

mcpp_taller7_john_caro

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1 Taller 7

Métodos Computacionales para Políticas Públicas - URSario

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1.1 Instrucciones:

- Guarde una copia de este *Jupyter Notebook* en su computador, idealmente en una carpeta destinada al material del curso.
- Modifique el nombre del archivo del *notebook*, agregando al final un guión inferior y su nombre y apellido, separados estos últimos por otro guión inferior. Por ejemplo, mi *notebook* se llamaría: mcpp_taller7_santiago_mataallana
- Marque el *notebook* con su nombre y e-mail en el bloque verde arriba. Reemplace el texto “[Su nombre acá]” con su nombre y apellido. Similar para su e-mail.
- Desarrolle la totalidad del taller sobre este *notebook*, insertando las celdas que sea necesario debajo de cada pregunta. Haga buen uso de las celdas para código y de las celdas tipo *markdown* según el caso.
- Recuerde salvar periódicamente sus avances.
- Cuando termine el taller:
 1. Descárguelo en PDF. Si tiene algún problema con la conversión, descárguelo en HTML.
 2. Suba todos los archivos a su repositorio en GitHub, en una carpeta destinada exclusivamente para este taller, antes de la fecha y hora límites.

(Todos los ejercicios tienen el mismo valor.)

Este taller tiene dos partes. Una obligatoria, relativamente fácil, y otra voluntaria y más retadora. Los invito a intentar desarrollar el taller en su totalidad.

En este taller exploraremos los datos de crimen de Chicago.

Descargue los datos de crimen del Chicago Data Portal solo para el año 2015 (<https://data.cityofchicago.org/Public-Safety/Crimes-2001-to-present/ijzp-q8t2>).

1.1.1 Parte obligatoria

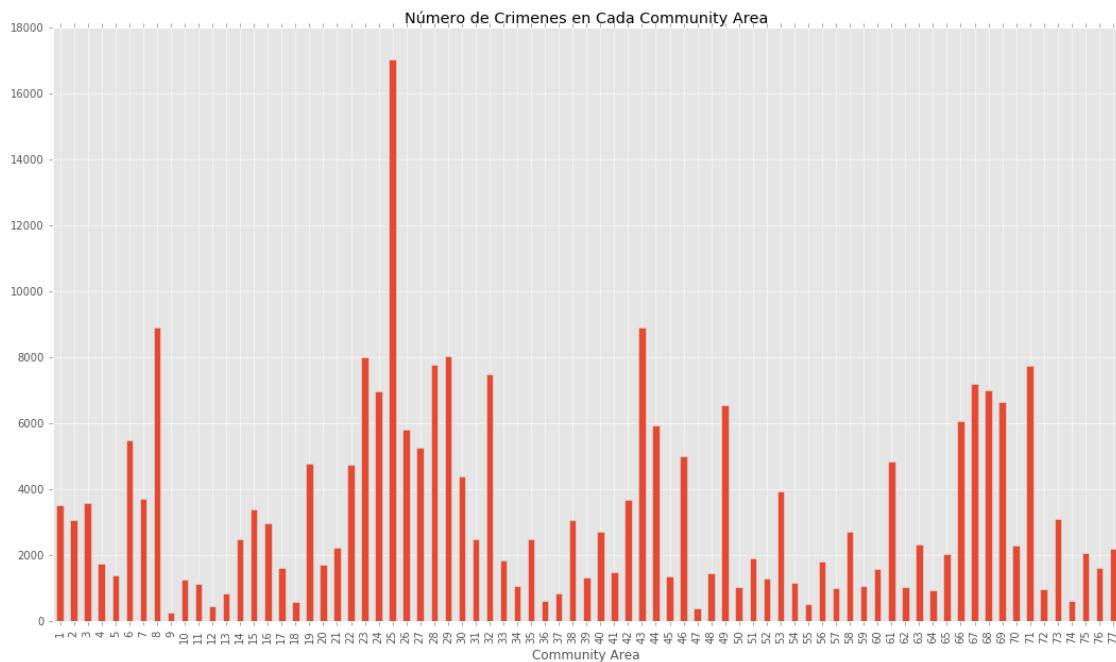
1.1.2 1.

Calcule el número de crímenes en cada Community Area en 2015. Haga un gráfico de barras que lo ilustre.

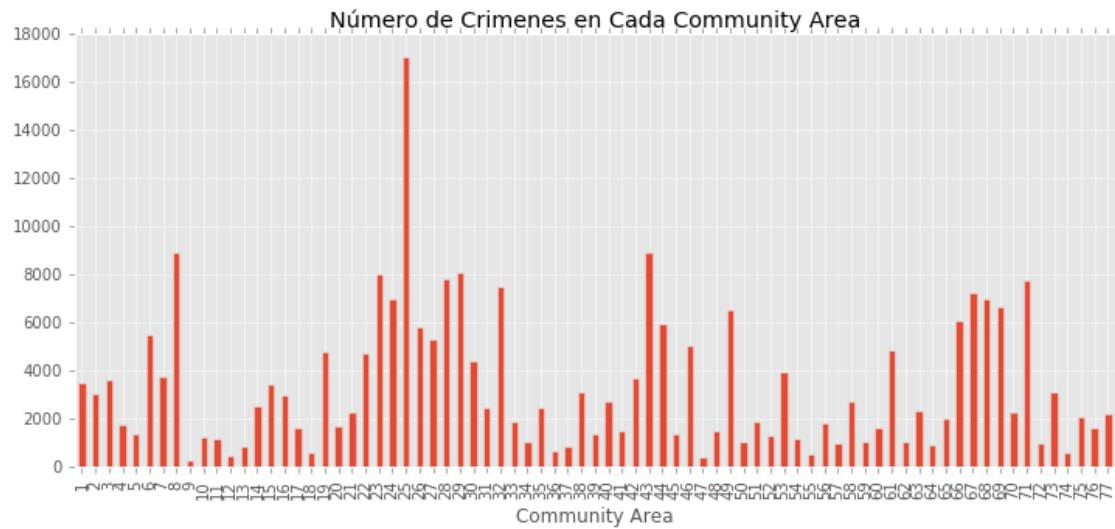
```
In [1]: import pandas as pd
import numpy as np
from numpy.random import randn
import matplotlib.pyplot as plt
%matplotlib inline
plt.rcParams["figure.figsize"] = [18.0, 10.0]
plt.style.use('ggplot')

crimes = pd.read_csv('Crimes_-_2001_to_present.csv', parse_dates=['Date'])

In [2]: numeros_crimeses_c_area = crimes.groupby('Community Area')['ID'].agg('count')
numeros_crimeses_c_area.plot(kind='bar',title="Número de Crímenes en Cada C
```



```
In [3]: numeros_crimeses_c_area.plot(kind='bar', figsize=(12,5),title="Número de Cr
```



