
796	50	100
797	50	160
798	80	110
799	80	160
800	80	110

800 rows × 2 columns

SLICING DATA FRAME

- Difference between selecting columns
  - Series and data frames
- Slicing and indexing series
- Reverse slicing
- From something to end

In [86]:
```
# Difference between selecting columns: series and dataframes
print(type(data["HP"]))     # series
print(type(data[["HP"]]))   # data frames
```

```
<class 'pandas.core.series.Series'>
<class 'pandas.core.frame.DataFrame'>
```

In [87]:
```
# Slicing and indexing series
data.loc[1:10,"HP":"Defense"]   # 10 and "Defense" are inclusive
```

Out[87]:

#	HP	Attack	Defense
1	45	49	49
2	60	62	63
3	80	82	83
4	80	100	123
5	39	52	43
6	58	64	58
7	78	84	78
8	78	130	111
9	78	104	78
10	44	48	65

In [88]:
```
# Reverse slicing
data.loc[10:1:-1,"HP":"Defense"]
```

Out[88]:

#	HP	Attack	Defense
10	44	48	65
9	78	104	78
8	78	130	111
7	78	84	78
6	58	64	58
5	39	52	43
4	80	100	123
3	80	82	83
2	60	62	63
1	45	49	49

In [89]:
```
# From something to end
data.loc[1:10,"Speed":]
```

Out[89]:

#	Speed	Generation	Legendary
1	45	1	False
2	60	1	False
3	80	1	False
4	80	1	False
5	65	1	False
6	80	1	False
7	100	1	False
8	100	1	False
9	100	1	False
10	43	1	False

FILTERING DATA FRAMES

Creating boolean series Combining filters Filtering column based others

In [90]:
```
# Creating boolean series
boolean = data.HP > 200
data[boolean]
```

Out[90]:

#	Name	Type 1	Type 2	HP	Attack	Defense	Sp. Atk	Sp. Def	Speed	Generation	Legendary
122	Chansey	Normal	NaN	250	5	5	35	105	50	1	False
262	Blissey	Normal	NaN	255	10	10	75	135	55	2	False

In [91]:
```
# Combining filters
first_filter = data.HP > 150
second_filter = data.Speed > 35
data[first_filter & second_filter]
```

Out[91]:

#	Name	Type 1	Type 2	HP	Attack	Defense	Sp. Atk	Sp. Def	Speed	Generation	Legendary
122	Chansey	Normal	NaN	250	5	5	35	105	50	1	False
262	Blissey	Normal	NaN	255	10	10	75	135	55	2	False
352	Wailord	Water	NaN	170	90	45	90	45	60	3	False
656	Alomomola	Water	NaN	165	75	80	40	45	65	5	False

In [92]:
```
# Filtering column based others
data.HP[data.Speed<15]
```

Out[92]:
```
#
231     20
360     45
487     50
496    135
659     44
Name: HP, dtype: int64
```

TRANSFORMING DATA

- Plain python functions
- Lambda function: to apply arbitrary python function to every element
- Defining column using other columns

In [93]:
```
# Plain python functions
def div(n):
    return n/2
data.HP.apply(div)
```

Out[93]:
```
#
1      22.5
2      30.0
3      40.0
4      40.0
5      19.5
6      29.0
7      39.0
8      39.0
9      39.0
10     22.0
11     29.5
12     39.5
13     39.5
14     22.5
15     25.0
16     30.0
17     20.0
18     22.5
19     32.5
20     32.5
21     20.0
22     31.5
23     41.5
24     41.5
25     15.0
26     27.5
27     20.0
28     32.5
29     17.5
30     30.0
       ...
771    47.5
772    39.0
773    33.5
774    25.0
775    22.5
776    34.0
777    45.0
778    28.5
779    21.5
780    42.5
781    24.5
782    22.0
783    27.0
784    29.5
785    32.5
786    27.5
787    37.5
788    42.5
789    27.5
790    47.5
791    20.0
792    42.5
793    63.0
794    63.0
795    54.0
796    25.0
797    25.0
798    40.0
799    40.0
800    40.0
Name: HP, Length: 800, dtype: float64
```

