mcpp_taller7_monica_gasca

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1 Taller 7

Métodos Computacionales para Políticas Públicas - URosario

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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_matallana
- 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

```
In [19]: import pandas as pd
         import numpy as np
         import matplotlib.pyplot as plt
         %matplotlib inline
         plt.rcParams["figure.figsize"] = [18.0, 10.0]
         plt.style.use("fivethirtyeight")
```

```
In [20]: crimes = pd.read_csv('Crimes_-_2001_to_present.csv', low_memory=False)
```

```
In [21]: communities= pd.read_csv('communities.csv')
```

```
In [22]: completecrimes= pd.merge(crimes, communities, on= "Community Area")
```

```
In [23]: completecrimes.head(2)
```

```
Out[23]:         ID Case Number                    Date                    Block
         0  10514462    HZ256372  01/01/2015 12:00:00 AM      073XX S EXCHANGE AVE
         1  10211621    HY369125  08/04/2015 05:24:00 PM  075XX S STONY ISLAND AVE

            IUCR         Primary Type         Description  \
         0  0281  CRIM SEXUAL ASSAULT      NON-AGGRAVATED
         1  2017            NARCOTICS  MANU/DELIVER:CRACK

                   Location Description Arrest Domestic        ...         \
         0  NURSING HOME/RETIREMENT HOME  False    False        ...
         1        VEHICLE NON-COMMERCIAL   True    False        ...

            Community Area  FBI Code  X Coordinate  Y Coordinate  Year  \
         0              43        02           NaN           NaN  2015
         1              43        18     1188123.0     1855151.0  2015

                        Updated On   Latitude  Longitude  \
         0  05/10/2016 03:56:50 PM        NaN        NaN
         1  05/12/2016 03:48:29 PM  41.757614 -87.586115

                                 Location  Community Name
         0                            NaN     South Shore
         1  (41.757614433, -87.586115266)     South Shore

         [2 rows x 23 columns]
```

1.1.2 1.

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

```
In [24]: completecrimes_by_community = completecrimes.groupby('Community Name')
```

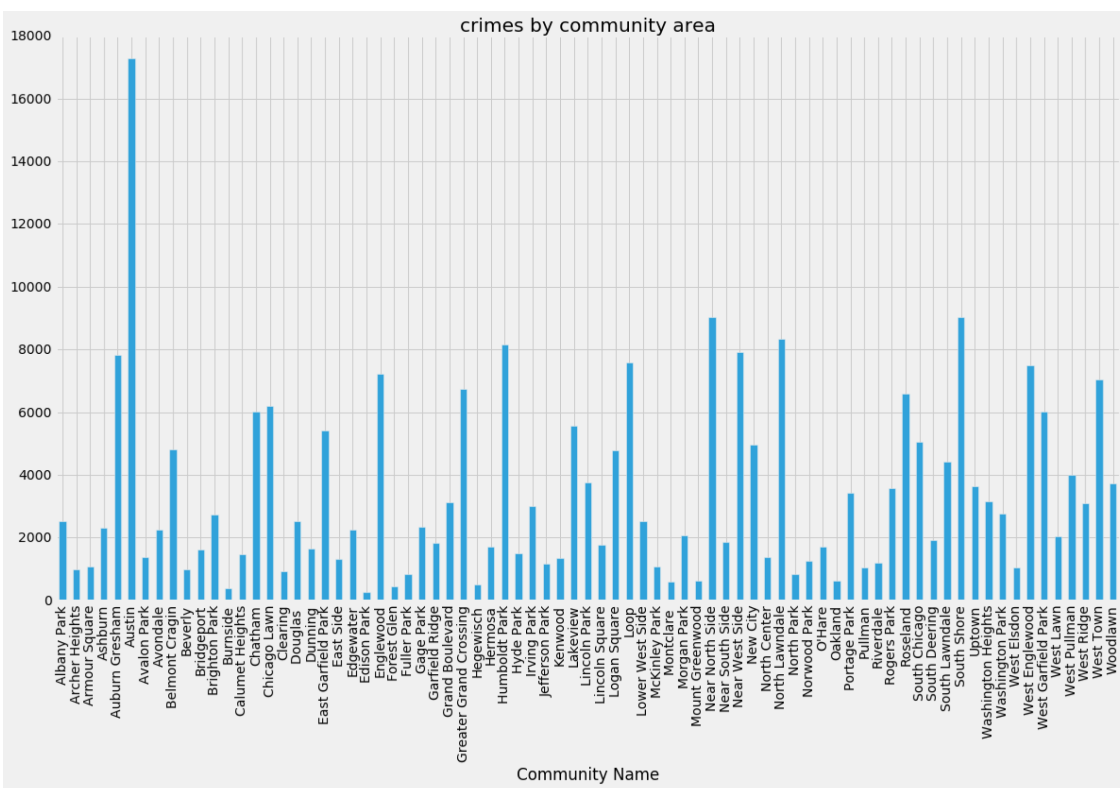
In [25]:
```
community_crime_count = completecrimes_by_community['Community Name'].agg
community_crime_count
tabla= community_crime_count.to_frame()
tabla
```

