Pandas

November 18, 2020

1 Tarea Nro. 2 - PANDAS

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- Fecha: 17/11/20

En esta tarea se examinara datos de terremotos. Comience importando pandas, numpy y matplolib.

Los datos de los terremotos están localizados en usgs_terremotos_2014.csv. Ni siquiera necesita descargalo, puede abrilo directamente con Pandas.

A continuación resuelva los siguientes items.

[1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
```

1.0.1 1) Use la función read_csv de Pandas directamente en esta url para abrirla como un DataFrame

(No use ninguna opción especial). Mostrar las primeras filas y la información del marco de datos. Debería haber visto que las fechas no se analizaron automáticamente en tipos de fecha y hora.

[2]:
```
data_df = pd.read_csv('usgs_terremotos_2014.csv')
data_df.head()
```

[2]:
```
                      time   latitude  longitude  depth   mag magType  nst  \
0  2014-01-31 23:53:37.000  60.252000  -152.7081  90.20  1.10      ml  NaN
1  2014-01-31 23:48:35.452  37.070300  -115.1309   0.00  1.33      ml  4.0
2  2014-01-31 23:47:24.000  64.671700  -149.2528   7.10  1.30      ml  NaN
3  2014-01-31 23:30:54.000  63.188700  -148.9575  96.50  0.80      ml  NaN
4  2014-01-31 23:30:52.210  32.616833  -115.6925  10.59  1.34      ml  6.0

      gap     dmin     rms net          id                   updated  \
0     NaN      NaN  0.2900  ak  ak11155107  2014-02-05T19:34:41.515Z
1  171.43  0.34200  0.0247  nn  nn00436847  2014-02-01T01:35:09.000Z
2     NaN      NaN  1.0000  ak  ak11151142  2014-02-01T00:03:53.010Z
3     NaN      NaN  1.0700  ak  ak11151135  2014-01-31T23:41:25.007Z
4  285.00  0.04321  0.2000  ci  ci37171541  2014-02-01T00:13:20.107Z

                        place        type
```

```
0  26km S of Redoubt Volcano, Alaska  earthquake
1             32km S of Alamo, Nevada  earthquake
2   12km NNW of North Nenana, Alaska  earthquake
3          22km S of Cantwell, Alaska  earthquake
4        10km WNW of Progreso, Mexico  earthquake
```

1.0.2 2) Vuelva a leer los datos de tal manera que todas las columnas de fechas se identifiquen como fechas y la identificación del terremoto se use como índice

[3]:
```python
data_df = pd.read_csv('usgs_terremotos_2014.csv',parse_dates=['time',
 ↪'updated'],index_col='id')
data_df.head()
```

[3]:
```
                              time   latitude  longitude  depth   mag magType  \
id
ak11155107 2014-01-31 23:53:37.000  60.252000  -152.7081  90.20  1.10      ml
nn00436847 2014-01-31 23:48:35.452  37.070300  -115.1309   0.00  1.33      ml
ak11151142 2014-01-31 23:47:24.000  64.671700  -149.2528   7.10  1.30      ml
ak11151135 2014-01-31 23:30:54.000  63.188700  -148.9575  96.50  0.80      ml
ci37171541 2014-01-31 23:30:52.210  32.616833  -115.6925  10.59  1.34      ml

            nst     gap     dmin     rms net                          updated  \
id
ak11155107  NaN     NaN      NaN  0.2900  ak 2014-02-05 19:34:41.515000+00:00
nn00436847  4.0  171.43  0.34200  0.0247  nn        2014-02-01 01:35:09+00:00
ak11151142  NaN     NaN      NaN  1.0000  ak 2014-02-01 00:03:53.010000+00:00
ak11151135  NaN     NaN      NaN  1.0700  ak 2014-01-31 23:41:25.007000+00:00
ci37171541  6.0  285.00  0.04321  0.2000  ci 2014-02-01 00:13:20.107000+00:00