1.1.3 2.

Ordene las Community Areas de acuerdo con el número de crímenes. ¿Qué Community Area (por nombre, idealmente) presenta el mayor número de crímenes? ¿El menor?

```
In [4]: numeros_crimeses_c_area_ordenado = numeros_crimeses_c_area.sort_values()
        C_area_menor_crimeses = numeros_crimeses_c_area_ordenado.head(1)
        C_area_mayor_crimeses = numeros_crimeses_c_area_ordenado.tail(1)
        numeros_crimeses_c_area_ordenado
```

```
Out[4]: Community Area
9        254
47       380
12       444
55       506
18       572
74       608
36       622
13       828
37       834
64       927
72       976
57      986
62     1030
50     1037
34     1057
59     1063
11     1140
54     1173
```

```
10      1259
52      1303
39      1340
45      1356
5        1375
48      1458
41      1493
60      1590
76      1622
17      1626
20      1703
4        1747
...
73      3109
15      3392
1        3519
3        3585
42      3665
7        3726
53      3949
30      4393
22      4737
19      4769
61      4842
46      5009
27      5270
6        5495
26      5794
44      5943
66      6081
49      6545
69      6653
24      6959
68      6991
67      7203
32      7489
71      7733
28      7788
23      8015
29      8039
43      8906
8        8920
25      17020
Name: ID, dtype: int64
```

```
In [5]: C_area_menor_crimes
```

```
Out[5]: Community Area
```

```
9      254
Name: ID, dtype: int64
```

```
In [6]: C_area_mayor_crimes
```

```
Out[6]: Community Area
25      17020
Name: ID, dtype: int64
```

1.1.4 3.

Cree una tabla cuyas filas sean días del año (yyyy-mm-dd) y las columnas las 77 Community Areas. En cada campo de la tabla deberá haber el correspondiente número de crímenes. Seleccione algunas Community Areas que le llamen la atención y haga un gráfico de serie de tiempo.

Pista: El siguiente código puede serle útil.

```
In [7]: # Create function to strip time from date field, and use it to create another
def to_day(timestamp):
    return timestamp.replace(minute=0, hour=0, second=0)
```

```
crimes['Day'] = crimes['Date'].apply(to_day)
```

```
In [11]: crimes_by_community_day = crimes.groupby(['Community Area', 'Day'])
```

```
crimes_by_community_day_count = crimes_by_community_day['ID'].agg('count')
crimes_by_community_day_count
```

```
Out[11]: Community Area  Day
1      2015-01-01      13
      2015-01-02       5
      2015-01-03       7
      2015-01-04      12
      2015-01-05       6
      2015-01-06       7
      2015-01-07       6
      2015-01-08       6
      2015-01-09      10
      2015-01-10       6
      2015-01-11       8
      2015-01-12       3
      2015-01-13      10
      2015-01-14      17
      2015-01-15       9
      2015-01-16      13
      2015-01-17      12
      2015-01-18      12
      2015-01-19       3
      2015-01-20       8
      2015-01-21      18
```

```

2015-01-22      7
2015-01-23     12
2015-01-24     14
2015-01-25      5
2015-01-26     10
2015-01-27      6
2015-01-28     15
2015-01-29      9
2015-01-30      8
..
77  2015-12-01      2
    2015-12-02      8
    2015-12-03      4
    2015-12-04      3
    2015-12-05      4
    2015-12-06      9
    2015-12-07      6
    2015-12-08      9
    2015-12-09      6
    2015-12-10      2
    2015-12-11      9
    2015-12-12      3
    2015-12-13      5
    2015-12-14     12
    2015-12-15      7
    2015-12-16      5
    2015-12-17      7
    2015-12-18      4
    2015-12-19      4
    2015-12-20      1
    2015-12-21      5
    2015-12-22      8
    2015-12-23      7
    2015-12-24      5
    2015-12-25      4
    2015-12-26      8
    2015-12-27      2
    2015-12-28      9
    2015-12-29      4
    2015-12-30      5

```

Name: ID, dtype: int64

```
In [12]: community_timeseries = crimes_by_community_day_count.unstack('Community Area')
community_timeseries
```

```
Out[12]: Community Area      1      2      3      4      5      6      7      8      9     10     ..
Day
2015-01-01      13.0    7.0   11.0    4.0    5.0   22.0   12.0   43.0    1.0    5.0     ..
```