Out[25]:
```
                               Community Name
Community Name
Albany Park                              2519
Archer Heights                            993
Armour Square                            1074
Ashburn                                  2303
Auburn Gresham                           7821
Austin                                  17284
Avalon Park                              1380
Avondale                                 2254
Belmont Cragin                           4812
Beverly                                   985
Bridgeport                               1607
Brighton Park                            2742
Burnside                                  386
Calumet Heights                          1474
Chatham                                  6021
Chicago Lawn                             6191
Clearing                                  932
Douglas                                  2514
Dunning                                  1651
East Garfield Park                       5425
East Side                                1315
Edgewater                                2244
Edison Park                               256
Englewood                                7218
Forest Glen                               445
Fuller Park                               841
Gage Park                                2358
Garfield Ridge                           1843
Grand Boulevard                          3130
Greater Grand Crossing                   6743
...                                       ...
Near North Side                          9027
Near South Side                          1869
Near West Side                           7906
New City                                 4970
North Center                             1390
North Lawndale                           8350
North Park                                840
Norwood Park                             1267
O'Hare                                   1719
Oakland                                   630
```

```
Portage Park                     3433
Pullman                          1043
Riverdale                        1185
Rogers Park                      3573
Roseland                         6604
South Chicago                    5064
South Deering                    1918
South Lawndale                   4433
South Shore                      9039
Uptown                           3645
Washington Heights               3147
Washington Park                  2752
West Elsdon                      1034
West Englewood                   7505
West Garfield Park               6011
West Lawn                        2046
West Pullman                     3992
West Ridge                       3091
West Town                        7053
Woodlawn                         3730

[77 rows x 1 columns]
```

In [10]:
```
community_crime_count.plot(kind="bar", title='crimes by community area');
#crimes_by_community['Community Area'].agg('count').plot(kind='bar');
```



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 [11]: tabla.sort_values("Community Name")
```

```
Out[11]:                         Community Name
         Community Name
         Edison Park                        256
         Burnside                           386
         Forest Glen                        445
         Hegewisch                          512
         Montclare                          586
         Mount Greenwood                    614
         Oakland                            630
         North Park                         840
         Fuller Park                        841
         Clearing                           932
         Beverly                            985
         Archer Heights                     993
         West Elsdon                       1034
         Pullman                           1043
         Armour Square                     1074
         McKinley Park                     1080
         Jefferson Park                    1154
         Riverdale                         1185
         Norwood Park                      1267
         East Side                         1315
         Kenwood                           1358
         Avalon Park                       1380
         North Center                      1390
         Calumet Heights                   1474
         Hyde Park                         1507
         Bridgeport                        1607
         Dunning                           1651
         O'Hare                            1719
         Hermosa                           1725
         Lincoln Square                    1765
         ...                                ...
         Washington Heights                3147
         Portage Park                      3433
         Rogers Park                       3573
         Uptown                            3645
```

```
Woodlawn                         3730
Lincoln Park                     3750
West Pullman                     3992
South Lawndale                   4433
Logan Square                     4777
Belmont Cragin                   4812
New City                         4970
South Chicago                    5064
East Garfield Park               5425
Lakeview                         5571
West Garfield Park               6011
Chatham                          6021
Chicago Lawn                     6191
Roseland                         6604
Greater Grand Crossing           6743
West Town                        7053
Englewood                        7218
West Englewood                   7505
Loop                             7572
Auburn Gresham                   7821
Near West Side                   7906
Humboldt Park                    8152
North Lawndale                   8350
Near North Side                  9027
South Shore                      9039
Austin                          17284

[77 rows x 1 columns]
```

```
In [12]: tabla.min()
```

```
Out[12]: Community Name    256
         dtype: int64
```

```
In [13]: tabla.idxmin()
```

```
Out[13]: Community Name    Edison Park
         dtype: object
```

```
In [14]: tabla.max()
```

```
Out[14]: Community Name    17284
         dtype: int64
```

```
In [15]: tabla.idxmax()
```

```
Out[15]: Community Name    Austin
         dtype: object
```

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 [ ]: completecrimes['Date'] = pd.to_datetime(completecrimes['Date'], errors=True
```

```
In [30]: completecrimes['Day'] = completecrimes['Date'].dt.day
         completecrimes
```

```
Out[30]:              ID Case Number                Date                  Block
         0      10514462    HZ256372 2015-01-01 00:00:00      073XX S EXCHANGE AVE
         1      10211621    HY369125 2015-08-04 17:24:00  075XX S STONY ISLAND AVE
         2      10214258    HY370494 2015-08-05 17:05:00           015XX E 76TH ST
         3      10218176    HY381348 2015-08-13 19:33:00           015XX E 76TH PL
         4      10228811    HY233445 2015-04-23 16:49:27      072XX S PHILLIPS AVE
         5      10532988    HZ276332 2015-06-01 00:00:00           020XX E 69TH ST
         6       9950793    HY101687 2015-01-02 14:28:00  067XX S STONY ISLAND AVE
         7       9980167    HY116148 2015-01-15 15:45:00       076XX S SAGINAW AVE
         8       9980215    HY113809 2015-01-13 16:50:00           027XX E 76TH ST
         9       9999258    HY131054 2015-01-27 17:41:52       076XX S MERRILL AVE
         10     10303947    HY492220 2015-09-01 22:00:00        069XX S PAXTON AVE
         11     10422965    HZ159079 2015-10-01 00:01:00       068XX S MERRILL AVE
         12     10234442    HY398630 2015-08-26 17:16:00      069XX S JEFFERY BLVD
         13     10254733    HY428382 2015-09-18 13:05:00       070XX S CRANDON AVE
         14     10254810    HY427592 2015-09-17 18:39:00      069XX S JEFFERY BLVD
         15     10254842    HY427382 2015-09-17 14:37:03        078XX S YATES BLVD
         16     10520258    HZ262288 2015-06-01 00:00:00      078XX S EAST END AVE
         17     10038666    HY228605 2015-04-19 23:30:00     068XX S RIDGELAND AVE
         18     10219744    HY406729 2015-09-01 23:03:00  067XX S STONY ISLAND AVE
         19     10247450    HY279825 2015-05-29 13:37:00      077XX S PHILLIPS AVE
         20     10516924    HZ258812 2015-09-01 12:00:00        071XX S EUCLID AVE
         21     10265079    HY444719 2015-09-30 18:30:00           018XX E 72ND ST
         22      9911254    HY100210 2015-01-01 02:15:00       077XX S BURNHAM AVE
         23      9911308    HY100265 2015-01-01 04:10:00     030XX E CHELTENHAM PL
         24      9911493    HY100547 2015-01-01 11:45:00  071XX S STONY ISLAND AVE
         25      9911509    HY100544 2015-01-01 12:20:00           024XX E 71ST ST
         26      9911518    HY100584 2015-01-01 03:30:00         074XX S COLES AVE
         27      9911583    HY100609 2015-01-01 12:42:00       070XX S BENNETT AVE
         28      9911654    HY100713 2015-01-01 15:20:00      071XX S EAST END AVE
         29      9911739    HY100861 2015-01-01 17:00:00           016XX E 68TH ST
         ...         ...         ...                 ...                       ...
         262714 10324948    HY515179 2015-11-25 02:50:00        069XX N ORIOLE AVE
         262715 10327282    HY518096 2015-11-28 23:00:00       067XX N OLMSTED AVE
         262716 10327316    HY518178 2015-11-29 02:10:00     066XX N NORTHWEST HWY
         262717 10327405    HY518274 2015-11-29 05:30:00         072XX W DEVON AVE
         262718 10331508    HY521659 2015-12-02 03:34:00         071XX N ODELL AVE
```