                                        place        type
id
ak11155107  26km S of Redoubt Volcano, Alaska  earthquake
nn00436847            32km S of Alamo, Nevada  earthquake
ak11151142   12km NNW of North Nenana, Alaska  earthquake
ak11151135         22km S of Cantwell, Alaska  earthquake
ci37171541       10km WNW of Progreso, Mexico  earthquake
```

1.0.3 3) Obtener las estadísticas básicas de todas las columnas

[4]:
```python
data_df.describe()
```

[4]:
```
            latitude      longitude          depth            mag  \
count  120108.000000  120108.000000  120107.000000  120065.000000
mean       38.399579     -99.961402      28.375029       1.793958
std        21.938258      82.996858      62.215416       1.343466
min       -73.462000    -179.998900      -9.900000      -0.970000
25%        34.228917    -147.742025       4.100000       0.820000
```

```
50%        38.805300    -120.832000      9.200000       1.400000
75%        53.889500    -116.068100     22.880000       2.400000
max        86.651400     179.998000    697.360000       8.200000

                nst            gap          dmin            rms
count  59688.000000   94935.000000  85682.000000  119716.000000
mean      17.878284     124.048978      0.893198       0.358174
std       14.911369      68.518595      2.903966       0.364046
min        0.000000       9.000000      0.000000       0.000000
25%        8.000000      74.000000      0.020760       0.070000
50%       14.000000     107.000000      0.073670       0.200000
75%       22.000000     155.000000      0.447000       0.590000
max      365.000000     356.400000     64.498000       8.460000
```

1.0.4 4) Obtener los 20 terremotos más importantes por magnitud

Examina la estructura de la columna `place`. La información del país parece estar allí. ¿Cómo lo sacarías?

[5]:
```python
byMagnitud = data_df.sort_values("mag", ascending=False)[:20]
byMagnitud
```

[5]:
```
                             time  latitude  longitude   depth  mag magType  \
id
usc000nzvd 2014-04-01 23:46:47.260  -19.6097   -70.7691   25.00  8.2     mww
usc000rki5 2014-06-23 20:53:09.700   51.8486   178.7352  109.00  7.9     mww
usc000p27i 2014-04-03 02:43:13.110  -20.5709   -70.4931   22.40  7.7     mww
usc000phx5 2014-04-12 20:14:39.300  -11.2701   162.1481   22.56  7.6     mww
usb000pr89 2014-04-19 13:28:00.810   -6.7547   155.0241   43.37  7.5     mww
usc000piqj 2014-04-13 12:36:19.230  -11.4633   162.0511   39.00  7.4     mww
usb000slwn 2014-10-14 03:51:34.460   12.5262   -88.1225   40.00  7.3     mww
usb000pq41 2014-04-18 14:27:24.920   17.3970  -100.9723   24.00  7.2     mww
usc000pft9 2014-04-11 07:07:23.130   -6.5858   155.0485   60.53  7.1     mww
usc000sxh8 2014-11-15 02:31:41.720    1.8929   126.5217   45.00  7.1     mww
usc000stdc 2014-11-01 18:57:22.380  -19.6903  -177.7587  434.00  7.1     mww
usb000sk6k 2014-10-09 02:14:31.440  -32.1082  -110.8112   16.54  7.0     mww
usc000rngj 2014-06-29 07:52:55.170  -55.4703   -28.3669    8.00  6.9     mww
usb000rzki 2014-08-03 00:22:03.680    0.8295   146.1688   13.00  6.9     mww
usc000rkg5 2014-06-23 19:19:15.940  -29.9772  -177.7247   20.00  6.9     mww
usc000mnvj 2014-02-12 09:19:49.060   35.9053    82.5864   10.00  6.9     mww
usb000ruzk 2014-07-21 14:54:41.000  -19.8015  -178.4001  615.42  6.9     mww
usc000nzwm 2014-04-01 23:57:58.790  -19.8927   -70.9455   28.42  6.9     mww
usb000r2hc 2014-05-24 09:25:02.440   40.2893    25.3889    6.43  6.9     mww
usc000rr6a 2014-07-07 11:23:54.780   14.7240   -92.4614   53.00  6.9     mww

            nst   gap   dmin   rms net                          updated  \
id
usc000nzvd  NaN  23.0  0.609  0.66  us 2015-07-30 16:24:51.223000+00:00
```