2015-01-02	5.0	9.0	8.0	3.0	2.0	10.0	9.0	27.0	NaN	2.0	.
2015-01-03	7.0	11.0	9.0	7.0	4.0	6.0	11.0	27.0	1.0	3.0	.
2015-01-04	12.0	7.0	9.0	10.0	3.0	15.0	5.0	16.0	1.0	4.0	.
2015-01-05	6.0	7.0	5.0	4.0	5.0	15.0	7.0	11.0	1.0	3.0	.
2015-01-06	7.0	8.0	6.0	5.0	NaN	13.0	7.0	13.0	NaN	4.0	.
2015-01-07	6.0	2.0	4.0	5.0	1.0	8.0	6.0	17.0	1.0	2.0	.
2015-01-08	6.0	6.0	3.0	5.0	NaN	6.0	5.0	8.0	1.0	NaN	.
2015-01-09	10.0	5.0	10.0	2.0	4.0	14.0	6.0	21.0	NaN	3.0	.
2015-01-10	6.0	12.0	8.0	NaN	1.0	10.0	5.0	24.0	2.0	2.0	.
2015-01-11	8.0	6.0	11.0	5.0	4.0	20.0	4.0	26.0	1.0	2.0	.
2015-01-12	3.0	6.0	6.0	6.0	1.0	7.0	11.0	17.0	NaN	6.0	.
2015-01-13	10.0	10.0	9.0	5.0	4.0	8.0	6.0	15.0	NaN	3.0	.
2015-01-14	17.0	8.0	9.0	4.0	3.0	5.0	11.0	15.0	1.0	3.0	.
2015-01-15	9.0	8.0	8.0	6.0	7.0	9.0	11.0	18.0	1.0	4.0	.
2015-01-16	13.0	6.0	12.0	5.0	5.0	12.0	12.0	22.0	1.0	8.0	.
2015-01-17	12.0	5.0	5.0	2.0	5.0	16.0	7.0	30.0	1.0	4.0	.
2015-01-18	12.0	6.0	12.0	7.0	5.0	14.0	8.0	18.0	1.0	2.0	.
2015-01-19	3.0	12.0	7.0	3.0	5.0	10.0	11.0	25.0	NaN	3.0	.
2015-01-20	8.0	8.0	9.0	10.0	3.0	13.0	12.0	31.0	NaN	4.0	.
2015-01-21	18.0	8.0	8.0	10.0	9.0	12.0	9.0	29.0	2.0	2.0	.
2015-01-22	7.0	7.0	6.0	9.0	7.0	14.0	10.0	21.0	NaN	6.0	.
2015-01-23	12.0	11.0	6.0	4.0	6.0	8.0	6.0	27.0	1.0	5.0	.
2015-01-24	14.0	9.0	7.0	8.0	4.0	11.0	15.0	23.0	NaN	4.0	.
2015-01-25	5.0	9.0	3.0	5.0	2.0	20.0	6.0	29.0	NaN	2.0	.
2015-01-26	10.0	8.0	5.0	4.0	3.0	13.0	5.0	13.0	1.0	NaN	.
2015-01-27	6.0	8.0	6.0	3.0	3.0	6.0	3.0	13.0	NaN	3.0	.
2015-01-28	15.0	9.0	10.0	1.0	1.0	9.0	11.0	26.0	NaN	1.0	.
2015-01-29	9.0	9.0	11.0	2.0	3.0	11.0	7.0	26.0	1.0	6.0	.
2015-01-30	8.0	11.0	6.0	5.0	3.0	12.0	10.0	21.0	NaN	6.0	.
...
2015-12-02	12.0	7.0	11.0	4.0	7.0	12.0	11.0	23.0	1.0	1.0	.
2015-12-03	6.0	11.0	9.0	2.0	4.0	12.0	7.0	32.0	1.0	1.0	.
2015-12-04	8.0	9.0	8.0	4.0	5.0	10.0	4.0	26.0	NaN	3.0	.
2015-12-05	9.0	7.0	5.0	5.0	5.0	8.0	13.0	33.0	1.0	2.0	.
2015-12-06	9.0	11.0	11.0	2.0	NaN	20.0	8.0	24.0	NaN	2.0	.
2015-12-07	7.0	10.0	8.0	1.0	6.0	10.0	8.0	19.0	1.0	3.0	.
2015-12-08	5.0	9.0	4.0	3.0	6.0	17.0	12.0	33.0	3.0	7.0	.
2015-12-09	12.0	11.0	7.0	8.0	9.0	15.0	12.0	24.0	NaN	5.0	.
2015-12-10	3.0	6.0	9.0	8.0	6.0	25.0	13.0	29.0	1.0	3.0	.
2015-12-11	11.0	7.0	11.0	6.0	5.0	19.0	10.0	29.0	NaN	2.0	.
2015-12-12	10.0	5.0	7.0	8.0	4.0	25.0	15.0	38.0	1.0	2.0	.
2015-12-13	7.0	12.0	10.0	3.0	4.0	21.0	9.0	38.0	NaN	6.0	.
2015-12-14	15.0	12.0	11.0	9.0	6.0	9.0	10.0	27.0	1.0	4.0	.
2015-12-15	10.0	6.0	11.0	5.0	3.0	10.0	21.0	24.0	NaN	9.0	.
2015-12-16	6.0	7.0	12.0	5.0	4.0	19.0	9.0	20.0	1.0	3.0	.
2015-12-17	8.0	8.0	8.0	7.0	5.0	18.0	19.0	28.0	NaN	3.0	.
2015-12-18	13.0	7.0	6.0	6.0	2.0	17.0	19.0	27.0	NaN	3.0	.
2015-12-19	7.0	11.0	6.0	3.0	1.0	10.0	12.0	41.0	2.0	3.0	.