262719	10332906	HY523541	2015-11-21 20:00:00	075XX N OTTAWA AVE
262720	10334169	HY524778	2015-12-03 10:30:00	075XX N HARLEM AVE
262721	10335434	HY526443	2015-12-05 23:00:00	067XX N OLMSTED AVE
262722	10337605	HY528495	2015-12-07 17:00:00	072XX N OCTAVIA AVE
262723	10338877	HY529871	2015-12-08 13:30:00	068XX N NORTHWEST HWY
262724	10340811	HY531631	2015-12-08 10:00:00	067XX N OLMSTED AVE
262725	10343271	HY533930	2015-12-12 01:45:00	067XX N OLMSTED AVE
262726	10345491	HY536621	2015-12-08 08:00:00	074XX N OVERHILL AVE
262727	10348315	HY532230	2015-12-10 17:35:00	072XX W DEVON AVE
262728	10349138	HY539872	2015-12-16 09:00:00	072XX N OCTAVIA AVE
262729	10352176	HY543062	2015-12-19 13:40:00	072XX N OCONTO AVE
262730	10352663	HY543735	2015-12-20 02:40:00	067XX N OSHKOSH AVE
262731	10353845	HY545116	2015-12-14 09:00:00	073XX W HOWARD ST
262732	10358488	HY549540	2015-12-25 02:22:00	066XX N NORTHWEST HWY
262733	10358800	HY550006	2015-12-19 12:30:00	066XX N HARLEM AVE
262734	10391773	HZ128372	2015-12-30 16:00:00	073XX W TOUHY AVE
262735	10327734	HY518557	2015-11-28 23:30:00	066XX N OKETO AVE
262736	10137544	HY319440	2015-06-19 06:50:00	065XX N OLYMPIA AVE
262737	10178386	HY365719	2015-08-02 03:30:00	077XX W COLUMBIA AVE
262738	10215944	HY402236	2015-06-29 16:00:00	065XX N NORTHWEST HWY
262739	10285900	HY473530	2015-04-08 00:01:00	073XX N HARLEM AVE
262740	10314149	HY503431	2015-09-29 13:00:00	070XX N ORIOLE AVE
262741	10369125	HZ104086	2015-11-20 23:30:00	066XX N OLYMPIA AVE
262742	10108428	HY296946	2015-06-04 11:00:00	074XX N OLEANDER AVE
262743	10683241	HZ436234	2015-02-17 09:00:00	075XX W TOUHY AVE