```
usc000rki5  NaN   22.0  0.133  0.71  us 2015-04-18 21:54:08.699000+00:00
usc000p27i  NaN   44.0  1.029  0.82  us 2015-06-06 07:31:05.755000+00:00
usc000phx5  NaN   13.0  2.828  0.71  us 2015-04-18 21:54:27.398000+00:00
usb000pr89  NaN   16.0  3.820  1.25  us 2015-04-18 21:54:18.633000+00:00
usc000piqj  NaN   17.0  2.885  1.00  us 2015-08-13 19:29:13.018000+00:00
usb000slwn  NaN   18.0  1.078  0.70  us 2015-08-13 19:35:02.679000+00:00
usb000pq41  NaN   46.0  2.250  1.20  us 2015-08-13 19:30:39.599000+00:00
usc000pft9  NaN   21.0  3.729  0.88  us        2014-07-01 02:37:56+00:00
usc000sxh8  NaN   18.0  1.397  0.71  us 2015-03-20 18:42:02.735000+00:00
usc000stdc  NaN   13.0  4.415  0.84  us 2015-01-20 09:03:09.040000+00:00
usb000sk6k  NaN   22.0  5.127  0.43  us 2015-08-13 19:31:44.129000+00:00
usc000rngj  NaN   25.0  4.838  0.76  us        2014-09-26 11:49:45+00:00
usb000rzki  NaN   12.0  6.393  0.93  us        2014-10-29 19:52:55+00:00
usc000rkg5  NaN   35.0  0.751  0.99  us        2014-09-19 17:23:16+00:00
usc000mnvj  NaN   18.0  7.496  0.83  us 2015-01-30 23:03:45.902000+00:00
usb000ruzk  NaN   15.0  3.934  0.96  us        2014-10-17 21:12:13+00:00
usc000nzwm  NaN  119.0  0.828  0.93  us        2014-05-29 23:32:13+00:00
usb000r2hc  NaN   25.0  0.402  0.67  us 2015-01-28 09:17:17.266000+00:00
usc000rr6a  NaN   51.0  0.263  1.38  us 2015-01-28 13:08:13.282000+00:00

                                               place        type
id
usc000nzvd                94km NW of Iquique, Chile  earthquake
usc000rki5  19km SE of Little Sitkin Island, Alaska  earthquake
usc000p27i                53km SW of Iquique, Chile  earthquake
usc000phx5    93km SSE of Kirakira, Solomon Islands  earthquake
usb000pr89     70km SW of Panguna, Papua New Guinea  earthquake
usc000piqj     112km S of Kirakira, Solomon Islands  earthquake
usb000slwn          74km S of Intipuca, El Salvador  earthquake
usb000pq41             33km ESE of Petatlan, Mexico  earthquake
usc000pft9    56km WSW of Panguna, Papua New Guinea  earthquake
usc000sxh8      154km NW of Kota Ternate, Indonesia  earthquake
usc000stdc            144km NE of Ndoi Island, Fiji  earthquake
usb000sk6k               Southern East Pacific Rise  earthquake
usc000rngj            154km NNW of Visokoi Island,   earthquake
usb000rzki    Federated States of Micronesia region  earthquake
usc000rkg5    80km SSE of Raoul Island, New Zealand  earthquake
usc000mnvj               272km ESE of Hotan, China  earthquake
usb000ruzk            99km NNE of Ndoi Island, Fiji  earthquake
usc000nzwm               91km WNW of Iquique, Chile  earthquake
usb000r2hc         22km SSW of Kamariotissa, Greece  earthquake
usc000rr6a          4km W of Puerto Madero, Mexico  earthquake
```

1.0.5 5) Extraiga el país utilizando las funciones de datos de texto de Pandas

Agréguelo como una nueva columna al dataframe. (¿Es realmente solo un país? No, algunas filas tienen el nombre de un estado de EE. UU.) Corrija esto https://www.geeksforgeeks.org/python-pandas-working-with-text-data/.

Otra librería que puede ser útil https://pypi.org/project/us/ para identificar si es un estado de EEUU es **us**

[6]:
```
import us

# Funcion que devuelve "EE.UU" si el valor es un estado o region de EE.UU
def cleanStates(value):
    if value:
        return "EE.UU" if us.states.lookup(value.strip()) else value.strip()
    else:
        return value

