

Podstawy programowania

Biblioteki analizy danych: Shapely,
Psycopg2, Pandas

Inne Biblioteki GeoPythona

- Shapely
- Psypog2
- Pandas i Geopandas

Biblioteka shapely

Biblioteka służąca do przetwarzania i analizowania obiektów geometrycznych w formacie well-known text

```
from shapely.geometry import Polygon
from shapely.geometry import Point
from shapely.geometry import LineString

polygon = Polygon([(0, 0), (0, 1), (1, 1),(1, 0)])
polygon.area #obliczenie powierzchni
polygon.length #długość obwiedni
polygon.bounds #granice obwiedni
polygon.geom_type
Point(0,0).distance(Point(1,1)) #odległość
line = LineString([(0, 0), (1, 1)])
line.length
```

Shapely: analiza geometrii

```
import ogr, shapely.wkt

ds=ogr.Open(r'C:/GIS',1)
lyr=ds.GetLayer('gminy_wielkopolska')
lyr.SetAttributeFilter("jpt_nazwa_ = 'Poznań'")
feat = lyr.GetNextFeature()

geom = feat.GetGeometryRef()
wkt = geom.ExportToWkt()
#załadowanie do obiektu shapely
outline = shapely.wkt.loads(wkt)
#odczyt właściwości
print (outline.area, outline.length)
print(outline.bounds, outline.geom_type)
print (outline.centroid.x, outline.centroid.y)
```

Shapely – funkcja interpolate

```
>>> from shapely.geometry import Point, LineString
>>> line = LineString([(0, 0), (1, 1)])
>>> print( line)
LINESTRING (0 0, 1 1)
>>> point=Point(0,1)
>>> print(point)
POINT (0 1)
>>> pt_interpolate=line.interpolate(line.project(point))
>>> print (pt_interpolate)
POINT (0.5 0.5)
>>> point.distance(pt_interpolate)
0.7071067811865476
>>> pt_025=line.interpolate(0.25)
>>> print( pt_025)
POINT (0.1767766952966369 0.1767766952966369)
```

Biblioteka Psycopg2: import shapefile do bazy danych

```
import ogr, psycopg2
#psycopg2 –biblioteka przeznaczona do komunikacji z bazą danych PostgreSQL
#nawiązanie połączenia z bazą danych
connection = psycopg2.connect(database="wielkopolska", user="postgres", password="haslo")
#utworzenie obiektu cursor służącego do wykonywania zapytań sql
cursor = connection.cursor()
#wysłanie zapytania kasowania tabeli
cursor.execute("DROP TABLE IF EXISTS gis.lasy")
#wysłanie zapytania utworzenie nowej tabeli
cursor.execute("CREATE TABLE gis.lasy (" +
    "gid SERIAL PRIMARY KEY," +
    "typ VARCHAR," +
    "nazwa VARCHAR," +
    "geom geometry(multipolygon,2180)")")
#wysłanie zapytania nałożenie indeksu przestrzennego
cursor.execute("CREATE INDEX lasy_index ON gis.lasy USING GIST(geom)")
```

Biblioteka Psycopg2: import shapefile do bazy danych c.d.

#odczyt warstwy shapefile

```
ds = ogr.Open(r'C:/GIS/osm_landuse',1)
```

```
layer = ds.GetLayer('landuse')
```

```
layer.SetAttributeFilter("fclass='forest'")
```

for feat in layer:

```
    fclass = feat.GetField("fclass")
```

```
    name = feat.GetField("name")
```

```
    geometry = feat.GetGeometryRef()
```

```
    wkt = geometry.ExportToWkt
```

geometrii do postaci wkt

#wysłanie zapytania wstawianie danych do ()#przepisanie tabeli

```
    cursor.execute("INSERT INTO gis.lasy (typ, nazwa, geom) VALUES (%s, %s,  
    ST_Multi(ST_GeomFromText(%s,2180)))", (fclass, name, wkt))
```