	IUCR	Primary Type	Descript
0	0281	CRIM SEXUAL ASSAULT	NON-AGGRAVA
1	2017	NARCOTICS	MANU/DELIVER:CR
2	2017	NARCOTICS	MANU/DELIVER:CR
3	2027	NARCOTICS	POSS: CR
4	2024	NARCOTICS	POSS: HEROIN(WHI
5	1153	DECEPTIVE PRACTICE	FINANCIAL IDENTITY THEFT OVER $
6	1821	NARCOTICS	MANU/DEL:CANNABIS 10GM OR L
7	2017	NARCOTICS	MANU/DELIVER:CR
8	2017	NARCOTICS	MANU/DELIVER:CR
9	1812	NARCOTICS	POSS: CANNABIS MORE THAN 30
10	0281	CRIM SEXUAL ASSAULT	NON-AGGRAVA
11	1750	OFFENSE INVOLVING CHILDREN	CHILD AB
12	1812	NARCOTICS	POSS: CANNABIS MORE THAN 30
13	2024	NARCOTICS	POSS: HEROIN(WHI
14	2027	NARCOTICS	POSS: CR
15	2027	NARCOTICS	POSS: CR
16	0266	CRIM SEXUAL ASSAULT	PREDAT
17	0454	BATTERY	AGG PO HANDS NO/MIN INJ
18	0454	BATTERY	AGG PO HANDS NO/MIN INJ
19	2024	NARCOTICS	POSS: HEROIN(WHI
20	1130	DECEPTIVE PRACTICE	FRAUD OR CONFIDENCE G

```
21      2027                 NARCOTICS                       POSS: CR
22      031A                   ROBBERY                    ARMED: HAND
23      0420                   BATTERY      AGGRAVATED:KNIFE/CUTTING IN
24      0820                     THEFT                    $500 AND UN
25      2093                 NARCOTICS          FOUND SUSPECT NARCOT
26      0460                   BATTERY                            SIM
27      0820                     THEFT                    $500 AND UN
28      2820             OTHER OFFENSE                  TELEPHONE THR
29      0486                   BATTERY          DOMESTIC BATTERY SIM
...      ...                       ...
262714  1310           CRIMINAL DAMAGE                       TO PROPE
262715  0560                   ASSAULT                            SIM
262716  0460                   BATTERY                            SIM
262717  1310           CRIMINAL DAMAGE                       TO PROPE
262718  1320           CRIMINAL DAMAGE                        TO VEHI
262719  0810                     THEFT                         OVER $
262720  0560                   ASSAULT                            SIM
262721  0460                   BATTERY                            SIM
262722  0560                   ASSAULT                            SIM
262723  2825             OTHER OFFENSE          HARASSMENT BY TELEPH
262724  5000             OTHER OFFENSE       OTHER CRIME AGAINST PER
262725  0460                   BATTERY                            SIM
262726  1153        DECEPTIVE PRACTICE  FINANCIAL IDENTITY THEFT OVER $
262727  0470    PUBLIC PEACE VIOLATION                  RECKLESS COND
262728  0910       MOTOR VEHICLE THEFT                        AUTOMOB
262729  0486                   BATTERY          DOMESTIC BATTERY SIM
262730  1310           CRIMINAL DAMAGE                       TO PROPE
262731  2825             OTHER OFFENSE          HARASSMENT BY TELEPH
262732  0460                   BATTERY                            SIM
262733  1220        DECEPTIVE PRACTICE       THEFT OF LOST/MISLAID P
262734  1153        DECEPTIVE PRACTICE  FINANCIAL IDENTITY THEFT OVER $
262735  0610                  BURGLARY                    FORCIBLE EN
262736  1780  OFFENSE INVOLVING CHILDREN                  OTHER OFFE
262737  0486                   BATTERY          DOMESTIC BATTERY SIM
262738  1205        DECEPTIVE PRACTICE          THEFT BY LESSEE,NON-
262739  0820                     THEFT                    $500 AND UN
262740  1153        DECEPTIVE PRACTICE  FINANCIAL IDENTITY THEFT OVER $
262741  0930       MOTOR VEHICLE THEFT       THEFT/RECOVERY: AUTOMOB
262742  1130        DECEPTIVE PRACTICE         FRAUD OR CONFIDENCE G
262743  1195        DECEPTIVE PRACTICE      FINAN EXPLOIT-ELDERLY/DISAB

                  Location Description Arrest Domestic ...   FBI Code
0         NURSING HOME/RETIREMENT HOME  False    False ...         02
1               VEHICLE NON-COMMERCIAL   True    False ...         18
2               VEHICLE NON-COMMERCIAL   True    False ...         18
3                            RESIDENCE   True    False ...         18
4                            RESIDENCE   True    False ...         18
5                            RESIDENCE  False    False ...         11
```

```
6          PARKING LOT/GARAGE(NON.RESID.)   True    False ...          18
7                  VEHICLE NON-COMMERCIAL   True    False ...          18
8                  VEHICLE NON-COMMERCIAL   True    False ...          18
9                               RESIDENCE   True    False ...          18
10                              APARTMENT   True     True ...          02
11                              RESIDENCE   True    False ...          20
12                              APARTMENT   True    False ...          18
13                 VEHICLE NON-COMMERCIAL   True    False ...          18
14                              RESIDENCE   True    False ...          18
15                              RESIDENCE   True    False ...          18
16                              APARTMENT  False    False ...          02
17                                 STREET   True    False ...         08B
18                           CTA BUS STOP   True    False ...         08B
19                              APARTMENT   True    False ...          18
20                              RESIDENCE  False    False ...          11
21                              RESIDENCE   True    False ...          18
22                                 STREET  False    False ...          03
23                                 STREET  False    False ...         04B
24                              RESIDENCE  False    False ...          06
25           NURSING HOME/RETIREMENT HOME   True    False ...          26
26                              RESIDENCE  False    False ...         08B
27                 DRIVEWAY - RESIDENTIAL   True    False ...          06