In [94]:
```
# Or we can use lambda function
data.HP.apply(lambda n : n/2)
```

Out[94]:
```
#
1      22.5
2      30.0
3      40.0
4      40.0
5      19.5
6      29.0
7      39.0
8      39.0
9      39.0
10     22.0
11     29.5
12     39.5
13     39.5
14     22.5
15     25.0
16     30.0
17     20.0
18     22.5
19     32.5
20     32.5
21     20.0
22     31.5
23     41.5
24     41.5
25     15.0
26     27.5
27     20.0
28     32.5
29     17.5
30     30.0
       ...
771    47.5
772    39.0
773    33.5
774    25.0
775    22.5
776    34.0
777    45.0
778    28.5
779    21.5
780    42.5
781    24.5
782    22.0
783    27.0
784    29.5
785    32.5
786    27.5
787    37.5
788    42.5
789    27.5
790    47.5
791    20.0
792    42.5
793    63.0
794    63.0
795    54.0
796    25.0
797    25.0
798    40.0
799    40.0
800    40.0
Name: HP, Length: 800, dtype: float64
```

In [95]:
```
# Defining column using other columns
data["total_power"] = data.Attack + data.Defense
data.head()
```

Out[95]:

#	Name	Type 1	Type 2	HP	Attack	Defense	Sp. Atk	Sp. Def	Speed	Generation	Legendary	total_power
1	Bulbasaur	Grass	Poison	45	49	49	65	65	45	1	False	98
2	Ivysaur	Grass	Poison	60	62	63	80	80	60	1	False	125
3	Venusaur	Grass	Poison	80	82	83	100	100	80	1	False	165
4	Mega Venusaur	Grass	Poison	80	100	123	122	120	80	1	False	223
5	Charmander	Fire	NaN	39	52	43	60	50	65	1	False	95

INDEX OBJECTS AND LABELED DATA

index: sequence of label

In [96]:
```
# our index name is this:
print(data.index.name)
# lets change it
data.index.name = "index_name"
data.head()
```

#

Out[96]:

index_name	Name	Type 1	Type 2	HP	Attack	Defense	Sp. Atk	Sp. Def	Speed	Generation	Legendary	total_power
1	Bulbasaur	Grass	Poison	45	49	49	65	65	45	1	False	98
2	Ivysaur	Grass	Poison	60	62	63	80	80	60	1	False	125
3	Venusaur	Grass	Poison	80	82	83	100	100	80	1	False	165
4	Mega Venusaur	Grass	Poison	80	100	123	122	120	80	1	False	223
5	Charmander	Fire	NaN	39	52	43	60	50	65	1	False	95

In [97]:
```
# Overwrite index
# if we want to modify index we need to change all of them.
data.head()
# first copy of our data to data3 then change index
data3 = data.copy()
# lets make index start from 100. It is not remarkable change but it is just example
data3.index = range(100,900,1)
data3.head()
```

Out[97]:

	Name	Type 1	Type 2	HP	Attack	Defense	Sp. Atk	Sp. Def	Speed	Generation	Legendary	total_power
100	Bulbasaur	Grass	Poison	45	49	49	65	65	45	1	False	98
101	Ivysaur	Grass	Poison	60	62	63	80	80	60	1	False	125
102	Venusaur	Grass	Poison	80	82	83	100	100	80	1	False	165
103	Mega Venusaur	Grass	Poison	80	100	123	122	120	80	1	False	223
104	Charmander	Fire	NaN	39	52	43	60	50	65	1	False	95

In [98]:
```
# We can make one of the column as index. I actually did it at the beginning of manipulating data frames with pandas se
# It was like this
# data= data.set_index("#")
# also you can use
# data.index = data["#"]
```

HIERARCHICAL INDEXING

- Setting indexing

In [99]:
```
# lets read data frame one more time to start from beginning
data = pd.read_csv('../input/pokemon.csv')
data.head()
# As you can see there is index. However we want to set one or more column to be index
```

Out[99]:

	#	Name	Type 1	Type 2	HP	Attack	Defense	Sp. Atk	Sp. Def	Speed	Generation	Legendary
0	1	Bulbasaur	Grass	Poison	45	49	49	65	65	45	1	False
1	2	Ivysaur	Grass	Poison	60	62	63	80	80	60	1	False
2	3	Venusaur	Grass	Poison	80	82	83	100	100	80	1	False
3	4	Mega Venusaur	Grass	Poison	80	100	123	122	120	80	1	False
4	5	Charmander	Fire	NaN	39	52	43	60	50	65	1	False