#zatwierdzenie zmian w bazie danych

```
connection.commit()
```

Biblioteka Psycopg2: odczyt z bazy danych PostGIS

```
import ogr, psycopg2
```

```
#nawiązanie połączenia
```

```
connection = psycopg2.connect(database="wielkopolska", user="postgres",  
    password="haslo")
```

```
cursor = connection.cursor()
```

```
#wykonanie zapytania
```

```
cursor.execute("SELECT gid, name, ST_Area(geom) as area FROM gis.landuse  
    ORDER BY name LIMIT 10")
```

```
#wyświetlenie wyników
```

```
for gid, name, area in cursor:  
    print(gid, name, area)
```


Biblioteka Pandas

Biblioteka wprowadza nowe typy danych:

- Serie
- DataFrame

Serie

Seria to jednowymiarowa tablica zawierająca sekwencję wartości indeksowanych liczbami lub dowolnymi wartościami

```
>>> import pandas as pd
```

```
>>> obj = pd.Series([4, 7, -5, 3])
```

```
>>> obj2 = pd.Series([4, 7, -5, 3], index=['d', 'b', 'a', 'c'])
```

Serie

```
>>> S = pd.Series([11, 28, 72, 3, 5, 8])
```

```
>>> S
```

```
0  11
```

```
1  28
```

```
2  72
```

```
3   3
```

```
4   5
```

```
5   8
```

```
dtype: int64
```

```
>>> print(S.index)
```

```
RangeIndex(start=0, stop=6, step=1)
```

```
>>> print(S.values)
```

```
[11 28 72  3  5  8]
```

#Serie są podobne do tablic numpy

```
>>> import numpy as np
```

```
>>> X = np.array([11, 28, 72, 3, 5, 8])
```

```
>>> print(X)
```

```
[11 28 72  3  5  8]
```

Serie

```
>>> fruits = ['apples', 'oranges', 'cherries', 'pears']
```

```
>>> quantities = [20, 33, 52, 10]
```

```
>>> S = pd.Series(quantities, index=fruits)
```

```
>>> S
```

```
apples    20
```

```
oranges   33
```

```
cherries  52
```

```
pears     10
```

```
dtype: int64
```

W efekcie powstała seria indeksowana nazwami w przeciwieństwie do numpy

Takie same serie można do siebie dodawać:

```
>>> S2 = pd.Series([17, 13, 31, 32], index=fruits)
```

```
>>> print(S + S2)
```

```
apples    37
```

```
oranges   46
```

```
cherries  83
```

```
pears     42
```

```
dtype: int64
```

```
>>>
```

Serie

- Dodawanie serii z różnymi indeksami

```
>>> fruits = ['peaches', 'oranges', 'cherries', 'pears']
>>> fruits2 = ['raspberries', 'oranges', 'cherries', 'pears']
>>> S = pd.Series([20, 33, 52, 10], index=fruits)
>>> S2 = pd.Series([17, 13, 31, 32], index=fruits2)
>>> print(S + S2)
cherries      83.0
oranges       46.0
peaches       NaN
pears         42.0
raspberries   NaN
dtype: float64
```

Obliczenia w seriach

```
>>> obj2 = pd.Series([4, 7, -5, 3], index=['d', 'b', 'a', 'c'])
```

```
>>> obj2[obj2 > 0]
```

```
d    4
```

```
b    7
```

```
c    3
```

```
dtype: int64
```

```
>>> obj2 * 2
```

```
d    8
```

```
b   14
```

```
a  -10
```

```
c    6
```

```
dtype: int64
```

```
>>> import numpy as np
```

```
>>> np.exp(obj2)
```

```
d    54.598150
```

```
b  1096.633158
```

```
a    0.006738
```

```
c   20.085537
```

```
dtype: float64
```