# Funcion que extrae el nombre de los paises y estados de la columna Place
def cleanPlace(value):
    trash = ["southern", "western", "eastern", "northern",
             "of", "south", "west", "east", "north", "the", "region",␣
↪"central", "offshore"]

    if value:
        if value.strip() != "":
            tokens = value.split(",")

            for token in tokens[1:]:
                for retoken in token.split(" "):
                    state = us.states.lookup(retoken.lower())
                    if state != None:
                        return state.name

            pais = tokens[-1]
            newPais = []
            for token in pais.split(" "):
                if token.lower() not in trash:
                    newPais.append(token)

            newPaisStr = ' '.join(newPais).strip()
            return newPaisStr if newPaisStr != "" else "UNDEFINED"
        elif value.strip() == "":
            return "UNDEFINED"
        else:
            return value.strip()
    else:
        return "UNDEFINED"
```

[7]:
```
# Limpiamos los lugares que esten vacios y nulos
data_df.dropna(axis=0, subset=["place"], inplace=True)
isEmpty = data_df["place"].apply(lambda x: x.strip() == "")
data_df = data_df.drop(data_df[isEmpty].index)
```

```python
data_df = data_df.drop(data_df[data_df["type"] != "earthquake"].index)
```

[8]:
```python
# Extremos los paises y estados en una nueva columna
data_df["pais"] = data_df["place"].apply(lambda x: cleanPlace(x))
data_df.sample(10)
```

[8]:
```
                               time  latitude  longitude    depth   mag  \
id
ak11270157 2014-05-23 05:53:57.000   65.0082  -150.1986  14.3000  0.80
nn00455072 2014-07-28 22:02:02.702   39.7524  -120.6126   0.3818  0.53
ak11376279 2014-09-01 10:39:31.000   65.1407  -149.0027  13.5000  2.00
nc72161791 2014-02-10 15:24:40.800   37.6318  -119.0160   4.6000  0.30
ak11250128 2014-05-04 13:50:02.000   63.4834  -147.7437   4.2000  0.60
usb000pw9i 2014-04-23 17:00:40.910   -6.6045   155.0158  48.0600  4.60
ak11284483 2014-06-06 09:40:23.000   61.4846  -140.6704   5.7000  0.70
usb000prvt 2014-04-20 07:45:43.640  -11.0021   161.5968  10.0000  5.00
ak11427435 2014-10-24 02:12:13.000   65.1637  -149.0614   8.4000  1.50
ak11210056 2014-04-02 19:25:08.000   63.2478  -150.9130   2.5000  1.40

           magType   nst         gap      dmin     rms net  \
id
ak11270157      ml  12.0  136.799989  0.229969  0.7400  ak
nn00455072      ml   5.0  113.960000  0.133000  0.0821  nn
ak11376279      ml  10.0   82.799993       NaN  0.5100  ak
nc72161791      Md   NaN   90.000000  0.008983  0.1200  nc
ak11250128      ml   NaN         NaN       NaN  0.6000  ak
usb000pw9i      mb   NaN   78.000000  3.716000  0.4500  us
ak11284483      ml   7.0  115.199991       NaN  0.4600  ak
usb000prvt      mb   NaN   25.000000  2.247000  0.5800  us
ak11427435      ml   NaN         NaN       NaN  0.5500  ak
ak11210056      ml   NaN         NaN       NaN  0.8300  ak

                                    updated  \
id
ak11270157 2014-06-03 15:43:46.836000+00:00
nn00455072 2014-08-06 19:45:05.386000+00:00
ak11376279 2014-09-09 23:57:06.399000+00:00
nc72161791 2014-02-22 04:15:10.561000+00:00
ak11250128 2014-05-12 23:44:03.094000+00:00
usb000pw9i        2014-07-14 20:11:12+00:00
ak11284483 2014-06-20 02:51:28.105000+00:00
usb000prvt        2014-07-04 01:34:30+00:00
ak11427435 2014-10-28 20:14:17.546000+00:00
ak11210056 2014-04-02 19:44:08.878000+00:00

                                            place        type  \
id
```

```
ak11270157   20km E of Manley Hot Springs, Alaska  earthquake
nn00455072        13km WSW of Portola, California  earthquake
ak11376279               56km NW of Ester, Alaska  earthquake
nc72161791   4km WSW of Mammoth Lakes, California  earthquake
ak11250128             61km E of Cantwell, Alaska  earthquake
usb000pw9i  60km WSW of Panguna, Papua New Guinea  earthquake
ak11284483       Southern Yukon Territory, Canada  earthquake
usb000prvt  70km SSW of Kirakira, Solomon Islands  earthquake
ak11427435               60km NW of Ester, Alaska  earthquake
ak11210056             99km W of Cantwell, Alaska  earthquake

