Pandas Data Frames

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Pandas is a python implementation of the R or SQL style data frame or data table

Indexing is a bit different, and there are some other "wrinkles" to id

There are a lot of member functions (aka methods) in Pandas to do a lot of basic data processing

Pandas data frames have variables along columns, which can be of different types

More resources

https://pandas.pydata.org/

In [1]:
```
import pandas as pd
```

we will load a data frame descriping public wifi access sites in Boston

the file is called wicked_free_wifi_boston.csv

There is a read_csv function in pandas, that will attempt to assign variable types to columns

You will need to insert the full file path into the variable infile below, or make sure that the file is in the current working directory

below is the command from the os library to show the current working directory

we can use os.chdir() to change the current working directory

In [2]:
```
import os

os.getcwd()
```

Out[2]:
```
'C:\\Users\\cmilinazzo\\Documents\\USB Drive\\R and Python Programming\\Module 02
\\Pair Programming'
```

In [3]:
```
os.chdir('C:\\Users\\cmilinazzo\\Documents\\USB Drive\\R and Python Programming\\Mo
```

In [4]:
```
infile="Wicked_Free_WiFi_Locations.csv"

wifi=pd.read_csv(infile)
```

In [5]:
```
# head function,  called as a methd belonging to the dataframe (a python object) ca

# wifi is said to be an instance of a python dataframe
```

```
wifi.head(7)
```

Out[5]:

	X	Y	neighborhood_id	neighborhood_name	device_serial
0	NaN	NaN	L_601230550253963849	Mobile WiFi Kit 1	Q3AK-SUL7-7FC4
1	NaN	NaN	L_601230550253963849	Mobile WiFi Kit 1	Q2ZY-RF99-YN45
2	-7.912255e+06	5.206228e+06	L_601230550253964116	Nubian-Bus-Stop	Q3AE-QFTK-E55W
3	NaN	NaN	L_601230550253964116	Nubian-Bus-Stop	Q3AK-DU9C-2UXZ
4	NaN	NaN	L_601230550253964116	Nubian-Bus-Stop	Q3AK-FGAN-3AR9
5	-7.913037e+06	5.209642e+06	N_568579452955527921	Parks	Q2EK-4PWN-GALS
6	-7.913800e+06	5.210828e+06	N_579275502070532581	Roxbury	Q2CK-SSY2-PBYW

In [6]:
```
#unlike the R data frames, head doesn't show us the data types
# we need to do that manually, looking at the attribute dtypes

wifi.dtypes
```

Out[6]:
```
X                      float64
Y                      float64
neighborhood_id         object
neighborhood_name       object
device_serial           object
device_connectedto      object
device_address          object
device_lat             float64
device_long            float64
device_tags             object
etl_updatedtimestamp    object
is_current               int64
org1                    object
org2                    object
inside_outside          object
landmark                object
ObjectId                 int64
dtype: object
```

What is the data type "object" in Pandas

An object is a string storage form

In [7]:
```
# Generating a Summary
# describes only numeric values

wifi.describe()
```

Out[7]:

	X	Y	device_lat	device_long	is_current	ObjectId
count	2.830000e+02	2.830000e+02	283.000000	283.000000	297.0	297.000000
mean	-7.912135e+06	5.210210e+06	42.327796	-71.075917	1.0	149.000000
std	3.034883e+03	4.447129e+03	0.029537	0.027263	0.0	85.880731
min	-7.922403e+06	5.198613e+06	42.250739	-71.168161	1.0	1.000000
25%	-7.913761e+06	5.207725e+06	42.311295	-71.090520	1.0	75.000000
50%	-7.912078e+06	5.210305e+06	42.328431	-71.075407	1.0	149.000000
75%	-7.910171e+06	5.214371e+06	42.355431	-71.058271	1.0	223.000000
max	-7.904348e+06	5.218989e+06	42.386080	-71.005970	1.0	297.000000

Subsetting and slicing in pandas

In [8]:
```
#accessing a column,  there are several options

n_name=wifi.neighborhood_name
w_address=wifi["device_address"]
```

Pandas series

If we extract a column it is in the form of a pandas data series, which still has a lot of pandas style member functions

In [9]:
```
type(n_name)
```

Out[9]:
```
pandas.core.series.Series
```

In [10]:
```
# we can convert this to a list, using a member function

n_name_list=n_name.to_list()
type(n_name_list)
```

Out[10]: list

In [11]:
```
# dimensions of a dataframe are obtained using the attribute shape
print(wifi.shape)
print(n_name.shape)
```

```
(297, 17)
(297,)
```

In [12]:
```
#indexing several columns

wifi[["X","Y"]].head()

# When you use single brackets [] with a pandas DataFrame, you're primarily selecti
# Single brackets will return a pandas Series (a one-dimensional labeled array).

# When you use double brackets [[]], you're selecting multiple columns.
# You're passing a list of column names within the outer brackets.
```

Out[12]:

	X	Y
0	NaN	NaN
1	NaN	NaN
2	-7.912255e+06	5.206228e+06
3	NaN	NaN
4	NaN	NaN

Question/Action

use head to show the first 5 rows of the neighborhood id and name

In [13]:
```
wifi[["neighborhood_id","neighborhood_name"]].head(5)
```

Out[13]:

	neighborhood_id	neighborhood_name
0	L_601230550253963849	Mobile WiFi Kit 1
1	L_601230550253963849	Mobile WiFi Kit 1
2	L_601230550253964116	Nubian-Bus-Stop
3	L_601230550253964116	Nubian-Bus-Stop
4	L_601230550253964116	Nubian-Bus-Stop

In [14]:
```
#Basic calculations

print(wifi.device_lat.max())
```

```
print(wifi.device_lat.min())
print(wifi.device_lat.mean())
```

```
42.38608
42.2507393
42.32779576223686
```