2015-12-20	12.0	8.0	13.0	7.0	3.0	18.0	10.0	21.0	1.0	2.0	.
2015-12-21	6.0	2.0	11.0	4.0	NaN	6.0	11.0	32.0	NaN	3.0	.
2015-12-22	13.0	11.0	15.0	5.0	4.0	13.0	9.0	26.0	NaN	NaN	.
2015-12-23	12.0	11.0	14.0	6.0	5.0	18.0	12.0	28.0	NaN	3.0	.
2015-12-24	8.0	11.0	2.0	6.0	3.0	19.0	11.0	26.0	NaN	7.0	.
2015-12-25	2.0	6.0	3.0	3.0	NaN	5.0	5.0	10.0	1.0	5.0	.
2015-12-26	6.0	11.0	12.0	1.0	1.0	17.0	5.0	26.0	NaN	9.0	.
2015-12-27	14.0	8.0	6.0	3.0	1.0	16.0	11.0	32.0	NaN	1.0	.
2015-12-28	7.0	8.0	5.0	2.0	2.0	10.0	8.0	19.0	NaN	3.0	.
2015-12-29	6.0	7.0	12.0	8.0	3.0	8.0	5.0	25.0	NaN	1.0	.
2015-12-30	5.0	8.0	7.0	4.0	1.0	11.0	15.0	27.0	1.0	6.0	.
2015-12-31	NaN	NaN	NaN	NaN	NaN	1.0	NaN	NaN	NaN	NaN	.
Community Area	68	69	70	71	72	73	74	75	76	77	
Day											
2015-01-01	29.0	23.0	9.0	44.0	2.0	8.0	2.0	5.0	6.0	8.0	
2015-01-02	12.0	21.0	5.0	17.0	1.0	11.0	1.0	2.0	6.0	5.0	
2015-01-03	23.0	12.0	8.0	18.0	NaN	8.0	1.0	7.0	3.0	3.0	
2015-01-04	13.0	15.0	9.0	12.0	1.0	5.0	NaN	1.0	6.0	1.0	
2015-01-05	16.0	12.0	8.0	17.0	NaN	5.0	2.0	2.0	7.0	5.0	
2015-01-06	15.0	14.0	6.0	11.0	2.0	8.0	2.0	3.0	6.0	4.0	
2015-01-07	11.0	7.0	4.0	16.0	3.0	7.0	NaN	3.0	7.0	1.0	
2015-01-08	9.0	9.0	6.0	10.0	2.0	4.0	1.0	5.0	3.0	3.0	
2015-01-09	18.0	14.0	10.0	20.0	1.0	9.0	2.0	8.0	5.0	2.0	
2015-01-10	9.0	13.0	6.0	28.0	3.0	3.0	1.0	5.0	5.0	2.0	
2015-01-11	17.0	8.0	11.0	17.0	2.0	10.0	2.0	4.0	2.0	4.0	
2015-01-12	12.0	18.0	6.0	19.0	3.0	5.0	1.0	4.0	4.0	3.0	
2015-01-13	19.0	12.0	9.0	11.0	2.0	6.0	NaN	4.0	6.0	6.0	
2015-01-14	21.0	16.0	6.0	24.0	NaN	5.0	1.0	1.0	2.0	6.0	
2015-01-15	19.0	20.0	4.0	21.0	3.0	7.0	2.0	6.0	6.0	5.0	
2015-01-16	18.0	17.0	8.0	16.0	4.0	5.0	NaN	5.0	7.0	3.0	
2015-01-17	29.0	13.0	7.0	15.0	2.0	6.0	2.0	5.0	10.0	3.0	
2015-01-18	20.0	22.0	3.0	20.0	1.0	11.0	NaN	8.0	2.0	4.0	
2015-01-19	24.0	19.0	3.0	28.0	NaN	13.0	NaN	6.0	8.0	4.0	
2015-01-20	19.0	15.0	5.0	23.0	1.0	10.0	NaN	8.0	6.0	7.0	
2015-01-21	11.0	12.0	7.0	29.0	5.0	2.0	2.0	6.0	3.0	9.0	
2015-01-22	19.0	13.0	11.0	22.0	1.0	5.0	1.0	6.0	4.0	6.0	
2015-01-23	26.0	18.0	6.0	20.0	1.0	7.0	3.0	4.0	6.0	8.0	
2015-01-24	10.0	13.0	5.0	17.0	1.0	8.0	NaN	3.0	5.0	10.0	
2015-01-25	15.0	13.0	7.0	15.0	3.0	4.0	1.0	6.0	3.0	5.0	
2015-01-26	18.0	16.0	10.0	29.0	1.0	8.0	1.0	9.0	2.0	8.0	
2015-01-27	20.0	16.0	9.0	20.0	2.0	11.0	2.0	6.0	3.0	5.0	
2015-01-28	13.0	16.0	3.0	18.0	2.0	7.0	1.0	6.0	5.0	6.0	
2015-01-29	19.0	20.0	4.0	24.0	2.0	6.0	1.0	8.0	4.0	5.0	
2015-01-30	20.0	22.0	6.0	20.0	5.0	7.0	NaN	6.0	2.0	4.0	
...	
2015-12-02	23.0	13.0	6.0	23.0	1.0	8.0	4.0	6.0	6.0	8.0	
2015-12-03	16.0	19.0	7.0	17.0	2.0	7.0	3.0	3.0	2.0	4.0	