                        pais
id
ak11270157            Alaska
nn00455072        California
ak11376279            Alaska
nc72161791        California
ak11250128            Alaska
usb000pw9i  Papua New Guinea
ak11284483            Canada
usb000prvt   Solomon Islands
ak11427435            Alaska
ak11210056            Alaska
```

[9]:

```python
# Reemplazamos los estados de EE.UU
data_df["pais"] = data_df["pais"].apply(lambda x: cleanStates(x))
data_df.sample(10)
```

[9]:

```
                              time   latitude   longitude   depth   mag  \
id
ak11434349 2014-11-05 17:10:41.000  59.178600 -136.278000    5.60  2.30
ak11234999 2014-04-19 19:24:27.000  62.918000 -150.374100   69.30  1.10
ak11472630 2014-12-24 07:39:14.000  62.971100 -150.999900  118.70  1.40
nc72324926 2014-10-11 09:53:15.970  38.836498 -122.799667    2.52  1.03
ak11140430 2014-01-20 07:01:24.000  62.583600 -149.513000   56.60  2.20
nc72354541 2014-11-25 04:19:22.610  37.629000 -118.869667    9.43  0.46
ak11322224 2014-07-10 00:32:32.000  61.971000 -151.581400   85.10  1.40
nc72177191 2014-03-01 09:47:10.300  38.792200 -122.745000    1.60  0.70
nc72315881 2014-09-28 17:18:19.070  37.640000 -118.948667    7.83  0.97
ci37248368 2014-07-19 23:48:37.660  33.496333 -116.572333   11.28 -0.45

           magType   nst        gap      dmin   rms net  \
id
ak11434349      ml   NaN        NaN       NaN  0.44  ak
ak11234999      ml   NaN        NaN       NaN  1.04  ak
ak11472630      ml   NaN        NaN       NaN  0.27  ak
nc72324926      md  22.0  62.000000  0.007527  0.02  nc
```

```
ak11140430      ml  38.0   43.199997  0.393462  0.68  ak
nc72354541      md  19.0   96.000000  0.026540  0.05  nc
ak11322224      ml   NaN         NaN       NaN  0.58  ak
nc72177191      Md   NaN   79.200000  0.008983  0.03  nc
nc72315881      md  28.0   66.000000  0.024480  0.03  nc
ci37248368      ml   6.0  227.000000  0.025010  0.03  ci

                                    updated  \
id
ak11434349 2014-11-12 21:24:35.380000+00:00
ak11234999 2014-04-20 01:55:02.846000+00:00
ak11472630 2015-01-01 00:05:47.806000+00:00
nc72324926 2014-10-11 10:57:04.545000+00:00
ak11140430 2014-01-20 07:10:57.670000+00:00
nc72354541 2014-12-03 18:39:39.818000+00:00
ak11322224 2014-07-10 00:50:24.748000+00:00
nc72177191 2014-03-01 10:37:04.485000+00:00
nc72315881 2014-10-10 17:10:05.901000+00:00
ci37248368 2014-07-21 15:27:39.015000+00:00

                                           place        type   pais
id
ak11434349              47km W of Haines, Alaska  earthquake  EE.UU
ak11234999          67km NNW of Talkeetna, Alaska  earthquake  EE.UU
ak11472630          85km NNW of Talkeetna, Alaska  earthquake  EE.UU
nc72324926            6km WNW of Cobb, California  earthquake  EE.UU
ak11140430           42km NE of Talkeetna, Alaska  earthquake  EE.UU
nc72354541  8km ESE of Mammoth Lakes, California  earthquake  EE.UU
ak11322224             85km WNW of Willow, Alaska  earthquake  EE.UU
nc72177191    1km NNE of The Geysers, California  earthquake  EE.UU
nc72315881  2km ESE of Mammoth Lakes, California  earthquake  EE.UU
ci37248368            11km SE of Anza, California  earthquake  EE.UU
```

[10]:
```python
# Eliminamos los datos cuyos paises no fueron definidos
data_df = data_df.drop(data_df[data_df["pais"] == "UNDEFINED"].index)
```

[11]:
```python
byPais = data_df[['pais', 'mag']].groupby(['pais'])["mag"].describe()
byPais
```

[11]:

	count	mean	std	min	25%	50%	75%	max
pais								
Afghanistan	148.0	4.336486	0.320533	3.7	4.100	4.30	4.500	5.6
Africa	37.0	4.591892	0.316560	4.0	4.400	4.60	4.700	5.5
Alaska Peninsula	19.0	1.957895	0.386316	1.1	1.700	2.00	2.200	2.7
Albania	15.0	4.300000	0.333809	3.8	4.100	4.20	4.450	5.0
Aleutian Islands	2.0	2.150000	0.212132	2.0	2.075	2.15	2.225	2.3
…	…	…	…	…	…	…	…	…