28                              APARTMENT  False     True ...          26
29                              RESIDENCE  False    False ...         08B
...                                   ...    ...      ... ...         ...
262714          RESIDENCE PORCH/HALLWAY  False    False ...          14
262715                           STREET   True    False ...         08A
262716                         SIDEWALK  False    False ...         08B
262717                       RESTAURANT   True    False ...          14
262718                           STREET  False    False ...          14
262719                           STREET  False    False ...          06
262720         SCHOOL, PUBLIC, BUILDING  False    False ...         08A
262721                    BAR OR TAVERN  False    False ...         08B
262722                        RESIDENCE  False     True ...         08A
262723                        RESIDENCE  False    False ...          26
262724                            OTHER  False    False ...          26
262725   PARKING LOT/GARAGE(NON.RESID.)  False    False ...         08B
262726                        RESIDENCE  False    False ...          11
262727                         AIRCRAFT  False    False ...          24
262728                           STREET  False    False ...          07
262729                        RESIDENCE  False     True ...         08B
262730                            OTHER  False    False ...          14
262731                        RESIDENCE  False    False ...          26
262732                         SIDEWALK  False    False ...         08B
262733     VEHICLE - OTHER RIDE SERVICE  False    False ...          11
262734                        RESIDENCE  False    False ...          11
262735  CHURCH/SYNAGOGUE/PLACE OF WORSHIP   True    False ...          05
262736                        RESIDENCE  False     True ...          26
```

```
262737                        RESIDENCE  False     True ...       08B
262738                            OTHER  False    False ...        11
262739                        RESIDENCE  False    False ...        06
262740                        RESIDENCE  False    False ...        11
262741          DRIVEWAY - RESIDENTIAL  False    False ...        07
262742                        RESIDENCE  False    False ...        11
262743                        RESIDENCE  False    False ...        11

        X Coordinate  Y Coordinate  Year             Updated On   Latitud
0                NaN           NaN  2015  05/10/2016 03:56:50 PM        Na
1          1188123.0     1855151.0  2015  05/12/2016 03:48:29 PM  41.75761
2          1187947.0     1854903.0  2015  05/12/2016 03:48:29 PM  41.75693
3          1187741.0     1854562.0  2015  05/12/2016 03:48:29 PM  41.75600
4          1193762.0     1857383.0  2015  05/12/2016 03:48:29 PM  41.76360
5                NaN           NaN  2015  05/24/2016 04:07:34 PM        Na
6          1188026.0     1860714.0  2015  04/15/2016 03:49:27 PM  41.77288
7          1195252.0     1854729.0  2015  04/15/2016 03:49:27 PM  41.75628
8          1195900.0     1855200.0  2015  04/15/2016 03:49:27 PM  41.75756
9          1191864.0     1854642.0  2015  04/15/2016 03:49:27 PM  41.75612
10         1192077.0     1859385.0  2015  05/17/2016 03:46:43 PM  41.76913
11         1191726.0     1859962.0  2015  05/18/2016 03:48:26 PM  41.77073
12         1190743.0     1859341.0  2015  05/19/2016 03:48:45 PM  41.76904
13         1192537.0     1858884.0  2015  05/19/2016 03:48:45 PM  41.76775
14         1190742.0     1859375.0  2015  05/19/2016 03:48:45 PM  41.76914
15         1193558.0     1853476.0  2015  05/19/2016 03:48:45 PM  41.75288
16         1188897.0     1853358.0  2015  05/19/2016 03:48:45 PM  41.75267
17         1189046.0     1859972.0  2015  05/23/2016 03:48:54 PM  41.77082
18         1188025.0     1860797.0  2015  05/23/2016 03:48:54 PM  41.77311
19         1193875.0     1854031.0  2015  05/23/2016 03:48:54 PM  41.75440
20               NaN           NaN  2015  05/30/2016 03:48:05 PM        Na
21               NaN           NaN  2015  06/04/2016 03:47:07 PM        Na
22         1196068.0     1854082.0  2015  08/17/2015 03:03:40 PM  41.75448
23         1197539.0     1853286.0  2015  08/17/2015 03:03:40 PM  41.75226
24         1188042.0     1858120.0  2015  08/17/2015 03:03:40 PM  41.76576
25               NaN           NaN  2015  08/17/2015 03:03:40 PM        Na
26         1195223.0     1856584.0  2015  08/17/2015 03:03:40 PM  41.76137
27         1190092.0     1858687.0  2015  08/17/2015 03:03:40 PM  41.76727
28         1188770.0     1857964.0  2015  08/17/2015 03:03:40 PM  41.76531
29         1188590.0     1860222.0  2015  08/17/2015 03:03:40 PM  41.77151
...              ...           ...   ...                    ...        ..
262714     1124733.0     1945581.0  2015  12/02/2015 03:54:47 PM  42.00704
262715     1124429.0     1943939.0  2015  12/05/2015 03:54:02 PM  42.00254
262716     1124963.0     1943907.0  2015  12/06/2015 03:54:27 PM  42.00244
262717     1126959.0     1942100.0  2015  12/06/2015 03:54:27 PM  41.99745
262718     1126219.0     1947063.0  2015  12/09/2015 04:04:49 PM  42.01108
262719     1124407.0     1949432.0  2015  12/07/2015 03:57:35 PM  42.01761
262720     1127392.0     1949341.0  2015  12/10/2015 03:54:20 PM  42.01731
262721     1124429.0     1943939.0  2015  12/12/2015 03:57:45 PM  42.00254
```

```
262722     1126725.0     1947492.0  2015  12/14/2015 04:15:12 PM  42.01225
262723     1123909.0     1944791.0  2015  12/15/2015 04:02:04 PM  42.00489
262724     1124409.0     1943953.0  2015  12/15/2015 04:02:04 PM  42.00258
262725     1124477.0     1943903.0  2015  12/19/2015 03:58:51 PM  42.00244