Zamiana słowników w serie

```
>>> cities = {"London": 8615246,  
             "Berlin": 3562166,  
             "Madrid": 3165235,  
             "Rome": 2874038,  
             "Paris": 2273305,  
             "Vienna": 1805681,  
             "Bucharest":1803425,  
             "Hamburg": 1760433,  
             "Budapest": 1754000,  
             "Warsaw": 1740119,  
             "Barcelona":1602386,  
             "Munich": 1493900,  
             "Milan": 1350680}
```

```
>>> city_series = pd.Series(cities)
```

```
>>> print(city_series)
```

```
Barcelona 1602386  
Berlin    3562166  
Bucharest 1803425  
Budapest  1754000  
Hamburg   1760433  
London    8615246  
Madrid    3165235  
Milan     1350680  
Munich    1493900  
Paris     2273305  
Rome      2874038  
Vienna    1805681  
Warsaw    1740119  
dtype: int64
```

DataFrame

- Podstawą utworzenia typu DataFrame jest możliwość pracy na danych w postaci Arkuszy jak w Excelu
- Każda kolumna może przechowywać różne wartości jednego typu, natomiast kolumny mogą być różnych typów
- Dataframe jest połączeniem serii będących kolumnami

Tworzenie DataFrame z serii

```
>>> years = range(2014, 2018)
>>> shop1 = pd.Series([2409.14, 2941.01, 3496.83, 3119.55], index=years)
>>> shop2 = pd.Series([1203.45, 3441.62, 3007.83, 3619.53], index=years)
>>> shop3 = pd.Series([3412.12, 3491.16, 3457.19, 1963.10], index=years)
>>> shops_df = pd.concat([shop1, shop2, shop3], axis=1)
>>> shops_df
```

```
      0      1      2
2014 2409.14 1203.45 3412.12
2015 2941.01 3441.62 3491.16
2016 3496.83 3007.83 3457.19
2017 3119.55 3619.53 1963.10
```

#Dodanie nazw do kolumn

```
>>> cities = ["Zürich", "Winterthur", "Freiburg"]
>>> shops_df.columns = cities
>>> shops_df
```

```
      Zürich Winterthur Freiburg
2014 2409.14  1203.45  3412.12
2015 2941.01  3441.62  3491.16
2016 3496.83  3007.83  3457.19
2017 3119.55  3619.53  1963.10
```

Tworzenie DataFrame ze słownika zawierającego tablice

```
>>>cities = {"name": ["London", "Berlin", "Madrid", "Rome", "Paris",  
    "Vienna", "Bucharest", "Hamburg", "Budapest", "Warsaw", "Barcelona",  
    "Munich", "Milan"],  
"population": [8615246, 3562166, 3165235, 2874038, 2273305, 1805681,  
    1803425, 1760433, 1754000, 1740119, 1602386, 1493900, 1350680],  
"country": ["England", "Germany", "Spain", "Italy", "France", "Austria",  
    "Romania", "Germany", "Hungary", "Poland", "Spain", "Germany", "Italy"]}  
  
>>>city_frame = pd.DataFrame(cities)
```

DataFrame ze słownika

```
>>> city_frame
```

```
   country      name  population
0  England  London   8615246
1  Germany  Berlin   3562166
2   Spain  Madrid   3165235
3   Italy   Rome    2874038
4   France  Paris   2273305
5  Austria  Vienna   1805681
6  Romania Bucharest  1803425
7  Germany  Hamburg  1760433
8  Hungary  Budapest  1754000
9   Poland  Warsaw   1740119
10  Spain  Barcelona  1602386
11  Germany  Munich   1493900
12  Italy   Milan    1350680
```

Ustawienie indeksu wierszy

```
city_frame.set_index("country", inplace=True)
```

```
          name  population
country
England  London    8615246
Germany  Berlin    3562166
Spain    Madrid    3165235
Italy    Rome      2874038
France   Paris     2273305
Austria  Vienna    1805681
Romania  Bucharest  1803425
Germany  Hamburg    1760433
Hungary  Budapest   1754000
Poland   Warsaw     1740119
Spain    Barcelona   1602386
Germany  Munich     1493900
Italy    Milan      1350680
```