```
Volcano Islands       1.0  4.000000       NaN  4.0  4.000  4.00  4.000  4.0
Wallis and Futuna    62.0  4.556452  0.550892  4.0  4.200  4.40  4.675  6.7
Xizang                1.0  4.500000       NaN  4.5  4.500  4.50  4.500  4.5
Yemen                34.0  4.291176  0.215136  4.0  4.100  4.30  4.400  4.9
Zambia                7.0  4.457143  0.435343  4.1  4.100  4.40  4.600  5.3

[223 rows x 8 columns]
```

1.0.6 6) Encuentra los 10 países con el mayor número de terremotos

[12]:
```python
# TOP 10 por num de terremotos
top10numTerr = byPais[['count']].sort_values("count", ascending=False)[:10]
top10numTerr
```

[12]:
```
                      count
pais
EE.UU              100165.0
Indonesia            2124.0
Papua New Guinea     1356.0
Japan                1217.0
Chile                1196.0
New Zealand           763.0
Philippines           749.0
Fiji                  700.0
Mexico                667.0
Solomon Islands       600.0
```

1.0.7 7) Encuentra los 10 principales países donde ocurrieron los terremotos más fuertes y más débiles

[13]:
```python
# Top 10 max magnitud
top10maxMag = byPais[['max']].sort_values("max", ascending=False)[:10]
top10maxMag
```

[13]:
```
                  max
pais
Chile             8.2
EE.UU             7.9
Solomon Islands   7.6
Papua New Guinea  7.5
El Salvador       7.3
Mexico            7.2
Fiji              7.1
Indonesia         7.1
Pacific Rise      7.0
New Zealand       6.9
```

[14]:
```
# Top 10 min magnitud
top10minMag = byPais[['min']].sort_values("min", ascending=True)[:10]
top10minMag
```

[14]:
```
                              min
pais
EE.UU                       -0.97
Sierra Leone                 0.00
Off coast Northwest Africa   0.00
Canada                       0.20
Mexico                       0.96
Southeastern Alaska          1.00
Alaska Peninsula             1.10
Carolina                     1.80
Aleutian Islands             2.00
Gulf Alaska                  2.30
```

1.0.8 8) Cree un conjunto de datos filtrado que solo tenga terremotos de magnitud 4 o mayores

[15]:
```
# Filtro
isMore4Mag = data_df['mag'] >= 4

# Aplicar el filtro
by4Magnitud = data_df[isMore4Mag]
by4Magnitud.head()
```

[15]:
```
                               time  latitude  longitude   depth  mag magType  \
id
usc000mqlp 2014-01-31 23:08:03.660   -4.9758   153.9466  110.18  4.2      mb
usc000mqln 2014-01-31 22:54:32.970  -28.1775  -177.9058   95.84  4.3      mb
usc000mqls 2014-01-31 22:49:49.740  -23.1192   179.1174  528.34  4.4      mb
usc000mf1x 2014-01-31 22:19:44.330   51.1569  -178.0910   37.50  4.2      mb
usc000mqlm 2014-01-31 21:56:44.320   -4.8800   153.8434  112.66  4.3      mb

            nst    gap   dmin   rms net                   updated  \
id
usc000mqlp  NaN   98.0  1.940  0.61  us 2014-04-08 01:43:19+00:00
usc000mqln  NaN  104.0  1.063  1.14  us 2014-04-08 01:43:19+00:00
usc000mqls  NaN   80.0  5.439  0.95  us 2014-04-08 01:43:19+00:00
usc000mf1x  NaN    NaN    NaN  0.83  us 2014-04-08 01:43:19+00:00
usc000mqlm  NaN  199.0  1.808  0.79  us 2014-04-08 01:43:19+00:00