262726     1124075.0     1948731.0  2015  12/17/2015 03:51:50 PM  42.01569
262727     1127157.0     1942188.0  2015  12/21/2015 03:53:52 PM  41.99769
262728     1126725.0     1947471.0  2015  12/23/2015 03:53:55 PM  42.01219
262729     1127056.0     1947600.0  2015  12/26/2015 03:53:48 PM  42.01254
262730     1124414.0     1944151.0  2015  12/27/2015 03:54:13 PM  42.00312
262731     1126505.0     1949909.0  2015  12/24/2015 03:53:52 PM  42.01889
262732     1124943.0     1943924.0  2015  01/01/2016 03:54:40 PM  42.00249
262733     1127379.0     1943641.0  2015  12/28/2015 03:52:21 PM  42.00167
262734     1126312.0     1947255.0  2015  01/28/2016 03:54:45 PM  42.01161
262735     1126055.0     1943775.0  2015  02/10/2016 03:51:16 PM  42.00206
262736     1124646.0     1942688.0  2015  04/15/2016 03:49:27 PM  41.99910
262737     1123738.0     1944019.0  2015  04/15/2016 03:49:27 PM  42.00277
262738     1126382.0     1942727.0  2015  04/15/2016 03:49:27 PM  41.99918
262739     1127389.0     1948185.0  2015  04/15/2016 03:49:27 PM  42.01414
262740     1124734.0     1946137.0  2015  04/15/2016 03:49:27 PM  42.00857
262741     1125480.0     1943785.0  2015  04/15/2016 03:49:27 PM  42.00210
262742           NaN           NaN  2015  09/14/2016 03:49:23 PM        Na
262743           NaN           NaN  2015  09/16/2016 03:51:28 PM        Na

        Longitude                       Location Community Name  Day
0             NaN                            NaN    South Shore    1
1      -87.586115  (41.757614433, -87.586115266)    South Shore    4
2      -87.586768  (41.756938091, -87.586768161)    South Shore    5
3      -87.587534  (41.756007259, -87.587533939)    South Shore   13
4      -87.565376  (41.763602949, -87.565376421)    South Shore   23
5             NaN                            NaN    South Shore    1
6      -87.586294  (41.772882101, -87.586293688)    South Shore    2
7      -87.560003  (41.756283546, -87.560002816)    South Shore   15
8      -87.557613  (41.757559995, -87.557612516)    South Shore   13
9      -87.572422  (41.756127711, -87.572421724)    South Shore   27
10     -87.571487  (41.769137706, -87.571487193)    South Shore    1
11     -87.572755  (41.770729563, -87.572755066)    South Shore    1
12     -87.576378  (41.769049288, -87.576378338)    South Shore   26
13     -87.569817  (41.767751731, -87.569817384)    South Shore   18
14     -87.576381  (41.769142611, -87.576380906)    South Shore   17
15     -87.566252  (41.752886832, -87.566251796)    South Shore   17
16     -87.583336  (41.752675796, -87.583335985)    South Shore    1
17     -87.582578  (41.770821619, -87.582578436)    South Shore   19
18     -87.586295  (41.773109884, -87.586294711)    South Shore    1
19     -87.565072  (41.754402034, -87.565071979)    South Shore   29
20            NaN                            NaN    South Shore    1
21            NaN                            NaN    South Shore   30
22     -87.557034  (41.754487963, -87.557033804)    South Shore    1
23     -87.551670  (41.752267133, -87.551669667)    South Shore    1
```

```
24     -87.586318  (41.765763563, -87.586317625)    South Shore    1
25            NaN                            NaN    South Shore    1
26     -87.560048  (41.761374517, -87.560047985)    South Shore    1
27     -87.578786  (41.767270356, -87.578785582)    South Shore    1
28     -87.583654  (41.765318105, -87.583654287)    South Shore    1
29     -87.584242  (41.771518551, -87.584241952)    South Shore    1
...           ...                            ...            ...  ...
262714 -87.816440  (42.007044219, -87.816439639)    Edison Park   25
262715 -87.817595  (42.002543447, -87.817594525)    Edison Park   28
262716 -87.815631  (42.002446793, -87.815630651)    Edison Park   29
262717 -87.808328  (41.997454864, -87.808328147)    Edison Park   29
262718 -87.810939  (42.011086211, -87.810938991)    Edison Park    2
262719 -87.817554  (42.017617109, -87.817553708)    Edison Park   21
262720 -87.806571  (42.017317514, -87.806571373)    Edison Park    3
262721 -87.817595  (42.002543447, -87.817594525)    Edison Park    5
262722 -87.809068  (42.012254936, -87.809067503)    Edison Park    7
262723 -87.819489  (42.004889996, -87.819488794)    Edison Park    8
262724 -87.817668  (42.002582195, -87.817667795)    Edison Park    8
262725 -87.817419  (42.002443866, -87.817418731)    Edison Park   12
262726 -87.818791  (42.015698985, -87.818790931)    Edison Park    8
262727 -87.807598  (41.997693011, -87.807597777)    Edison Park   10
262728 -87.809068   (42.01219731, -87.809067976)    Edison Park   16
262729 -87.807847  (42.012545728, -87.807847131)    Edison Park   19
262730 -87.817645  (42.003125443, -87.817645013)    Edison Park   20
262731 -87.809823  (42.018891086, -87.809822614)    Edison Park   14
262732 -87.815704  (42.002493774, -87.815703853)    Edison Park   25
262733 -87.806748   (42.001676434, -87.80674823)    Edison Park   19
262734 -87.810592  (42.011611518, -87.810592484)    Edison Park   30
262735 -87.811616  (42.002066384, -87.811616151)    Edison Park   28
262736 -87.816824  (41.999106993, -87.816823946)    Edison Park   19
262737 -87.820135  (42.002774368, -87.820134951)    Edison Park    2
262738 -87.810437    (41.9991851, -87.810436674)    Edison Park   29
262739 -87.806609  (42.014145403, -87.806608589)    Edison Park    8
262740 -87.816424  (42.008569918, -87.816423608)    Edison Park   29
262741 -87.813731  (42.002103419, -87.813731336)    Edison Park   20
262742        NaN                            NaN    Edison Park    4
262743        NaN                            NaN    Edison Park   17

[262744 rows x 24 columns]
```