Dodanie nowej kolumny z listy

```
>>> area = [1572, 891.85, 605.77, 1285,  
            105.4, 414.6, 228, 755,  
            525.2, 517, 101.9, 310.4,  
            181.8]  
>>> city_frame["area"] = area
```

	name	population	area
country			
England	London	8615246	1572.00
Germany	Berlin	3562166	891.85
Spain	Madrid	3165235	605.77
Italy	Rome	2874038	1285.00
France	Paris	2273305	105.40
Austria	Vienna	1805681	414.60
Romania	Bucharest	1803425	228.00
Germany	Hamburg	1760433	755.00
Hungary	Budapest	1754000	525.20
Poland	Warsaw	1740119	517.00
Spain	Barcelona	1602386	101.90
Germany	Munich	1493900	310.40
Italy	Milan	1350680	181.80

Dostęp do kolumn

Kolumna DataFrame jest seria

```
>>> s=city_frame["area"]
```

```
name  
London      1572.00  
Berlin       891.85  
Madrid       605.77  
Rome        1285.00  
Paris        105.40  
Vienna       414.60  
Bucharest    228.00  
Hamburg       755.00  
Budapest     525.20  
Warsaw       517.00  
Barcelona    101.90  
Munich       310.40  
Milan        181.80  
Name: area, dtype: float64
```

Przykład II : DataFrame

```
>>>cities = {"name": ["London", "Berlin", "Madrid", "Rome", "Paris", "Vienna", "Bucharest",  
    "Hamburg", "Budapest", "Warsaw", "Barcelona", "Munich", "Milan"],  
"population": [8615246, 3562166, 3165235, 2874038, 2273305, 1805681, 1803425, 1760433,  
    1754000, 1740119, 1602386, 1493900, 1350680],  
"area" : [1572, 891.85, 605.77, 1285, 105.4, 414.6, 228, 755, 525.2, 517, 101.9, 310.4, 181.8] }  
>>>city_frame = pd.DataFrame(cities,  
    columns=["population", "area"],  
    index=cities["name"])  
>>> print(city_frame)
```

	population	area
London	8615246	1572.00
Berlin	3562166	891.85
Madrid	3165235	605.77
Rome	2874038	1285.00
Paris	2273305	105.40
Vienna	1805681	414.60
Bucharest	1803425	228.00
Hamburg	1760433	755.00
Budapest	1754000	525.20
Warsaw	1740119	517.00
Barcelona	1602386	101.90
Munich	1493900	310.40
Milan	1350680	181.80

Dodanie kolumny do DataFrame

```
>>> city_frame['density']=city_frame['population']/city_frame['area']
```

```
>>> city_frame
```

```
      population    area    density
London      8615246  1572.00  5480.436387
Berlin      3562166   891.85  3994.131300
Madrid      3165235   605.77  5225.143206
Rome        2874038  1285.00  2236.605447
Paris       2273305   105.40 21568.358634
Vienna      1805681   414.60  4355.236372
Bucharest   1803425   228.00  7909.758772
Hamburg     1760433   755.00  2331.699338
Budapest    1754000   525.20  3339.680122
Warsaw      1740119   517.00  3365.800774
Barcelona   1602386   101.90 15725.083415
Munich      1493900   310.40  4812.822165
Milan       1350680   181.80  7429.482948
```