In [15]:
```
# filtering rows using conditional dependence

#let's find all devices with latitude above 42.3271405

above_wifi=wifi[wifi.device_lat>=42.3271405]
above_wifi.head()
```

Out[15]:

	X	Y	neighborhood_id	neighborhood_name	device_serial
6	-7.913800e+06	5.210828e+06	N_579275502070532581	Roxbury	Q2CK-SSY2-PBYW
7	-7.913800e+06	5.210828e+06	N_579275502070532581	Roxbury	Q2CK-SU8N-5VU8
15	-7.912357e+06	5.210581e+06	N_579275502070532581	Roxbury	Q2CK-HDFV-VYBC
18	-7.912846e+06	5.210317e+06	N_579275502070532581	Roxbury	Q2CK-SF4S-8JL2
20	-7.912858e+06	5.210361e+06	N_579275502070532581	Roxbury	Q2CK-MR56-4QY6

In [16]:
```
#slicing by values in a set, notice that pandas has a isin() member function for th

wifi[wifi.neighborhood_name.isin(["Parks","Charlestown"])]

# .isin() itself returns a boolean Series.
# when you put that boolean Series inside the wifi[...], you're using it to filter
```

Out[16]:

	X	Y	neighborhood_id	neighborhood_name	device_seri
5	-7.913037e+06	5.209642e+06	N_568579452955527921	Parks	Q2EK 4PWN-GAL
28	-7.910979e+06	5.214437e+06	N_568579452955527921	Parks	Q3AK-CVAE CUZ
44	-7.916707e+06	5.202882e+06	N_568579452955527921	Parks	Q2AK-U4TT J95
188	-7.910482e+06	5.218089e+06	N_568579452955538062	Charlestown	Q2CK-V3LS 5V6
202	-7.910805e+06	5.214387e+06	N_568579452955527921	Parks	Q3AK-DGSZ GM7
203	-7.911261e+06	5.214274e+06	N_568579452955527921	Parks	Q3AK-EK6U T4FV
205	-7.910482e+06	5.218089e+06	N_568579452955538062	Charlestown	Q2CK CWUY RBGV
214	-7.911012e+06	5.214442e+06	N_568579452955527921	Parks	Q3AK-DRLE LEZ
223	-7.910482e+06	5.218089e+06	N_568579452955538062	Charlestown	Q2CK-SNTE WJW
226	-7.911133e+06	5.214283e+06	N_568579452955527921	Parks	Q3AK-CR6K YPB
227	-7.916761e+06	5.208413e+06	N_568579452955527921	Parks	Q2CK-7ANU RF7
228	-7.910954e+06	5.213995e+06	N_568579452955527921	Parks	Q3AK-CR92 A99
229	-7.916761e+06	5.208413e+06	N_568579452955527921	Parks	Q2CD-6YGI H7PV

	X	Y	neighborhood_id	neighborhood_name	device_seri
230	-7.910787e+06	5.214274e+06	N_568579452955527921	Parks	Q3AK DGWD-NEF
231	-7.910746e+06	5.214357e+06	N_568579452955527921	Parks	Q3AK CVAW H5UI
240	-7.916761e+06	5.208413e+06	N_568579452955527921	Parks	Q2CK-7CSF NUQ
241	-7.911216e+06	5.214476e+06	N_568579452955527921	Parks	Q3AK CRWB-RXV
242	-7.910801e+06	5.214373e+06	N_568579452955527921	Parks	Q3AK CQWK-ZYP

In [17]:
```
# there is also a str.contains function, which searches for a regex string within t
# we will talk about regex in more detail later

# notice the use of .str.contains(),   a string function within pandas

# see https://pandas.pydata.org/docs/user_guide/text.html for a bunch of examples o

wifi[wifi.neighborhood_name.str.contains("town")]
```

Out[17]:

	X	Y	neighborhood_id	neighborhood_name	device_seri
53	-7.910171e+06	5.215103e+06	N_601230550253961310	Downtown Boston - City Hall - Quincy Market	Q3AE-4FLA SJ
54	-7.910171e+06	5.215103e+06	N_601230550253961310	Downtown Boston - City Hall - Quincy Market	Q3AE-HJRC D68
55	-7.909698e+06	5.215107e+06	N_601230550253961310	Downtown Boston - City Hall - Quincy Market	Q3AE-ARNE HFA
56	-7.909702e+06	5.215082e+06	N_601230550253961310	Downtown Boston - City Hall - Quincy Market	Q3AE PMFQ-JUX
57	-7.910171e+06	5.215103e+06	N_601230550253961310	Downtown Boston - City Hall - Quincy Market	Q3AE-3S8D CZF
58	-7.909943e+06	5.215065e+06	N_601230550253961310	Downtown Boston - City Hall - Quincy Market	Q3AK-C98I JUR
59	-7.910171e+06	5.215103e+06	N_601230550253961310	Downtown Boston - City Hall - Quincy Market	Q3AE-TBT5 D72
61	-7.909943e+06	5.215065e+06	N_601230550253961310	Downtown Boston - City Hall - Quincy Market	Q3AK D5DU-9HS
62	-7.910171e+06	5.215103e+06	N_601230550253961310	Downtown Boston - City Hall - Quincy Market	Q3AE-ZUF3 Y73
69	-7.909890e+06	5.215063e+06	N_601230550253961310	Downtown Boston - City Hall - Quincy Market	Q3AE-F6RV VVH
70	-7.910171e+06	5.215103e+06	N_601230550253961310	Downtown Boston - City Hall - Quincy Market	Q3AE-ZXW8 H9ZV
71	-7.910171e+06	5.215103e+06	N_601230550253961310	Downtown Boston - City Hall - Quincy Market	Q3AE-3A2V JNV
152	-7.910171e+06	5.215103e+06	N_601230550253966673	Downtown Boston - City Hall Plaza and Pavilion	Q3AE-JBPI DSN
153	-7.910171e+06	5.215103e+06	N_601230550253966673	Downtown Boston - City Hall Plaza and Pavilion	Q3AE-ZDPZ 2LN