                                           place        type              pais
id
usc000mqlp  115km ESE of Taron, Papua New Guinea  earthquake  Papua New Guinea
usc000mqln  120km N of Raoul Island, New Zealand  earthquake       New Zealand
```

```
usc000mqls              South of the Fiji Islands  earthquake      Fiji Islands
usc000mf1x     72km E of Amatignak Island, Alaska  earthquake             EE.UU
usc000mqlm   100km ESE of Taron, Papua New Guinea  earthquake  Papua New Guinea
```

1.0.9 9) Analice la distribución de las magnitudes del terremoto en la distribución filtrada

Haga un histograma del conteo del terremoto versus la magnitud. Asegúrese de usar una escala logarítmica.

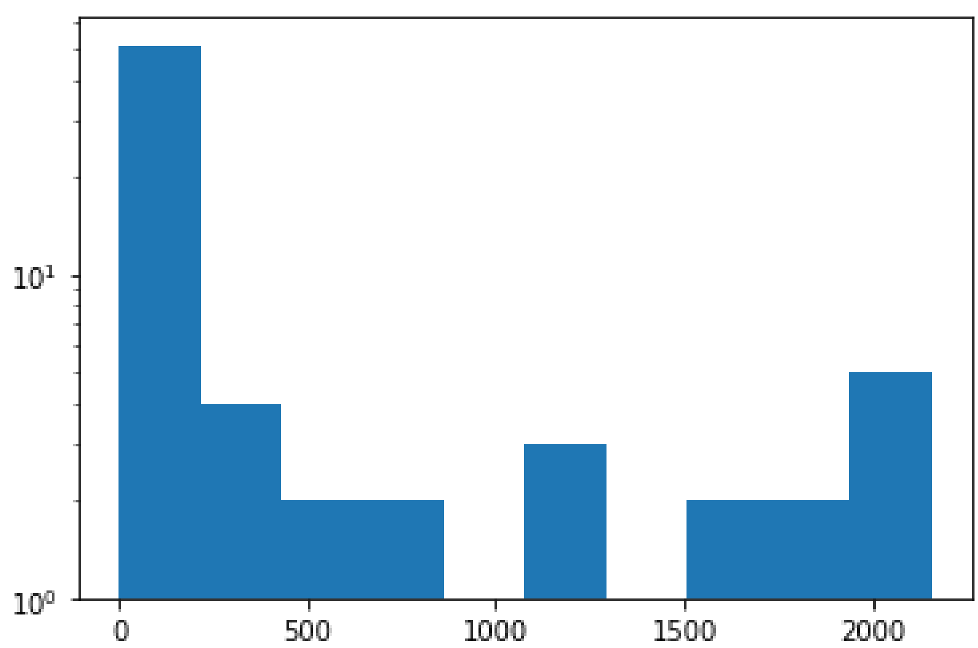
[16]:
```
# Agrupamos por la columna mag y realizamos una cuenta
dataHist = by4Magnitud[["mag", "pais"]].groupby(['mag']).count()

# Se renombra la columna pais por count, nombre mas acorde al dato que contiene␣
↪ahora
dataHist.columns = ['count']
```

[17]:
```
valuesHist = dataHist.iloc[:,0]
```

[18]:
```
plt.hist(valuesHist, bins=10, log=True, bottom=True)
```

[18]:
```
(array([50.,  3.,  1.,  1.,  0.,  2.,  0.,  1.,  1.,  4.]),
 array([1.0000e+00, 2.1640e+02, 4.3180e+02, 6.4720e+02, 8.6260e+02,
        1.0780e+03, 1.2934e+03, 1.5088e+03, 1.7242e+03, 1.9396e+03,
        2.1550e+03]),
 <BarContainer object of 10 artists>)
```



1.0.10 10) Visualice la ubicación de los terremotos haciendo un diagrama de dispersión de su latitud y longitud.

Usa los datos filtrados. Coloréalo por magnitud. Ej. plt.scatter(x, y, s=s, c=c, cmap=plt.cm.Oranges)

Con s y c podemos modificar el tamaño y el color respectivamente. Para el color, a cada valor numérico se le asigna un color a través de un mapa de colores; ese mapa se puede cambiar con el argumento cmap. Esa correspondencia se puede visualizar llamando a la función colorbar.