Odczyt wartości

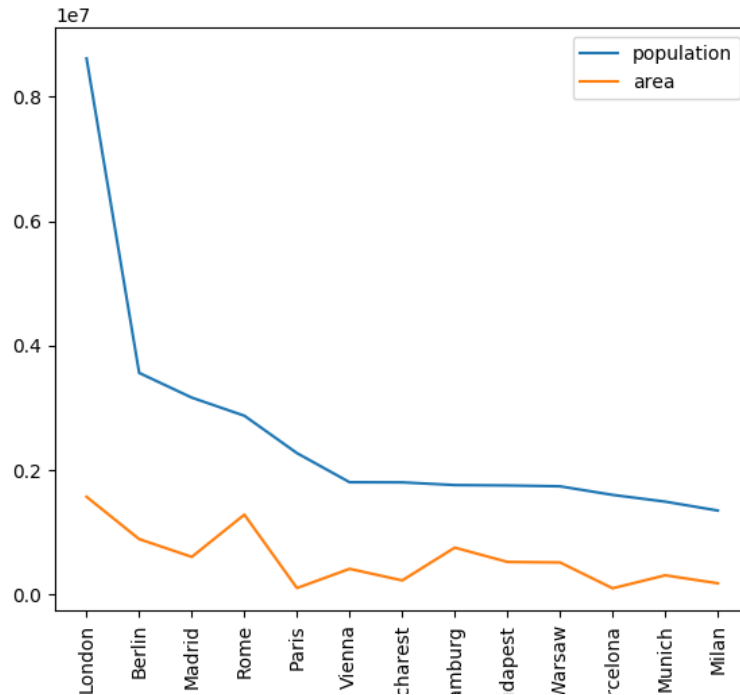
- `>>> city_frame.values`

```
array([[ 9.08821727e+00,  1.20000000e+01,  4.88713579e-02],
 [ 2.46278009e-01,  2.00000000e+00,  1.32434562e-03],
 [ 1.63085033e+02,  1.37000000e+02,  8.76980245e-01],
 [ 5.01244697e+02,  8.00000000e+01,  2.69541410e+00],
 [ 1.22170552e+00,  3.30000000e+01,  6.56965011e-03],
 [ 2.14093131e+01,  3.70000000e+01,  1.15127332e-01],
 [ 1.11063495e+01,  1.06000000e+02,  5.97237463e-02],
 [ 9.34994114e+00,  1.00000000e+00,  5.02787627e-02],
 [ 3.67497346e+01,  4.00000000e+00,  1.97619553e-01],
 [ 3.46469529e+00,  6.00000000e+00,  1.86311966e-02],
 [ 4.55218078e-01,  3.00000000e+00,  2.44790864e-03],
 [ 8.57256366e+01,  1.28000000e+02,  4.60984606e-01],
 [ 2.47586175e-02,  1.00000000e+00,  1.33138020e-04]])
```

...

Wykresy

```
import matplotlib.pyplot as plt
city_frame['population'].plot(use_index=True, xticks=range(len(city_frame.index)))
<matplotlib.axes._subplots.AxesSubplot object at 0x066BBFD0>
>>> plt.show()
```



Przykład III

```
c={'residential': 8572563.655673558, 'park': 45521.80777122383,  
  'forest': 50124469.74239494, 'meadow': 1110634.9548526453,  
  'orchard': 346469.5287002488, 'nature_reserve':  
  3674973.4626020906, 'cemetery': 24627.800913020037, 'retail':  
  2475.861748448573, 'military': 934994.1140836796, 'industrial':  
  2140931.312884256, 'allotments': 908821.7274399129, 'grass':  
  122170.55198922203, 'farm': 16308503.311590474}  
d={'residential': 128, 'park': 3, 'forest': 80, 'meadow': 106, 'orchard': 6,  
  'nature_reserve': 4, 'cemetery': 2, 'retail': 1, 'military': 1, 'industrial':  
  37, 'allotments': 12, 'grass': 33, 'farm': 137}
```

```
seria_area=pd.Series(c)/100000
```

```
seria_count=pd.Series(d)
```

Serie

```
allotments      9.088217
cemetery        0.246278
farm            163.085033
forest          501.244697
grass           1.221706
industrial      21.409313
meadow          11.106350
military        9.349941
nature_reserve  36.749735
orchard         3.464695
park            0.455218
residential     85.725637
retail          0.024759
dtype: float64
```

```
allotments      12
cemetery        2
farm            137
forest          80
grass           33
industrial      37
meadow          106
military        1
nature_reserve  4
orchard         6
park            3
residential     128
retail          1
dtype: int64
```