	X	Y	neighborhood_id	neighborhood_name	device_seri
154	-7.910171e+06	5.215103e+06	N_601230550253966673	Downtown Boston - City Hall Plaza and Pavilion	Q3AE-QYJ5 RXI
155	-7.910171e+06	5.215103e+06	N_601230550253966673	Downtown Boston - City Hall Plaza and Pavilion	Q3AE 2N4M BWU
156	-7.910171e+06	5.215103e+06	N_601230550253966673	Downtown Boston - City Hall Plaza and Pavilion	Q3AE-TF7U TX4
157	-7.910171e+06	5.215103e+06	N_601230550253966673	Downtown Boston - City Hall Plaza and Pavilion	Q3AE-95XZ 766
158	-7.910171e+06	5.215103e+06	N_601230550253966673	Downtown Boston - City Hall Plaza and Pavilion	Q3AE-M6TA MFW
159	-7.910171e+06	5.215103e+06	N_601230550253966673	Downtown Boston - City Hall Plaza and Pavilion	Q3AE-R6BC D5K
160	-7.910171e+06	5.215103e+06	N_601230550253966673	Downtown Boston - City Hall Plaza and Pavilion	Q3AE-M9YS PAT
161	-7.910171e+06	5.215103e+06	N_601230550253966673	Downtown Boston - City Hall Plaza and Pavilion	Q3AE-E75T LLQ
162	-7.910171e+06	5.215103e+06	N_601230550253966673	Downtown Boston - City Hall Plaza and Pavilion	Q3AE-BFV5 YGN
163	-7.910171e+06	5.215103e+06	N_601230550253966673	Downtown Boston - City Hall Plaza and Pavilion	Q3AE-8YNT BM6
164	-7.910171e+06	5.215103e+06	N_601230550253966673	Downtown Boston - City Hall Plaza and Pavilion	Q3AE CANN-4NB
167	-7.910171e+06	5.215103e+06	N_601230550253966673	Downtown Boston - City Hall Plaza and Pavilion	Q3AE-2F27 DVJ
168	-7.910171e+06	5.215103e+06	N_601230550253966673	Downtown Boston - City Hall Plaza and Pavilion	Q3AE-EETC KYU

	X	Y	neighborhood_id	neighborhood_name	device_seri
169	-7.910171e+06	5.215103e+06	N_601230550253966673	Downtown Boston - City Hall Plaza and Pavilion	Q3AE-A943 FE9
170	-7.910171e+06	5.215103e+06	N_601230550253966673	Downtown Boston - City Hall Plaza and Pavilion	Q3AE WU87-WVG
171	-7.910171e+06	5.215103e+06	N_601230550253966673	Downtown Boston - City Hall Plaza and Pavilion	Q3AE-JXU4 QPQ
172	-7.910171e+06	5.215103e+06	N_601230550253966673	Downtown Boston - City Hall Plaza and Pavilion	Q3AE-A793 TEM
188	-7.910482e+06	5.218089e+06	N_568579452955538062	Charlestown	Q2CK-V3LS 5V6
205	-7.910482e+06	5.218089e+06	N_568579452955538062	Charlestown	Q2CK CWUY RBGV
223	-7.910482e+06	5.218089e+06	N_568579452955538062	Charlestown	Q2CK-SNTE WJW
256	-7.910171e+06	5.215103e+06	N_601230550253961310	Downtown Boston - City Hall - Quincy Market	Q3AE-GDTF 3C3V
257	-7.910171e+06	5.215103e+06	N_601230550253961310	Downtown Boston - City Hall - Quincy Market	Q3AE MULH-9V9
258	-7.910171e+06	5.215103e+06	N_601230550253961310	Downtown Boston - City Hall - Quincy Market	Q3AE-JLUI 293
275	-7.910171e+06	5.215103e+06	N_601230550253966673	Downtown Boston - City Hall Plaza and Pavilion	Q3AE QMTD-57L
278	-7.910171e+06	5.215103e+06	N_601230550253966673	Downtown Boston - City Hall Plaza and Pavilion	Q3AE-Q4LC 6HK
289	-7.909896e+06	5.215085e+06	N_601230550253961310	Downtown Boston - City Hall - Quincy Market	Q3AE-Q7YC V97

In [18]:
```
# notna returns true or false depending on whether there are Nan values in the loca
# the list of True/False values produced by notna can be used to slice

wifi[wifi.X.notna()].head()
```

Out[18]:

	X	Y	neighborhood_id	neighborhood_name	device_serial
2	-7.912255e+06	5.206228e+06	L_601230550253964116	Nubian-Bus-Stop	Q3AE-QFTK-E55W
5	-7.913037e+06	5.209642e+06	N_568579452955527921	Parks	Q2EK-4PWN-GALS
6	-7.913800e+06	5.210828e+06	N_579275502070532581	Roxbury	Q2CK-SSY2-PBYW
7	-7.913800e+06	5.210828e+06	N_579275502070532581	Roxbury	Q2CK-SU8N-5VU8
8	-7.913466e+06	5.208391e+06	N_579275502070532581	Roxbury	Q2CK-H5VS-5UKS

In [19]:
```
# Row and column specification
# use paired conctions on [row,column]
# we now have to use the method .loc[] to do this

wifi.loc[wifi.X.notna(),"X"].head()

# (This returns the "X" column directly after filtering, and then uses .head() on t
```