```
N = 100
x = np.random.randn(N)
y = np.random.randn(N)
s = 50 + 50 * np.random.randn(N)
c = np.random.randn(N)

plt.scatter(x, y, s=s, c=c, cmap=plt.cm.Blues)
plt.colorbar()
```

Ref. adicional para colores: https://github.com/lsantiago/PythonBasico/raw/d36d9571a1ff6a2df8364a9055f71d70

[19]:
```
dataScatter = by4Magnitud[["latitude", "longitude", "mag", "depth"]]
dataScatter
```

[19]:

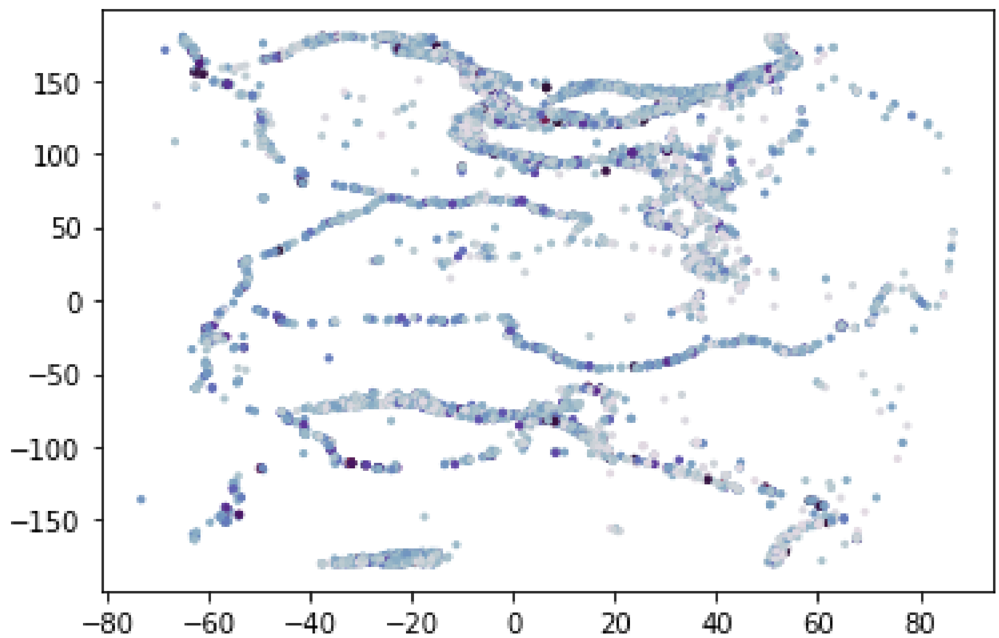
	latitude	longitude	mag	depth
id				
usc000mqlp	-4.9758	153.9466	4.2	110.18
usc000mqln	-28.1775	-177.9058	4.3	95.84
usc000mqls	-23.1192	179.1174	4.4	528.34
usc000mf1x	51.1569	-178.0910	4.2	37.50
usc000mqlm	-4.8800	153.8434	4.3	112.66
…	…	…	…	…
usc000t6yh	21.2031	143.5484	4.4	11.05
usc000t6y2	-7.8798	106.4275	4.3	52.10
usc000t6y1	7.1429	126.8844	4.3	176.67
usb000t1gp	37.2096	71.9458	4.2	95.57
usc000t6yn	-24.6340	-179.6018	4.5	470.86

[17202 rows x 4 columns]

[20]:
```
# Extraemos los datos a usar para facilitar el uso de las mismas
latitudes = dataScatter.iloc[:,0]
longitudes = dataScatter.iloc[:,1]
magnitudes = dataScatter.iloc[:,2]
profundidad = dataScatter.iloc[:,3]
```

[21]:
```
plt.scatter(latitudes, longitudes, s=magnitudes, c=magnitudes, cmap=plt.cm.
 ↪twilight)
```

[21]: <matplotlib.collections.PathCollection at 0x2209a0552b0>



1.0.11 11) Haz lo mismo para la profundidad

[22]:
```
plt.scatter(latitudes, longitudes, s=profundidad, c=profundidad, cmap=plt.cm.
 ↪twilight)
```

[22]: <matplotlib.collections.PathCollection at 0x2209938d9d0>