2015-12-04	18.0	15.0	3.0	21.0	1.0	7.0	NaN	6.0	2.0	3.0
2015-12-05	13.0	20.0	5.0	26.0	3.0	9.0	3.0	5.0	2.0	4.0
2015-12-06	19.0	20.0	6.0	22.0	5.0	10.0	1.0	1.0	4.0	9.0
2015-12-07	20.0	21.0	3.0	30.0	3.0	8.0	2.0	6.0	4.0	6.0
2015-12-08	9.0	16.0	9.0	29.0	1.0	6.0	2.0	1.0	1.0	9.0
2015-12-09	11.0	16.0	3.0	20.0	6.0	7.0	1.0	4.0	4.0	6.0
2015-12-10	19.0	16.0	8.0	20.0	2.0	8.0	4.0	5.0	3.0	2.0
2015-12-11	17.0	19.0	3.0	19.0	4.0	10.0	3.0	4.0	10.0	9.0
2015-12-12	17.0	16.0	9.0	19.0	1.0	7.0	2.0	NaN	5.0	3.0
2015-12-13	17.0	17.0	7.0	14.0	NaN	2.0	3.0	3.0	5.0	5.0
2015-12-14	18.0	29.0	11.0	12.0	4.0	4.0	2.0	6.0	3.0	12.0
2015-12-15	19.0	19.0	11.0	14.0	NaN	8.0	1.0	7.0	3.0	7.0
2015-12-16	18.0	15.0	10.0	23.0	1.0	9.0	2.0	4.0	4.0	5.0
2015-12-17	15.0	19.0	4.0	15.0	NaN	10.0	NaN	6.0	7.0	7.0
2015-12-18	15.0	16.0	7.0	19.0	3.0	9.0	NaN	4.0	5.0	4.0
2015-12-19	10.0	12.0	5.0	21.0	1.0	7.0	NaN	2.0	3.0	4.0
2015-12-20	15.0	23.0	5.0	15.0	3.0	7.0	2.0	2.0	5.0	1.0
2015-12-21	12.0	15.0	3.0	18.0	2.0	9.0	1.0	1.0	2.0	5.0
2015-12-22	26.0	16.0	3.0	16.0	2.0	6.0	NaN	5.0	2.0	8.0
2015-12-23	18.0	23.0	8.0	19.0	1.0	9.0	4.0	8.0	2.0	7.0
2015-12-24	16.0	22.0	4.0	19.0	3.0	3.0	2.0	5.0	3.0	5.0
2015-12-25	13.0	15.0	3.0	18.0	1.0	5.0	NaN	6.0	3.0	4.0
2015-12-26	15.0	18.0	6.0	17.0	1.0	10.0	NaN	3.0	7.0	8.0
2015-12-27	11.0	19.0	3.0	26.0	2.0	8.0	2.0	1.0	4.0	2.0
2015-12-28	12.0	22.0	9.0	14.0	2.0	6.0	2.0	2.0	3.0	9.0
2015-12-29	18.0	16.0	7.0	18.0	NaN	8.0	3.0	2.0	2.0	4.0
2015-12-30	11.0	23.0	6.0	14.0	2.0	8.0	1.0	7.0	5.0	5.0
2015-12-31	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN

[365 rows x 77 columns]

In [14]: community_timeseries.describe()

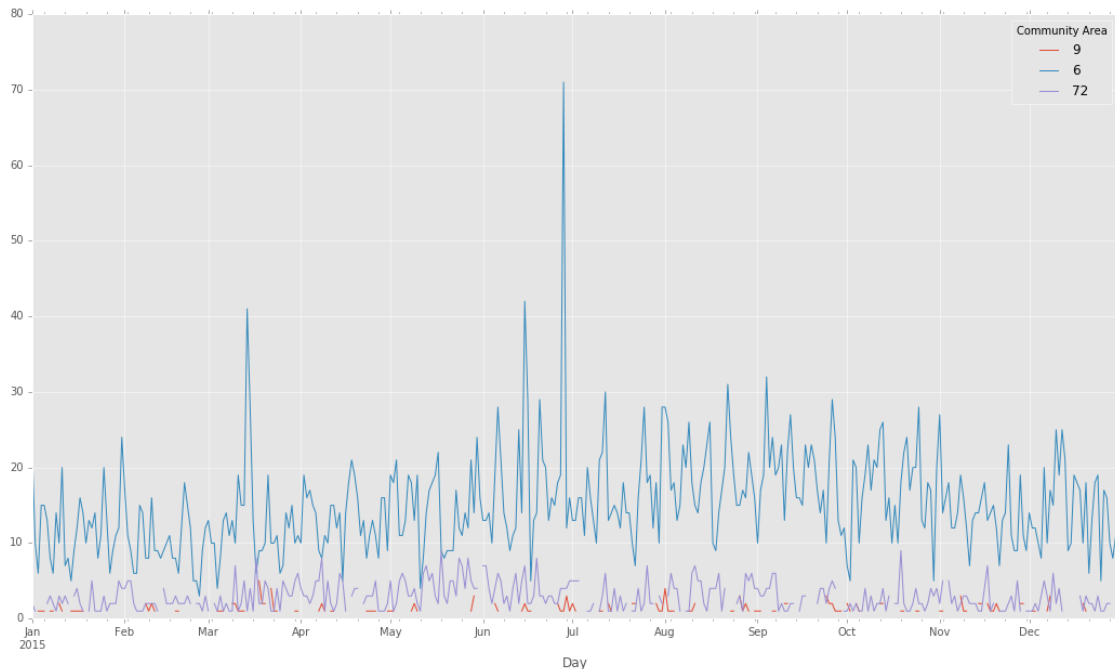
C:\Users\Usuario\Anaconda3\lib\site-packages\numpy\lib\function_base.py:3834: RuntimeWarning)