Out[19]:
```
2   -7.912255e+06
5   -7.913037e+06
6   -7.913800e+06
7   -7.913800e+06
8   -7.913466e+06
Name: X, dtype: float64
```

In [20]:
```
# you have to have a boolean return type in the row indexing function or a set of i
# we can send a list of column names to get several of them

wifi.loc[wifi.neighborhood_name.str.contains("Charlestown"),['device_lat','device_l
```

Out[20]:

	device_lat	device_long
188	42.380109	-71.06107
205	42.380109	-71.06107
223	42.380109	-71.06107

In [21]:
```
# Indexing using integer values is done using the iloc[] function

# so remember- used .loc for boolean and named columns,   .iloc for Integer locatio

wifi.iloc[0:8,0:6]

# Select rows with integer positions from 0 up to (but not including) 8, and column
```

Out[21]:

	X	Y	neighborhood_id	neighborhood_name	device_serial
0	NaN	NaN	L_601230550253963849	Mobile WiFi Kit 1	Q3AK-SUL7-7FC4
1	NaN	NaN	L_601230550253963849	Mobile WiFi Kit 1	Q2ZY-RF99-YN45
2	-7.912255e+06	5.206228e+06	L_601230550253964116	Nubian-Bus-Stop	Q3AE-QFTK-E55W
3	NaN	NaN	L_601230550253964116	Nubian-Bus-Stop	Q3AK-DU9C-2UXZ
4	NaN	NaN	L_601230550253964116	Nubian-Bus-Stop	Q3AK-FGAN-3AR9
5	-7.913037e+06	5.209642e+06	N_568579452955527921	Parks	Q2EK-4PWN-GALS
6	-7.913800e+06	5.210828e+06	N_579275502070532581	Roxbury	Q2CK-SSY2-PBYW
7	-7.913800e+06	5.210828e+06	N_579275502070532581	Roxbury	Q2CK-SU8N-5VU8

Plotting with Pandas functions

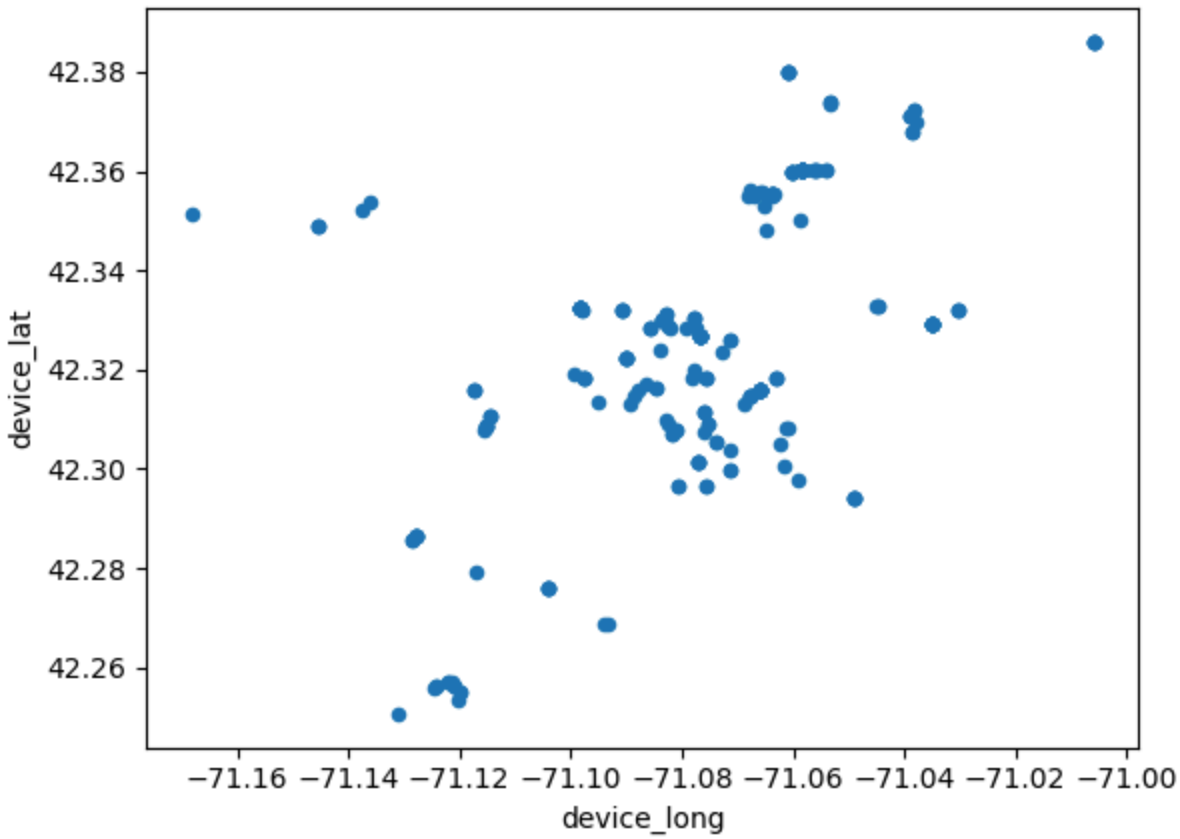
Pandas has basic plotting built in

I typically use Matplotlib, but Pandas has the basics

In [22]:
```
#Pandas built in plots

wifi.plot.scatter(x="device_long",y="device_lat")
```