Utworzenie DataFrame

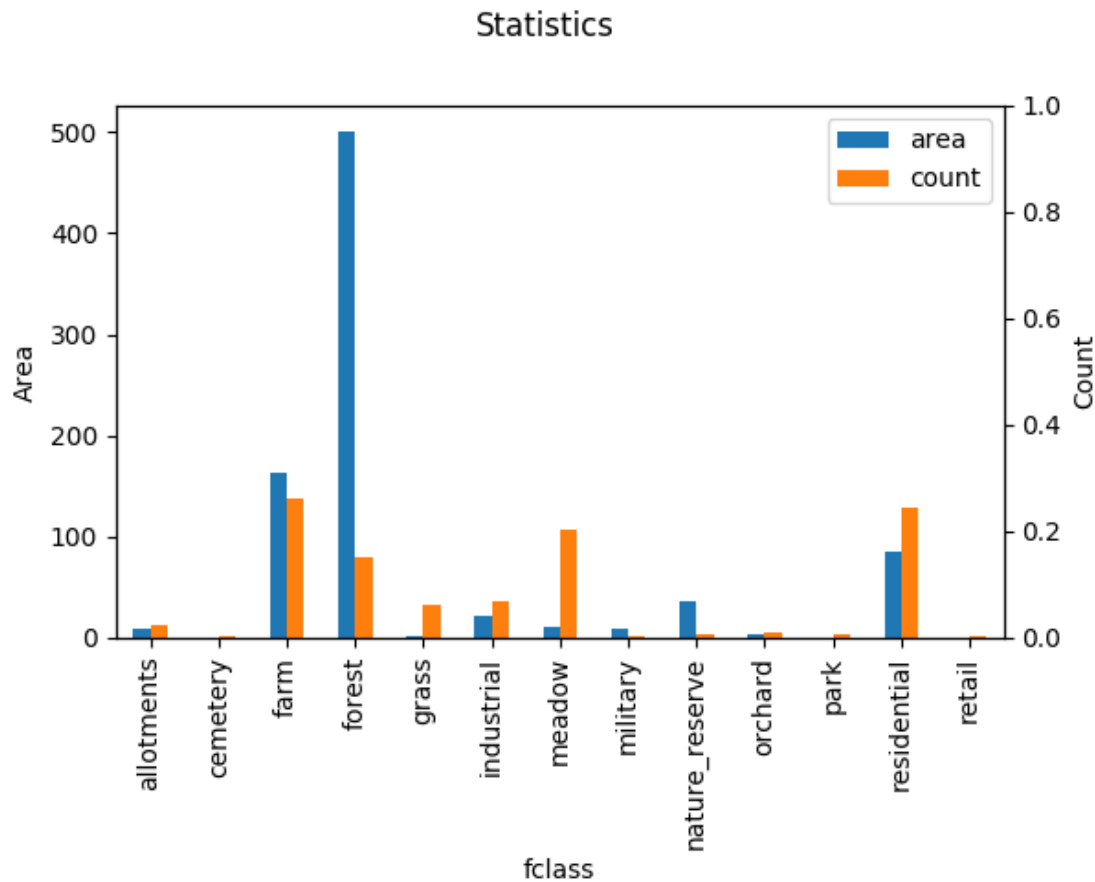
```
data_frame=pd.concat([seria_area,seria_count],axis=1)
data_frame.columns=["area","count"]
```

	area	count
allotments	9.088217	12
cemetery	0.246278	2
farm	163.085033	137
forest	501.244697	80
grass	1.221706	33
industrial	21.409313	37
meadow	11.106350	106
military	9.349941	1
nature_reserve	36.749735	4
orchard	3.464695	6
park	0.455218	3
residential	85.725637	128
retail	0.024759	1

```
#generowanie parametrów wykresu
fig, ax = plt.subplots()
fig.suptitle("Statistics")
ax.set_ylabel("Area")
ax.set_xlabel("fclass")
ax2 = ax.twinx()
ax2.set_ylabel("Count")
```