In [100…
```
# Setting index : type 1 is outer type 2 is inner index
data1 = data.set_index(["Type 1","Type 2"])
data1.head(100)
# data1.loc["Fire","Flying"] # howw to use indexes
```

Out[100]:

Type 1	Type 2	#	Name	HP	Attack	Defense	Sp. Atk	Sp. Def	Speed	Generation	Legendary
Grass	**Poison**	1	Bulbasaur	45	49	49	65	65	45	1	False
	Poison	2	Ivysaur	60	62	63	80	80	60	1	False
	Poison	3	Venusaur	80	82	83	100	100	80	1	False
	Poison	4	Mega Venusaur	80	100	123	122	120	80	1	False
Fire	**NaN**	5	Charmander	39	52	43	60	50	65	1	False
	NaN	6	Charmeleon	58	64	58	80	65	80	1	False
	Flying	7	Charizard	78	84	78	109	85	100	1	False
	Dragon	8	Mega Charizard X	78	130	111	130	85	100	1	False
	Flying	9	Mega Charizard Y	78	104	78	159	115	100	1	False
Water	**NaN**	10	Squirtle	44	48	65	50	64	43	1	False
	NaN	11	Wartortle	59	63	80	65	80	58	1	False
	NaN	12	Blastoise	79	83	100	85	105	78	1	False
	NaN	13	Mega Blastoise	79	103	120	135	115	78	1	False
Bug	**NaN**	14	Caterpie	45	30	35	20	20	45	1	False
	NaN	15	Metapod	50	20	55	25	25	30	1	False
	Flying	16	Butterfree	60	45	50	90	80	70	1	False
	Poison	17	Weedle	40	35	30	20	20	50	1	False
	Poison	18	Kakuna	45	25	50	25	25	35	1	False
	Poison	19	Beedrill	65	90	40	45	80	75	1	False
	Poison	20	Mega Beedrill	65	150	40	15	80	145	1	False
Normal	**Flying**	21	Pidgey	40	45	40	35	35	56	1	False
	Flying	22	Pidgeotto	63	60	55	50	50	71	1	False
	Flying	23	Pidgeot	83	80	75	70	70	101	1	False
	Flying	24	Mega Pidgeot	83	80	80	135	80	121	1	False
	NaN	25	Rattata	30	56	35	25	35	72	1	False
	NaN	26	Raticate	55	81	60	50	70	97	1	False
	Flying	27	Spearow	40	60	30	31	31	70	1	False
	Flying	28	Fearow	65	90	65	61	61	100	1	False
Poison	**NaN**	29	Ekans	35	60	44	40	54	55	1	False
	NaN	30	Arbok	60	85	69	65	79	80	1	False
...	**...**	...	...	...	...	...	...	...	...	...	...
Psychic	**NaN**	71	Alakazam	55	50	45	135	95	120	1	False
	NaN	72	Mega Alakazam	55	50	65	175	95	150	1	False
Fighting	**NaN**	73	Machop	70	80	50	35	35	35	1	False
	NaN	74	Machoke	80	100	70	50	60	45	1	False
	NaN	75	Machamp	90	130	80	65	85	55	1	False
Grass	**Poison**	76	Bellsprout	50	75	35	70	30	40	1	False
	Poison	77	Weepinbell	65	90	50	85	45	55	1	False
	Poison	78	Victreebel	80	105	65	100	70	70	1	False
Water	**Poison**	79	Tentacool	40	40	35	50	100	70	1	False
	Poison	80	Tentacruel	80	70	65	80	120	100	1	False
Rock	**Ground**	81	Geodude	40	80	100	30	30	20	1	False
	Ground	82	Graveler	55	95	115	45	45	35	1	False
	Ground	83	Golem	80	120	130	55	65	45	1	False
Fire	**NaN**	84	Ponyta	50	85	55	65	65	90	1	False
	NaN	85	Rapidash	65	100	70	80	80	105	1	False
Water	**Psychic**	86	Slowpoke	90	65	65	40	40	15	1	False
	Psychic	87	Slowbro	95	75	110	100	80	30	1	False
	Psychic	88	Mega Slowbro	95	75	180	130	80	30	1	False
Electric	**Steel**	89	Magnemite	25	35	70	95	55	45	1	False
	Steel	90	Magneton	50	60	95	120	70	70	1	False
Normal	**Flying**	91	Farfetch'd	52	65	55	58	62	60	1	False
	Flying	92	Doduo	35	85	45	35	35	75	1	False