Out[22]: <Axes: xlabel='device_long', ylabel='device_lat'>

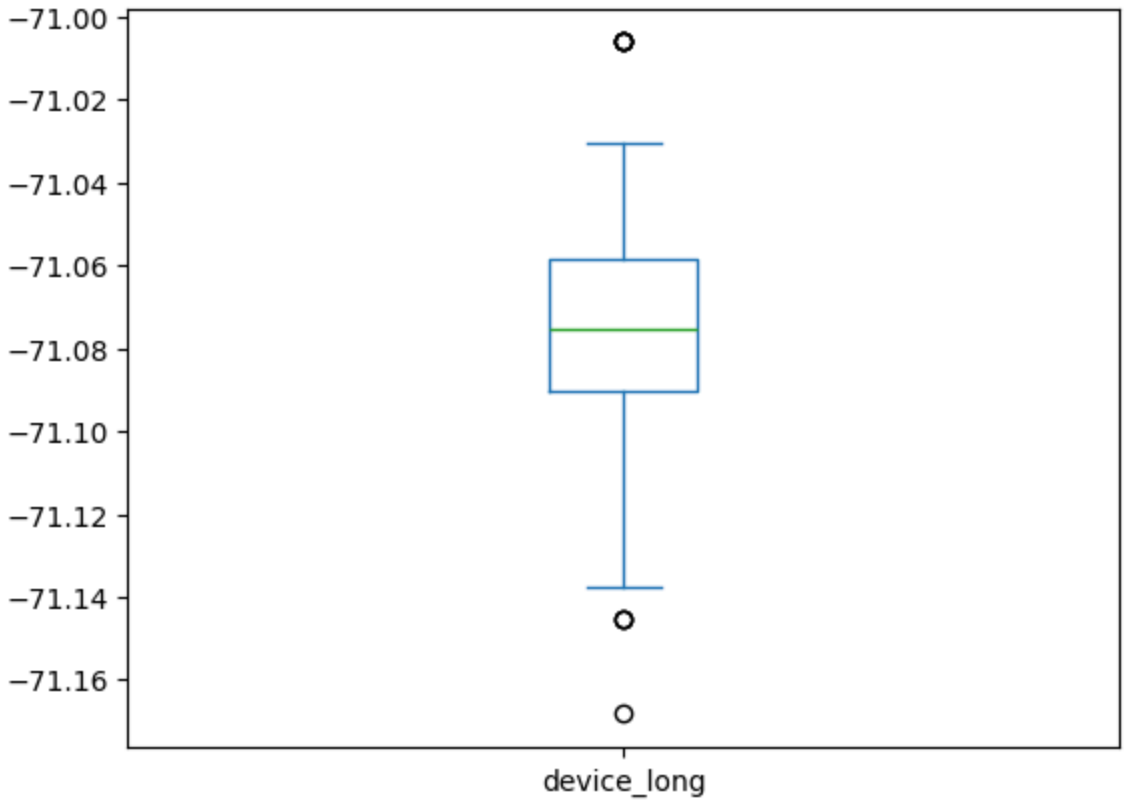


In [23]:
```
#here is a boxplot

wifi[["device_long"]].plot.box()

# "device_long" is a column name (a string).
# wifi[["device_long"]] is a DataFrame.
# wifi["device_long"] would be a Series.
```

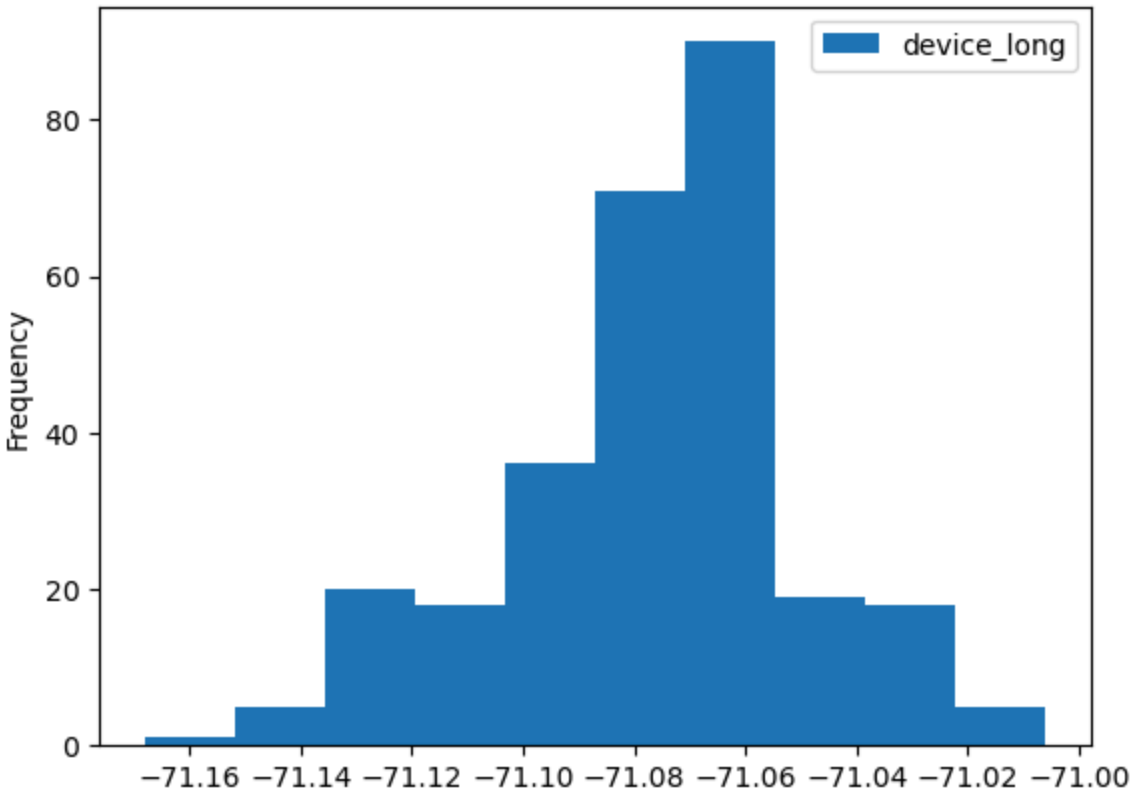
Out[23]: <Axes: >



In [24]:
```
#histogram

wifi[["device_long"]].plot.hist()
```

Out[24]: <Axes: ylabel='Frequency'>



In [25]:
```
#creating new columns

#just name the column and assign a value

# this is a nonsensical value, but it shows the idea

wifi["x over y"]= wifi.X/wifi.Y

wifi.head()
```