In [33]:
```
crimes_by_community_day = completecrimes.groupby(['Community Name', 'Day']
crimes_by_community_day
```

Out[33]:
```
<pandas.core.groupby.DataFrameGroupBy object at 0x00000266ABA78208>
```

In [35]:
```
crimes_by_community_day_count = crimes_by_community_day['ID'].agg('count')
crimes_by_community_day_count
```

Out[35]:
```
Community Name  Day
Albany Park     1       77
```

	2	72
	3	90
	4	70
	5	79
	6	85
	7	70
	8	80
	9	77
	10	86
	11	78
	12	88
	13	77
	14	88
	15	89
	16	105
	17	86
	18	82
	19	73
	20	96
	21	84
	22	93
	23	116
	24	78
	25	73
	26	77
	27	80
	28	71
	29	74
	30	83
		...
Woodlawn	2	129
	3	116
	4	108
	5	120
	6	109
	7	144
	8	113
	9	130
	10	133
	11	120
	12	108
	13	122
	14	126
	15	131
	16	122
	17	153
	18	117
	19	126

```
                20      123
                21      127
                22      120
                23      100
                24      132
                25      129
                26      122
                27      123
                28      113
                29      102
                30      104
                31       65
Name: ID, dtype: int64
```

In [40]:
```
community_crimes_timeseries = crimes_by_community_day_count.unstack('Commu
community_crimes_timeseries
```

Out[40]:
```
Community Name  Albany Park  Archer Heights  Armour Square  Ashburn  \
Day
1                        77              35             36       97
2                        72              45             35       79
3                        90              38             34       72
4                        70              30             31       78
5                        79              24             23       75
6                        85              37             38       74
7                        70              31             30       60
8                        80              47             29       76
9                        77              30             44       73
10                       86              32             36       75
11                       78              27             40       74
12                       88              26             38       72
13                       77              38             31       88
14                       88              41             26       79
15                       89              42             32       81
16                      105              40             41       97
17                       86              33             44       73
18                       82              23             35       76
19                       73              34             27       66
20                       96              37             45       77
21                       84              34             45       58
22                       93              28             38       76
23                      116              35             33       86
24                       78              36             38       75
25                       73              31             28       61
26                       77              27             39       78
27                       80              28             32       75
28                       71              23             25       76
29                       74              21             40       66
```

30	83	27	34	68
31	42	13	27	42

Community Name	Auburn Gresham	Austin	Avalon Park	Avondale	Belmont Cra
Day					
1	322	702	59	92	
2	230	604	42	68	
3	234	579	47	73	
4	255	530	52	78	
5	270	564	40	77	
6	246	562	50	86	
7	267	552	34	72	
8	214	572	34	76	
9	251	528	44	77	
10	238	557	42	80	
11	260	607	47	71	
12	243	592	41	76	
13	225	567	57	66	
14	268	582	56	69	
15	293	602	51	80	
16	260	571	43	55	
17	244	546	55	94	
18	253	536	43	73	
19	281	565	40	75	
20	266	605	62	84	
21	257	566	50	64	
22	248	556	44	71	
23	265	579	44	78	
24	269	561	36	66	
25	273	563	43	61	
26	271	545	47	80	
27	279	574	30	65	
28	249	556	42	72	
29	209	485	38	69	
30	246	480	41	68	
31	135	296	26	38	

Community Name	Beverly	...	Washington Heights	Washington Park	\
Day		...			
1	38	...	151	76	
2	36	...	109	92	
3	33	...	99	96	
4	30	...	102	88	
5	31	...	99	100	
6	37	...	105	79	
7	35	...	113	79	
8	27	...	97	79	
9	27	...	104	80	

10	34	...	91	100
11	31	...	114	81
12	37	...	98	101
13	32	...	99	84
14	30	...	95	94
15	37	...	101	101
16	26	...	112	86
17	35	...	103	112
18	32	...	100	106
19	40	...	116	96
20	23	...	112	100
21	31	...	103	100
22	23	...	95	96
23	30	...	98	87
24	31	...	86	82
25	33	...	94	85
26	38	...	98	103
27	36	...	124	106
28	31	...	97	74
29	23	...	87	62
30	37	...	95	80
31	21	...	50	47