Out[14]: Community Area	1	2	3	4	5
count	364.000000	364.000000	364.000000	357.000000	347.000000
mean	9.667582	8.403846	9.848901	4.893557	3.962536
std	3.396959	3.024070	3.656267	2.318680	2.097696
min	2.000000	2.000000	2.000000	1.000000	1.000000
25%	NaN	NaN	NaN	NaN	NaN
50%	NaN	NaN	NaN	NaN	NaN
75%	NaN	NaN	NaN	NaN	NaN
max	20.000000	21.000000	29.000000	13.000000	12.000000
Community Area	6	7	8	9	10

count	365.000000	364.000000	364.000000	180.000000	352.000000
mean	15.054795	10.236264	24.505495	1.411111	3.576705
std	6.664426	3.826715	7.202117	0.707414	1.924448
min	1.000000	2.000000	5.000000	1.000000	1.000000
25%	10.000000	NaN	NaN	NaN	NaN
50%	14.000000	NaN	NaN	NaN	NaN
75%	19.000000	NaN	NaN	NaN	NaN
max	71.000000	21.000000	53.000000	5.000000	10.000000
Community Area	...	68	69	70	71
count	...	364.000000	364.000000	364.000000	364.000000
mean	...	19.206044	18.277473	6.260989	21.244505
std	...	5.626469	5.052609	2.679483	5.210510
min	...	7.000000	5.000000	1.000000	10.000000
25%	...	NaN	NaN	NaN	NaN
50%	...	NaN	NaN	NaN	NaN
75%	...	NaN	NaN	NaN	NaN
max	...	41.000000	33.000000	16.000000	44.000000
Community Area	72	73	74	75	76
count	332.000000	364.000000	289.000000	362.000000	360.000000
mean	2.939759	8.541209	2.103806	5.668508	4.505556
std	1.820324	3.082154	1.275961	2.567764	2.141244
min	1.000000	1.000000	1.000000	1.000000	1.000000
25%	NaN	NaN	NaN	NaN	NaN
50%	NaN	NaN	NaN	NaN	NaN
75%	NaN	NaN	NaN	NaN	NaN
max	9.000000	20.000000	9.000000	15.000000	11.000000
Community Area	77				
count	362.000000				
mean	6.10221				
std	2.55641				
min	1.000000				
25%	NaN				
50%	NaN				
75%	NaN				
max	14.000000				

[8 rows x 77 columns]

```
In [15]: community_timeseries[[9,6,72]].plot();
```



1.1.5 Parte voluntaria

Descargue la base de datos de información socioeconómica (<https://data.cityofchicago.org/Health-Human-Services/Census-Data-Selected-socioeconomic-indicators-in-C/kn9c-c2s2>).

1.1.6 4.

Cree una tabla que agregue el número de crímenes por Community Area. Una esa tabla con la de datos socioeconómicos y cree un “scatter plot” de número de crímenes vs ingreso per cápita. Explique la relación en palabras.

```
In [79]: n_c=numeros_crimeses_c_area
```

```
In [41]: crimes2 = pd.read_csv('Census_Data_-_Selected_socioeconomic_indicators_in_
```

```
In [49]: crimes2
```

```
Out[49]:
```

	Community Area Number	COMMUNITY AREA NAME	PERCENT OF HOUSING CROW
0	1.0	Rogers Park	
1	2.0	West Ridge	
2	3.0	Uptown	
3	4.0	Lincoln Square	
4	5.0	North Center	
5	6.0	Lake View	
6	7.0	Lincoln Park	

7	8.0	Near North Side
8	9.0	Edison Park
9	10.0	Norwood Park
10	11.0	Jefferson Park
11	12.0	Forest Glen
12	13.0	North Park
13	14.0	Albany Park
14	15.0	Portage Park
15	16.0	Irving Park
16	17.0	Dunning
17	18.0	Montclair
18	19.0	Belmont Cragin
19	20.0	Hermosa
20	21.0	Avondale
21	22.0	Logan Square
22	23.0	Humboldt park
23	24.0	West Town
24	25.0	Austin
25	26.0	West Garfield Park
26	27.0	East Garfield Park
27	28.0	Near West Side
28	29.0	North Lawndale
29	30.0	South Lawndale
..
48	49.0	Roseland
49	50.0	Pullman
50	51.0	South Deering
51	52.0	East Side
52	53.0	West Pullman
53	54.0	Riverdale
54	55.0	Hegewisch
55	56.0	Garfield Ridge
56	57.0	Archer Heights
57	58.0	Brighton Park
58	59.0	McKinley Park
59	60.0	Bridgeport
60	61.0	New City
61	62.0	West Elsdon
62	63.0	Gage Park
63	64.0	Clearing
64	65.0	West Lawn
65	66.0	Chicago Lawn
66	67.0	West Englewood
67	68.0	Englewood
68	69.0	Greater Grand Crossing
69	70.0	Ashburn
70	71.0	Auburn Gresham
71	72.0	Beverly

72	73.0	Washington Height
73	74.0	Mount Greenwood
74	75.0	Morgan Park
75	76.0	O'Hare
76	77.0	Edgewater
77	NaN	CHICAGO