Type 1	Type 2	#	Name	HP	Attack	Defense	Sp. Atk	Sp. Def	Speed	Generation	Legendary
	Flying	93	Dodrio	60	110	70	60	60	100	1	False
Water	**NaN**	94	Seel	65	45	55	45	70	45	1	False
	Ice	95	Dewgong	90	70	80	70	95	70	1	False
Poison	**NaN**	96	Grimer	80	80	50	40	50	25	1	False
	NaN	97	Muk	105	105	75	65	100	50	1	False
Water	**NaN**	98	Shellder	30	65	100	45	25	40	1	False
	Ice	99	Cloyster	50	95	180	85	45	70	1	False
Ghost	**Poison**	100	Gastly	30	35	30	100	35	80	1	False

100 rows × 10 columns

PIVOTING DATA FRAMES

- pivoting: reshape tool

In [101…
```
dic = {"treatment":["A","A","B","B"],"gender":["F","M","F","M"],"response":[10,45,5,9],"age":[15,4,72,65]}
df = pd.DataFrame(dic)
df
```

Out[101]:

	treatment	gender	response	age
0	A	F	10	15
1	A	M	45	4
2	B	F	5	72
3	B	M	9	65

In [102…
```
# pivoting
df.pivot(index="treatment",columns = "gender",values="response")
```

Out[102]:

gender	F	M
treatment		
A	10	45
B	5	9

STACKING and UNSTACKING DATAFRAME

- deal with multi label indexes
- level: position of unstacked index
- swaplevel: change inner and outer level index position

In [103…
```
df1 = df.set_index(["treatment","gender"])
df1
# lets unstack it
```

Out[103]:

		response	age
treatment	**gender**		
A	**F**	10	15
	M	45	4
B	**F**	5	72
	M	9	65

In [104…
```
# level determines indexes
df1.unstack(level=0)
```

Out[104]:

	response		age	
treatment	**A**	**B**	**A**	**B**
gender				
F	10	5	15	72
M	45	9	4	65

In [105…
```
df1.unstack(level=1)
```

Out[105]:

	response		age	
gender	F	M	F	M
treatment				
A	10	45	15	4
B	5	9	72	65

In [106…
```
# change inner and outer level index position
df2 = df1.swaplevel(0,1)
df2
```

Out[106]:

		response	age
gender	treatment		
F	A	10	15
M	A	45	4
F	B	5	72
M	B	9	65

MELTING DATA FRAMES

- Reverse of pivoting

In [107…
```
df
```

Out[107]:

	treatment	gender	response	age
0	A	F	10	15
1	A	M	45	4
2	B	F	5	72
3	B	M	9	65

In [108…
```
# df.pivot(index="treatment",columns = "gender",values="response")
pd.melt(df,id_vars="treatment",value_vars=["age","response"])
```

Out[108]:

	treatment	variable	value
0	A	age	15
1	A	age	4
2	B	age	72
3	B	age	65
4	A	response	10
5	A	response	45
6	B	response	5
7	B	response	9

CATEGORICALS AND GROUPBY

In [109…
```
# We will use df
df
```

Out[109]:

	treatment	gender	response	age
0	A	F	10	15
1	A	M	45	4
2	B	F	5	72
3	B	M	9	65

In [110…
```
# according to treatment take means of other features
df.groupby("treatment").mean()   # mean is aggregation / reduction method
# there are other methods like sum, std,max or min
```

Out[110]:

treatment	response	age
A	27.5	9.5
B	7.0	68.5

In [111…
```
# we can only choose one of the feature
df.groupby("treatment").age.max()
```

Out[111]:
```
treatment
A    15
B    72
Name: age, dtype: int64
```

In [112…
```
# Or we can choose multiple features
df.groupby("treatment")[["age","response"]].min()
```

Out[112]:

treatment	age	response
A	4	10
B	65	5

In [113…
```
df.info()
# as you can see gender is object
# However if we use groupby, we can convert it categorical data.
# Because categorical data uses less memory, speed up operations like groupby
#df["gender"] = df["gender"].astype("category")
#df["treatment"] = df["treatment"].astype("category")
#df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 4 entries, 0 to 3
Data columns (total 4 columns):
treatment    4 non-null object
gender       4 non-null object
response     4 non-null int64
age          4 non-null int64
dtypes: int64(2), object(2)
memory usage: 208.0+ bytes
```