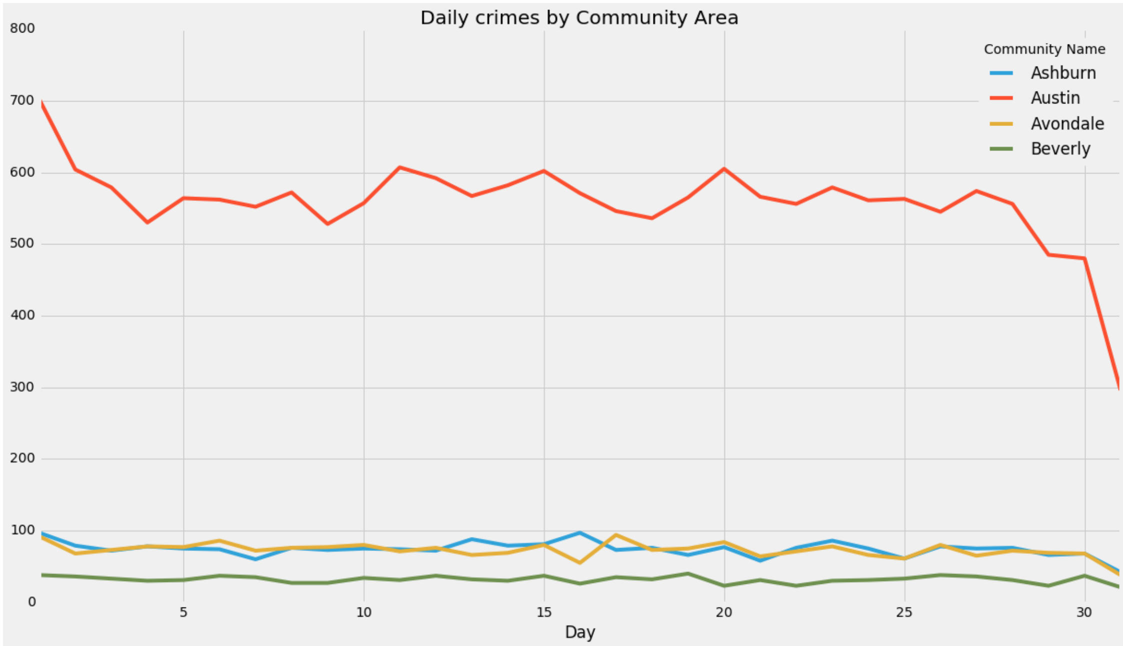
Community Name	West Elsdon	West Englewood	West Garfield Park	West Lawn
Day				
1	34	292	207	89
2	38	232	205	77
3	34	288	182	62
4	36	262	187	75
5	27	261	185	72
6	35	266	205	77
7	28	199	187	80
8	37	226	179	57
9	30	234	201	45
10	41	257	193	65
11	36	260	201	59
12	42	222	189	63
13	35	238	189	75
14	31	265	214	76
15	38	241	193	53
16	25	236	203	82
17	33	253	216	76
18	32	250	195	50
19	24	241	251	54
20	36	248	235	61
21	32	261	216	69
22	40	277	182	62
23	38	238	209	75

```
24                      34            243                  185          74
25                      29            234                  188          69
26                      26            258                  179          65
27                      37            215                  180          70
28                      47            244                  186          59
29                      35            219                  150          59
30                      24            216                  208          62
31                      20            129                  111          34

Community Name  West Pullman  West Ridge  West Town  Woodlawn
Day
1                        143         142        268       143
2                        128         108        223       129
3                        118         101        232       116
4                        125         120        215       108
5                        108          99        269       120
6                        111         117        257       109
7                        121         103        233       144
8                        108         116        221       113
9                        123          84        205       130
10                       135         103        209       133
11                       152          77        213       120
12                       143          78        229       108
13                       140         103        218       122
14                       140         103        247       126
15                       134         101        223       131
16                       141          92        236       122
17                       147          97        251       153
18                       106          84        232       117
19                       138         108        208       126
20                       142         106        225       123
21                       118          91        231       127
22                       117         103        279       120
23                       148         103        217       100
24                       137          92        244       132
25                       138         100        203       129
26                       137         105        248       122
27                       133         100        220       123
28                       130         106        242       113
29                       120         105        216       102
30                       126          90        221       104
31                        85          54        118        65

[31 rows x 77 columns]
```

```
In [41]: community_arrest_timeseries[["Ashburn","Austin","Avondale","Beverly"]].plo
```



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 [61]: socioeconomica = pd.read_csv('info_socioeconomica.csv', low_memory=False)

In [62]: socioeconomica

Out[62]:     Community Area           Community Name  PERCENT OF HOUSING CROWDED  \
         0              1.0             Rogers Park                         7.7
         1              2.0             West Ridge                          7.8
         2              3.0                Uptown                           3.8
         3              4.0           Lincoln Square                        3.4
         4              5.0            North Center                         0.3
         5              6.0              Lake View                          1.1
         6              7.0             Lincoln Park                        0.8
         7              8.0          Near North Side                        1.9
```

8	9.0	Edison Park	1.1
9	10.0	Norwood Park	2.0
10	11.0	Jefferson Park	2.7
11	12.0	Forest Glen	1.1
12	13.0	North Park	3.9
13	14.0	Albany Park	11.3
14	15.0	Portage Park	4.1
15	16.0	Irving Park	6.3
16	17.0	Dunning	5.2
17	18.0	Montclaire	8.1
18	19.0	Belmont Cragin	10.8
19	20.0	Hermosa	6.9
20	21.0	Avondale	6.0
21	22.0	Logan Square	3.2
22	23.0	Humboldt park	14.8
23	24.0	West Town	2.3
24	25.0	Austin	6.3
25	26.0	West Garfield Park	9.4
26	27.0	East Garfield Park	8.2
27	28.0	Near West Side	3.8
28	29.0	North Lawndale	7.4
29	30.0	South Lawndale	15.2
..	...	...	...
48	49.0	Roseland	2.5
49	50.0	Pullman	1.5
50	51.0	South Deering	4.0
51	52.0	East Side	6.8
52	53.0	West Pullman	3.3
53	54.0	Riverdale	5.8
54	55.0	Hegewisch	3.3
55	56.0	Garfield Ridge	2.6
56	57.0	Archer Heights	8.5
57	58.0	Brighton Park	14.4
58	59.0	McKinley Park	7.2
59	60.0	Bridgeport	4.5
60	61.0	New City	11.9
61	62.0	West Elsdon	11.1
62	63.0	Gage Park	15.8
63	64.0	Clearing	2.7
64	65.0	West Lawn	5.8
65	66.0	Chicago Lawn	7.6
66	67.0	West Englewood	4.8
67	68.0	Englewood	3.8
68	69.0	Greater Grand Crossing	3.6
69	70.0	Ashburn	4.0
70	71.0	Auburn Gresham	4.0
71	72.0	Beverly	0.9
72	73.0	Washington Height	1.1

```
73             74.0        Mount Greenwood                             1.0
74             75.0            Morgan Park                             0.8
75             76.0                 O'Hare                             3.6
76             77.0              Edgewater                             4.1
77              NaN                CHICAGO                             4.7

    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 [67]: completesocio= pd.merge(socioeconomica, tabla, on= "Community Name")

In [68]: completesocio

Out[68]: Empty DataFrame
         Columns: [Community Area , Community Name, PERCENT OF HOUSING CROWDED, PEF
         Index: []
```