	PERCENT HOUSEHOLDS BELOW POVERTY	PERCENT AGED 16+ UNEMPLOYED \
0	23.6	8.7
1	17.2	8.8
2	24.0	8.9
3	10.9	8.2
4	7.5	5.2
5	11.4	4.7
6	12.3	5.1
7	12.9	7.0
8	3.3	6.5
9	5.4	9.0
10	8.6	12.4
11	7.5	6.8
12	13.2	9.9
13	19.2	10.0
14	11.6	12.6
15	13.1	10.0
16	10.6	10.0
17	15.3	13.8
18	18.7	14.6
19	20.5	13.1
20	15.3	9.2
21	16.8	8.2
22	33.9	17.3
23	14.7	6.6
24	28.6	22.6
25	41.7	25.8
26	42.4	19.6
27	20.6	10.7
28	43.1	21.2
29	30.7	15.8
..
48	19.8	20.3
49	21.6	22.8
50	29.2	16.3
51	19.2	12.1
52	25.9	19.4
53	56.5	34.6
54	17.1	9.6
55	8.8	11.3
56	14.1	16.5

57	23.6	13.9
58	18.7	13.4
59	18.9	13.7
60	29.0	23.0
61	15.6	16.7
62	23.4	18.2
63	8.9	9.5
64	14.9	9.6
65	27.9	17.1
66	34.4	35.9
67	46.6	28.0
68	29.6	23.0
69	10.4	11.7
70	27.6	28.3
71	5.1	8.0
72	16.9	20.8
73	3.4	8.7
74	13.2	15.0
75	15.4	7.1
76	18.2	9.2
77	19.7	12.9

PERCENT AGED 25+ WITHOUT HIGH SCHOOL DIPLOMA \

0	18.2
1	20.8
2	11.8
3	13.4
4	4.5
5	2.6
6	3.6
7	2.5
8	7.4
9	11.5
10	13.4
11	4.9
12	14.4
13	32.9
14	19.3
15	22.4
16	16.2
17	23.5
18	37.3
19	41.6
20	24.7
21	14.8
22	35.4
23	12.9
24	24.4

25	24.5
26	21.3
27	9.6
28	27.6
29	54.8
..	...
48	16.9
49	13.1
50	21.0
51	31.9
52	20.5
53	27.5
54	19.2
55	19.3
56	35.9
57	45.1
58	32.9
59	22.2
60	41.5
61	37.0
62	51.5
63	18.8
64	33.6
65	31.2
66	26.3
67	28.5
68	16.5
69	17.7
70	18.5
71	3.7
72	13.7
73	4.3
74	10.8
75	10.9
76	9.7
77	19.5

	PERCENT AGED UNDER 18 OR OVER 64	PER CAPITA INCOME	HARDSHIP INDEX
0	27.5	23939	39.0
1	38.5	23040	46.0
2	22.2	35787	20.0
3	25.5	37524	17.0
4	26.2	57123	6.0
5	17.0	60058	5.0
6	21.5	71551	2.0
7	22.6	88669	1.0
8	35.3	40959	8.0
9	39.5	32875	21.0

10	35.5	27751	25.0
11	40.5	44164	11.0
12	39.0	26576	33.0
13	32.0	21323	53.0
14	34.0	24336	35.0
15	31.6	27249	34.0
16	33.6	26282	28.0
17	38.6	22014	50.0
18	37.3	15461	70.0
19	36.4	15089	71.0
20	31.0	20039	42.0
21	26.2	31908	23.0
22	38.0	13781	85.0
23	21.7	43198	10.0
24	37.9	15957	73.0
25	43.6	10934	92.0
26	43.2	12961	83.0
27	22.2	44689	15.0
28	42.7	12034	87.0
29	33.8	10402	96.0
..
48	41.2	17949	52.0
49	38.6	20588	51.0
50	39.5	14685	65.0
51	42.8	17104	64.0
52	42.1	16563	62.0
53	51.5	8201	98.0
54	42.9	22677	44.0
55	38.1	26353	32.0
56	39.2	16134	67.0
57	39.3	13089	84.0
58	35.6	16954	61.0
59	31.3	22694	43.0
60	38.9	12765	91.0
61	37.7	15754	69.0
62	38.8	12171	93.0
63	37.6	25113	29.0
64	39.6	16907	56.0
65	40.6	13231	80.0
66	40.7	11317	89.0
67	42.5	11888	94.0
68	41.0	17285	66.0
69	36.9	23482	37.0
70	41.9	15528	74.0
71	40.5	39523	12.0
72	42.6	19713	48.0
73	36.8	34381	16.0
74	40.3	27149	30.0

75	30.3	25828	24.0
76	23.8	33385	19.0
77	33.5	28202	NaN

[78 rows x 9 columns]

```
In [69]: precapita=crimes2.loc[0:76,['Community Area Number',"PER CAPITA INCOME "]]
```

```
In [70]: precapita
```

```
Out[70]:
```

	Community Area Number	PER CAPITA INCOME
0	1.0	23939
1	2.0	23040
2	3.0	35787
3	4.0	37524
4	5.0	57123
5	6.0	60058
6	7.0	71551
7	8.0	88669
8	9.0	40959
9	10.0	32875
10	11.0	27751
11	12.0	44164
12	13.0	26576
13	14.0	21323
14	15.0	24336
15	16.0	27249
16	17.0	26282
17	18.0	22014
18	19.0	15461
19	20.0	15089
20	21.0	20039
21	22.0	31908
22	23.0	13781
23	24.0	43198
24	25.0	15957
25	26.0	10934
26	27.0	12961
27	28.0	44689
28	29.0	12034
29	30.0	10402
..
47	48.0	28887
48	49.0	17949
49	50.0	20588
50	51.0	14685
51	52.0	17104
52	53.0	16563