Out[25]:

	X	Y	neighborhood_id	neighborhood_name	device_serial
0	NaN	NaN	L_601230550253963849	Mobile WiFi Kit 1	Q3AK-SUL7-7FC4
1	NaN	NaN	L_601230550253963849	Mobile WiFi Kit 1	Q2ZY-RF99-YN45
2	-7.912255e+06	5.206228e+06	L_601230550253964116	Nubian-Bus-Stop	Q3AE-QFTK-E55W
3	NaN	NaN	L_601230550253964116	Nubian-Bus-Stop	Q3AK-DU9C-2UXZ
4	NaN	NaN	L_601230550253964116	Nubian-Bus-Stop	Q3AK-FGAN-3AR9

Aggregation or grouping for tables and statistics

Pandas has a nice groupby function, reminiscent of the dplyr methods

In [26]:
```
# we specify the columns we want to work with in the dataframe, then specify which

# at the end, we add a Pandas summary function

# Note, if we had more grouping variables the input to groupby could be a list


wifi[["device_long","device_lat","neighborhood_name"]].groupby("neighborhood_name")

# To get useful results from a GroupBy object, you need to apply an aggregation fun
# For example, .mean() or .sum()
# Otherwise you get a GroupBy object (that represents the grouping operation)
```

Out[26]:

neighborhood_name	device_long	device_lat
2 Center Plaza	-71.060201	42.359796
Alston Brighton	-71.146410	42.350730
BCYF Indoor	-71.084504	42.320980
BCYF Tremont	-71.098229	42.332227
BCYF-Curley	-71.035150	42.329115
Bolling	-71.083664	42.330141
Charlestown	-71.061070	42.380109
City Hall Truck	NaN	NaN
Dorchester	-71.067166	42.306111
Downtown Boston - City Hall - Quincy Market	-71.057176	42.360229
Downtown Boston - City Hall Plaza and Pavilion	-71.058271	42.360291
East Boston	-71.038550	42.370514
East Boston Senior Center	-71.005970	42.386080
Hyde Park	-71.122637	42.255603
Jamaica Plain	-71.114836	42.309554
Maintenance	-71.063579	42.347038
Mattahunt BCYF	-71.103910	42.275826
Mattapan-Bus-stop	-71.093735	42.268617
Mobile WiFi Kit 1	NaN	NaN
Mobile WiFi Kit 2	NaN	NaN
Mobile WiFi Kit 3	NaN	NaN
Mobile WiFi Kit 4	NaN	NaN
Mobile WiFi Kit 5	NaN	NaN
NOC-TEST	-71.076985	42.331899
Navy Yard	-71.053276	42.373728
Nubian-Bus-Stop	-71.077000	42.301350
OPAT	-71.082958	42.331086
Parks	-71.080528	42.340156
Roslindale	-71.128088	42.286149

neighborhood_name	device_long	device_lat
Roxbury	-71.082860	42.320404
South Boston	-71.037557	42.332484
Strand Theatre - External	-71.065961	42.315948
Strand Theatre - Internal	-71.065961	42.315948
YEE Tremont	-71.098240	42.332229

Multiple grouping variables

In [27]:
```
# we can use groupby to get counts per grouping variable as well
# I tried using is_current as a grouping variable, but they are all 1, indicating c

wifi[["device_long","device_lat","neighborhood_name","is_current"]].groupby(["neigh
```

Out[27]:

		device_long	device_lat
neighborhood_name	is_current		
2 Center Plaza	**1**	6	6
Alston Brighton	**1**	6	6
BCYF Indoor	**1**	27	27
BCYF Tremont	**1**	9	9
BCYF-Curley	**1**	12	12
Bolling	**1**	6	6
Charlestown	**1**	3	3
City Hall Truck	**1**	0	0
Dorchester	**1**	24	24
Downtown Boston - City Hall - Quincy Market	**1**	16	16
Downtown Boston - City Hall Plaza and Pavilion	**1**	21	21
East Boston	**1**	9	9
East Boston Senior Center	**1**	5	5
Hyde Park	**1**	12	12
Jamaica Plain	**1**	6	6
Maintenance	**1**	6	6
Mattahunt BCYF	**1**	5	5
Mattapan-Bus-stop	**1**	2	2
Mobile WiFi Kit 1	**1**	0	0
Mobile WiFi Kit 2	**1**	0	0
Mobile WiFi Kit 3	**1**	0	0
Mobile WiFi Kit 4	**1**	0	0
Mobile WiFi Kit 5	**1**	0	0
NOC-TEST	**1**	2	2
Navy Yard	**1**	3	3
Nubian-Bus-Stop	**1**	5	5
OPAT	**1**	2	2
Parks	**1**	15	15
Roslindale	**1**	5	5

		device_long	device_lat
neighborhood_name	is_current		
Roxbury	**1**	52	52
South Boston	**1**	6	6
Strand Theatre - External	**1**	3	3
Strand Theatre - Internal	**1**	10	10
YEE Tremont	**1**	5	5

Categorical data

We can set data to be of type Categorical, which is akin to a factor

It is also possible to use integer group codes or dummy coding to represent categories or factors, this is done using utility tools in libraries such as scikit-learn or keras that focus on modeling