Wykres na podstawie DataFrame

```
data_frame.plot( ax=ax, use_index=True, rot=90, kind="bar",xticks=range(len(data_frame.index)))  
plt.show()
```



Dodatkowe obliczenia

```
data_frame["prcn"]=data_frame["area"]/(clip_geom.GetArea()/10000)*100
```

	area	count	prcn
allotments	9.088217	12	0.048871
cemetery	0.246278	2	0.001324
farm	163.085033	137	0.876980
forest	501.244697	80	2.695414
grass	1.221706	33	0.006570
industrial	21.409313	37	0.115127
meadow	11.106350	106	0.059724
military	9.349941	1	0.050279
nature_reserve	36.749735	4	0.197620
orchard	3.464695	6	0.018631
park	0.455218	3	0.002448
residential	85.725637	128	0.460985
retail	0.024759	1	0.000133

Obliczenia statystyk

```
>>> data_frame.describe()
```

```
          area      count      prcn
count    13.000000    13.000000    13.000000
mean     64.859352    42.307692     0.348777
std     139.230125    51.791867     0.748702
min       0.024759     1.000000     0.000133
25%       1.221706     3.000000     0.006570
50%       9.349941    12.000000     0.050279
75%      36.749735    80.000000     0.197620
max     501.244697   137.000000     2.695414
```


Sumy skumulowane

- `>>> data_frame["cumsum_area"]=data_frame["area"].cumsum()`

	area	count	prcn	cumsum_area
allotments	9.088217	12	0.048871	9.088217
cemetery	0.246278	2	0.001324	9.334495
farm	163.085033	137	0.876980	172.419528
forest	501.244697	80	2.695414	673.664226
grass	1.221706	33	0.006570	674.885931
industrial	21.409313	37	0.115127	696.295244
meadow	11.106350	106	0.059724	707.401594
military	9.349941	1	0.050279	716.751535
nature_reserve	36.749735	4	0.197620	753.501270
orchard	3.464695	6	0.018631	756.965965
park	0.455218	3	0.002448	757.421183
residential	85.725637	128	0.460985	843.146820
retail	0.024759	1	0.000133	843.171578

Sortowanie DataFrame

- `>>> data_frame.sort_values(by='area')`

```
      area  count      prcn  cumsum_area
retail    0.024759      1  0.000133    843.171578
cemetery  0.246278      2  0.001324     9.334495
park      0.455218      3  0.002448   757.421183
grass     1.221706     33  0.006570   674.885931
orchard   3.464695      6  0.018631   756.965965
allotments 9.088217     12  0.048871     9.088217
military  9.349941      1  0.050279   716.751535
meadow    11.106350    106  0.059724   707.401594
industrial 21.409313     37  0.115127   696.295244
nature_reserve 36.749735      4  0.197620   753.501270
residential 85.725637    128  0.460985   843.146820
farm     163.085033    137  0.876980   172.419528
forest   501.244697     80  2.695414   673.664226
```

Odczyt plików csv do DataFrame

```
csv_fn=r'C:/Users/Robert/Desktop/GIS/GI22.csv'
```

```
>>> df = pd.read_csv(csv_fn, sep=',')
```

```
>>>df = pd.read_csv(csv_fn, sep=',', index_col=['id'])
```

```
>>>df
```

```
>>> df
```

	y	x	z
id			
BAZA	5.815040e+06	6.428067e+06	85.0300
F1	5.815040e+06	6.428064e+06	85.0773
F2	5.815046e+06	6.428066e+06	85.1258
F3	5.815055e+06	6.428065e+06	85.2699
F4	5.815071e+06	6.428069e+06	85.3996
F5	5.815076e+06	6.428068e+06	85.4192
F6	5.815082e+06	6.428062e+06	85.4937
F7	5.815089e+06	6.428069e+06	85.4030
F8	5.815103e+06	6.428069e+06	85.4383
F9	5.815117e+06	6.428079e+06	85.4079