53	54.0	8201
54	55.0	22677
55	56.0	26353
56	57.0	16134
57	58.0	13089
58	59.0	16954
59	60.0	22694
60	61.0	12765
61	62.0	15754
62	63.0	12171
63	64.0	25113
64	65.0	16907
65	66.0	13231
66	67.0	11317
67	68.0	11888
68	69.0	17285
69	70.0	23482
70	71.0	15528
71	72.0	39523
72	73.0	19713
73	74.0	34381
74	75.0	27149
75	76.0	25828
76	77.0	33385

[77 rows x 2 columns]

```
In [77]: n_c.iloc[0:77,]
```

```
Out[77]:
```

	ID
Community Area	
1	3519
2	3059
3	3585
4	1747
5	1375
6	5495
7	3726
8	8920
9	254
10	1259
11	1140
12	444
13	828
14	2501
15	3392
16	2960
17	1626

18	572
19	4769
20	1703
21	2232
22	4737
23	8015
24	6959
25	17020
26	5794
27	5270
28	7788
29	8039
30	4393
...	...
48	1458
49	6545
50	1037
51	1900
52	1303
53	3949
54	1173
55	506
56	1796
57	986
58	2706
59	1063
60	1590
61	4842
62	1030
63	2334
64	927
65	2027
66	6081
67	7203
68	6991
69	6653
70	2279
71	7733
72	976
73	3109
74	608
75	2052
76	1622
77	2209

[77 rows x 1 columns]

In [60]: precapita

```

Out[60]:
Community Area Number  PER CAPITA INCOME
0                      1.0          23939
1                      2.0          23040
2                      3.0          35787
3                      4.0          37524
4                      5.0          57123
5                      6.0          60058
6                      7.0          71551
7                      8.0          88669
8                      9.0          40959
9                     10.0          32875
10                    11.0          27751
11                    12.0          44164
12                    13.0          26576
13                    14.0          21323
14                    15.0          24336
15                    16.0          27249
16                    17.0          26282
17                    18.0          22014
18                    19.0          15461
19                    20.0          15089
20                    21.0          20039
21                    22.0          31908
22                    23.0          13781
23                    24.0          43198
24                    25.0          15957
25                    26.0          10934
26                    27.0          12961
27                    28.0          44689
28                    29.0          12034
29                    30.0          10402
..                    ...
47                    48.0          28887
48                    49.0          17949
49                    50.0          20588
50                    51.0          14685
51                    52.0          17104
52                    53.0          16563
53                    54.0           8201
54                    55.0          22677
55                    56.0          26353
56                    57.0          16134
57                    58.0          13089
58                    59.0          16954
59                    60.0          22694
60                    61.0          12765
61                    62.0          15754
62                    63.0          12171

```

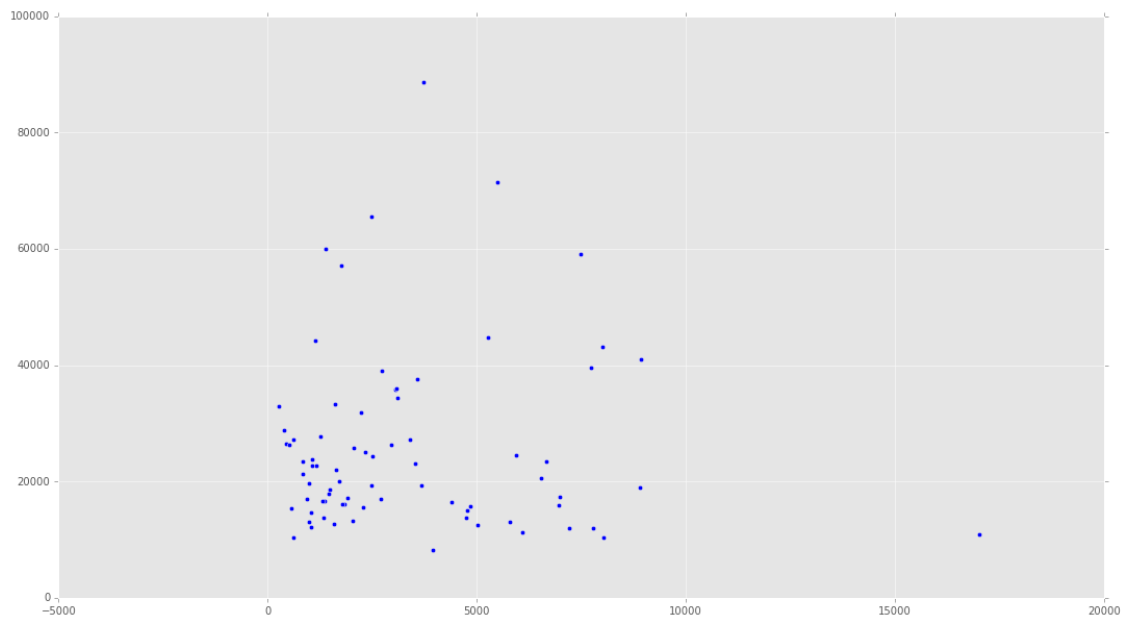
63	64.0	25113
64	65.0	16907
65	66.0	13231
66	67.0	11317
67	68.0	11888
68	69.0	17285
69	70.0	23482
70	71.0	15528
71	72.0	39523
72	73.0	19713
73	74.0	34381
74	75.0	27149
75	76.0	25828
76	77.0	33385

[77 rows x 2 columns]

```
In [94]: precapita["Crimes"]=n_c.iloc[0:77,]
```

```
#df_tmp["tmp_factorial"] = df_tmp["tmp"].apply(np.math.factorial)
```

```
In [97]: plt.scatter(precapita["Crimes"],precapita["PER CAPITA INCOME "])
plt.show()
```



```
In [ ]:
```