In [28]:
```
wifi['neighborhood_name']=pd.Categorical(wifi.neighborhood_name)

wifi.head()

# This code changes the way pandas stores and handles the "neighborhood_name" colum
# Instead of storing the full text of each neighborhood name for every row, pandas
# This can save memory and sometimes make things faster.
```

Out[28]:

	X	Y	neighborhood_id	neighborhood_name	device_serial
0	NaN	NaN	L_601230550253963849	Mobile WiFi Kit 1	Q3AK-SUL7-7FC4
1	NaN	NaN	L_601230550253963849	Mobile WiFi Kit 1	Q2ZY-RF99-YN45
2	-7.912255e+06	5.206228e+06	L_601230550253964116	Nubian-Bus-Stop	Q3AE-QFTK-E55W
3	NaN	NaN	L_601230550253964116	Nubian-Bus-Stop	Q3AK-DU9C-2UXZ
4	NaN	NaN	L_601230550253964116	Nubian-Bus-Stop	Q3AK-FGAN-3AR9

In [29]:
```
# did this work?

wifi.dtypes
```

```
# yes.
```

Out[29]:
```
X                       float64
Y                       float64
neighborhood_id          object
neighborhood_name      category
device_serial            object
device_connectedto       object
device_address           object
device_lat              float64
device_long             float64
device_tags              object
etl_updatedtimestamp     object
is_current                int64
org1                     object
org2                     object
inside_outside           object
landmark                 object
ObjectId                  int64
x over y                float64
dtype: object
```

Question/Action

What other variables should be Categorical variables (there aren't many)

Convert this variable to a category

In [30]:
```
# It could make sense to set neighborhood_id, device_connectedto and inside_outside

wifi['neighborhood_id']=pd.Categorical(wifi.neighborhood_id)
wifi['device_connectedto']=pd.Categorical(wifi.device_connectedto)
wifi['inside_outside']=pd.Categorical(wifi.inside_outside)

wifi.dtypes
```

Out[30]:
```
X                      float64
Y                      float64
neighborhood_id       category
neighborhood_name     category
device_serial           object
device_connectedto    category
device_address          object
device_lat             float64
device_long            float64
device_tags             object
etl_updatedtimestamp    object
is_current               int64
org1                    object
org2                    object
inside_outside        category
landmark                object
ObjectId                 int64
x over y               float64
dtype: object
```

Dummy Coding

It looks like Pandas can generate dummy codes for us

Pandas does not have a 'factor' variable, so in models like multiple regression, logisitic regression or neural networks, we use dummy coding to code categorical variables. You will see more on this later.

What does this look like?

What does a True in this table seem to mean?

This is also called "one-hot" encoding, since there is only one "True" per row of the table

In [31]:
```
pd.get_dummies(wifi.neighborhood_name)

# pd.get_dummies() transforms a column with categories into a set of columns repres
# Each row will have a "1" in the column for its category and "0" in all the other
# This is also known as "one-hot encoding."

# The primary value of the dummy variable DataFrame lies in its relationship to the
# The rows in the get_dummies() DataFrame correspond exactly to the rows in the ori
# This is how the model can "learn" the relationships between the original features
# If you isolate the get_dummies() DataFrame, you lose this crucial contextual info
```

Out[31]:

	2 Center Plaza	Alston Brighton	BCYF Indoor	BCYF Tremont	BCYF-Curley	Bolling	Charlestown	City Hall Truck	Dorchester
0	False	False	False	False	False	False	False	False	False
1	False	False	False	False	False	False	False	False	False
2	False	False	False	False	False	False	False	False	False
3	False	False	False	False	False	False	False	False	False
4	False	False	False	False	False	False	False	False	False
...	...	...	...	...	...	...	...	...	...
292	False	False	False	False	False	False	False	False	False
293	False	False	False	False	False	True	False	False	False
294	False	False	False	False	False	True	False	False	False
295	False	False	False	False	False	True	False	False	False
296	False	False	False	False	False	True	False	False	False

297 rows × 34 columns

Question/Action

Create a dummy coding for the variable that you turned into a Categorical variable in the Question above

In [32]:
```
pd.get_dummies(wifi.inside_outside)
```

Out[32]:

	Inside	Outside
0	False	False
1	False	False
2	False	False
3	False	False
4	False	False
...	...	...
292	False	False
293	True	False
294	True	False
295	True	False
296	True	False

297 rows × 2 columns

date-time values

It looks like we have one date-time variable in the dataset right now

etl_updatedtimestamp

it looks like a fairly standard format

In [33]:
```
wifi.etl_updatedtimestamp.head(5)
```

Out[33]:
```
0    2024/08/20 04:31:34+00
1    2024/08/20 04:31:34+00
2    2024/08/20 04:31:38+00
3    2024/08/20 04:31:38+00
4    2024/08/20 04:31:38+00
Name: etl_updatedtimestamp, dtype: object
```

In [34]:
```
wifi.etl_updatedtimestamp=pd.to_datetime(wifi.etl_updatedtimestamp)
wifi.etl_updatedtimestamp.head()
```

Out[34]:
```
0   2024-08-20 04:31:34+00:00
1   2024-08-20 04:31:34+00:00
2   2024-08-20 04:31:38+00:00
3   2024-08-20 04:31:38+00:00
4   2024-08-20 04:31:38+00:00
Name: etl_updatedtimestamp, dtype: datetime64[ns, UTC]
```

In [35]:
```
# We can now get days, months, years

wifi.etl_updatedtimestamp.dt.day.head()
```

Out[35]:
```
0    20
1    20
2    20
3    20
4    20
Name: etl_updatedtimestamp, dtype: int32
```

In [36]:
```
wifi.etl_updatedtimestamp.dt.month.head()
```

Out[36]:
```
0    8
1    8
2    8
3    8
4    8
Name: etl_updatedtimestamp, dtype: int32
```

In [37]:
```
wifi.etl_updatedtimestamp.dt.year.head()
```

Out[37]:
```
0    2024
1    2024
2    2024
3    2024
4    2024
Name: etl_updatedtimestamp, dtype: int32
```

Converting to Long form

uses the melt function

https://pandas.pydata.org/docs/reference/api/pandas.melt.html

Form more ideas on wide to long, look up

Pandas pivot pandas pivot_table pandas unstack pandas wide_to_long

In [38]:
```
df = pd.DataFrame({'A': {0: 'a', 1: 'b', 2: 'c'},
                   'B': {0: 1, 1: 3, 2: 5},
                   'C': {0: 2, 1: 4, 2: 6}})

df
```

Out[38]:

	A	B	C
0	a	1	2
1	b	3	4
2	c	5	6

In [39]:
```
# note we specify a list of i variables and a list of value variables,  much like i
# wide format to long format

# id_vars=['A'] specifies which column(s) should be used as identifier variables.
# These columns will be kept as-is in the melted DataFrame.

# value_vars=['B','C'] specifies which column(s) should be unpivoted.
# These columns will be transformed into rows.

pd.melt(df, id_vars=['A'], value_vars=['B','C'])
```

Out[39]:

	A	variable	value
0	a	B	1
1	b	B	3
2	c	B	5
3	a	C	2
4	b	C	4
5	c	C	6

In [40]:
```
# alternative form, two id variables
# this is a "composite key" form

pd.melt(df, id_vars=['A','C'], value_vars=['B'])
```

Out[40]:

	A	C	variable	value
0	a	2	B	1
1	b	4	B	3
2	c	6	B	5

In [41]:
```
# create df2 for question/action

df2 = pd.DataFrame({'A': {0: 'a', 1: 'b', 2: 'c',3:'d'},
                    'B': {0: 1, 1: 3, 2: 5,3: 6},
                    'C': {0: 2, 1: 4, 2: 6,3: 8},
                    'D': {0:"Biscuit",1:"Chips",2:"Banana",3:"hard case"}})
df2
```

Out[41]:

	A	B	C	D
0	a	1	2	Biscuit
1	b	3	4	Chips
2	c	5	6	Banana
3	d	6	8	hard case

Question/Action

Melt df2 to wide form, using D and A as the index variables, assign the other two columns as values

In [42]:
```
pd.melt(df2, id_vars=['D','A'], value_vars=['B','C'])
```

Out[42]:

	D	A	variable	value
0	Biscuit	a	B	1
1	Chips	b	B	3
2	Banana	c	B	5
3	hard case	d	B	6
4	Biscuit	a	C	2
5	Chips	b	C	4
6	Banana	c	C	6
7	hard case	d	C	8

Joins

A join connects two dataframes (or SQL data tables) together based on matching values of keys (identifiers) in the two data frames or tables. You may have seen this in R, and we will see it again in SQL.

Joins are done on two dataframes (or tables) at a time, the first is called the "left" table and the second is called the "right" table and several different forms of joins exist.

Joins are done on Pandas data frames are done using the merge function

You can specify the type of join desired, inner, outer, left, right etc

https://pandas.pydata.org/docs/reference/api/pandas.merge.html

In [43]:
```
df1 = pd.DataFrame({'lkey': ['foo', 'bar', 'baz', 'foo',"bix"],'value': [1, 2, 3, 5
df2 = pd.DataFrame({'rkey': ['foo', 'bar', 'baz', 'foo'],'value': [5, 6, 7, 8]})
```

In [44]:
```
df1
```

Out[44]:

	lkey	value
0	foo	1
1	bar	2
2	baz	3
3	foo	5
4	bix	11

In [45]:
```
df2
```

Out[45]:

	rkey	value
0	foo	5
1	bar	6
2	baz	7
3	foo	8

In [46]:
```
# this is an inner join of the left frame df1 and the right frame df2
# An inner join returns only the rows where the join keys have matching values in b

# notice that "bix" was dropped

df1.merge(df2, left_on='lkey', right_on='rkey')
```

Out[46]:

	lkey	value_x	rkey	value_y
0	foo	1	foo	5
1	foo	1	foo	8
2	bar	2	bar	6
3	baz	3	baz	7
4	foo	5	foo	5
5	foo	5	foo	8

What's Happening:

- The first 'foo' in df1 (row 0) matches both 'foo's in df2 (rows 0 and 3). This results in two combined rows.
- 'bar' in df1 (row 1) matches 'bar' in df2 (row 1). This results in one combined row.
- 'baz' in df1 (row 2) matches 'baz' in df2 (row 2). This results in one combined row.
- The second 'foo' in df1 (row 3) also matches both 'foo's in df2 (rows 0 and 3). This results in two more combined rows.
- 'bix' in df1 (row 4) has no match in df2.

In [47]:
```
# here is a left join

# what happens to "bix"?

df1.merge(df2, how="left",left_on='lkey', right_on='rkey')
```

Out[47]:

	lkey	value_x	rkey	value_y
0	foo	1	foo	5.0
1	foo	1	foo	8.0
2	bar	2	bar	6.0
3	baz	3	baz	7.0
4	foo	5	foo	5.0
5	foo	5	foo	8.0
6	bix	11	NaN	NaN

A left merge (or left join) aims to keep all the rows from the left DataFrame (df1 in this case). For each row in the left DataFrame:

- If there's a matching value in the join key of the right DataFrame (df2), the corresponding columns from the right DataFrame are included in the result.
- If there's no matching value in the join key of the right DataFrame, the columns from the right DataFrame will have NaN (Not a Number) in the resulting row.