EDA

February 17, 2025

1 Exploratory data analysis

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

1.1 Load PL df and set headers

[3]:
```python
df_pol = pd.read_csv('/data/raw/PL.txt', delimiter="\t")
# df_pol.to_csv('PL.csv')
geonames_headers = [
    "geonameid", "name", "asciiname", "alternatenames", "latitude", "longitude",
    "feature_class", "feature_code", "country_code", "cc2", "admin1_code",
    "admin2_code", "admin3_code", "admin4_code", "population", "elevation",
    "dem", "timezone", "modification_date"
]
df_pol.columns=geonames_headers
df_pol.head()
```

[3]:
```
   geonameid                      name                 asciiname  \
0     477032               Variazhanka               Variazhanka
1     490932                  Sołokija                  Solokija
2     502656                      Rata                      Rata
3     558461  Hrodzyenskaye Uzvyshsha  Hrodzyenskaye Uzvyshsha
4     570570          Kanal Butsovskiy          Kanal Butsovskiy

                                      alternatenames  latitude  longitude  \
0  Mlynski Potok,Młyński Potok,Varenzhanka,Varezh…  50.63333   24.16667
1  Fluss Solokija,Fluss Sołokija,Reka Solokiya,Ri…  50.38333   24.25000
2                                              Rata,  50.35148   24.24569
3  Grodnenskaya Vozvyshennost',Grodnenskaya Vozvy…  53.66514   23.54748
4  Kanal Bucowski,Kanal Butsovski,Kanal Butsovski…  49.95000   22.93333

  feature_class feature_code country_code    cc2  admin1_code  admin2_code  \
0             H          STM           PL    NaN          0.0          NaN
1             H          STM           PL    NaN          0.0          NaN
2             H          STM           PL  PL,UA          0.0          NaN
3             T         HLLS           PL    NaN         81.0       2011.0
4             H          CNL           PL     UA         80.0          NaN
```

```
  admin3_code admin4_code  population  elevation  dem       timezone  \
0         NaN         NaN           0        NaN  179  Europe/Warsaw
1         NaN         NaN           0        NaN  182  Europe/Warsaw
2         NaN         NaN           0        NaN  189  Europe/Warsaw
3    201106.0         NaN           0        NaN  131  Europe/Warsaw
4         NaN         NaN           0        NaN  184  Europe/Warsaw

  modification_date
0        2021-08-04
1        2025-01-10
2        2023-11-07
3        2010-09-15
4        2014-03-05
```

1.2 Szukanie zamieszkałych lokalizacji

1.2.1 Kategorie lokalizacji z zerowa populacja

Kazda kategoria lokalizacji posiada jakies miejsca z zerowa pop

[4]:
```
df_pol[df_pol.population==0]['feature_class'].unique()
```

[4]:
```
array(['H', 'T', 'P', 'S', 'V', 'A', 'L', 'R', 'U'], dtype=object)
```

1.2.2 Kategorie lokalizacji z niezerowa populacja

[5]:
```
df_pol[df_pol.population>0]['feature_class'].unique()
```

[5]:
```
array(['P', 'A', 'L', 'S'], dtype=object)
```

Niezerowa populacja wystepuje w przypadku: - P: miast, wsi - A: kraj, wojewodztwo, region - L: park, obszar - S: miejsce, budynek, farma

[6]:
```
df_pol[df_pol.population>0]['feature_code'].unique()
```

[6]:
```
array(['PPL', 'PPLA3', 'PPLA2', 'PPLC', 'ADMD', 'PPLX', 'PPLA', 'PPLF',
       'PCLI', 'ADM1', 'RGN', 'ADM2', 'ADM4H', 'PPLA4', 'HTL', 'ADM3',
       'AREA', 'FRM', 'PPLH', 'BLDG'], dtype=object)
```

Oto lista kodów oznaczających obszary zamieszkane na podstawie danych z Twojego dataframe'u:

- PPL – miejscowość (miasto, wieś lub inna zamieszkana osada)
- PPLA – stolica jednostki administracyjnej pierwszego rzędu (np. województwa)
- PPLA2 – stolica jednostki administracyjnej drugiego rzędu (np. powiatu)
- PPLA3 – stolica jednostki administracyjnej trzeciego rzędu (np. gminy)
- PPLA4 – stolica jednostki administracyjnej czwartego rzędu
- PPLC – stolica kraju
- PPLF – wieś rolnicza

- PPLH – historyczna miejscowość (kiedyś zamieszkana, obecnie opuszczona)
- PPLX – część miejscowości

Inne kody w Twoim zbiorze danych, które niekoniecznie oznaczają obszary zamieszkane:

- ADMD, ADM1, ADM2, ADM3, ADM4H – jednostki administracyjne różnego szczebla
- PCLI – niezależne państwo
- RGN – region geograficzny
- AREA – obszar
- FRM – farma
- BLDG – budynek
- HTL – hotel

1.2.3 Jakie mamy klasy w kategorii P?

[3]:
```
df_pol[df_pol.feature_class =="P"]['feature_code'].unique()
```

[3]:
```
array(['PPL', 'PPLX', 'PPLA3', 'PPLA2', 'PPLQ', 'PPLC', 'PPLA', 'PPLF',
       'PPLL', 'PPLA4', 'PPLS', 'PPLR', 'PPLH', 'PPLW'], dtype=object)
```

W spopulowanych miejscach nie wystapily:

- PPLQ - abandoned populated place
- PPLL - populated locality
- PPLS - populated places
- PPLR - religious populated place
- PPLW - destroyed populated place

[8]:
```
df_pol[df_pol.feature_code == "PPLL"]
```

[8]:
```
       geonameid               name          asciiname  \
21962     775016        Brzuze Duże        Brzuze Duze
34858    3090999    Niedźwiedzi Ług    Niedzwiedzi Lug
48723    6354921    Sołtysi Koniec     Soltysi Koniec
49096    6698046          Brzeźniak          Brzezniak
53638    8379168             Ulicko             Ulicko
54438    8630240            Naborów            Naborow
54440    8630269         Borzymówka         Borzymowka
54597    8740564             Otręba             Otreba
54602    8740569          Gronowiec          Gronowiec
54618    8740585             Wągieł             Wagiel
54648    8740615  Przetocznica Mała  Przetocznica Mala
54686    8740653    Wilenko Kolonia    Wilenko Kolonia
54717    8740684          Fabryczka          Fabryczka
55695   10401952             Nowice             Nowice
55706   10401963               Ryki               Ryki
55707   10401964            Łaziska            Laziska
55897   11054906          Grebiszew          Grebiszew
57984   12451029          Gaworkowo          Gaworkowo
```

	alternatenames	latitude	longitude	\
21962	Brzoze Duze,Brzuze Duze,Brzuze Duże,Brzóze Duże	52.82119	21.45797	
34858	NaN	52.27320	15.14238	
48723	NaN	50.30696	20.01506	
49096	Birkholz,Brzezniak,Brzeźniak	53.14749	16.07353	
53638	Bergstrass,Bergstraß	50.92349	15.28284	
54438	NaN	51.27714	16.65918	
54440	NaN	52.12490	20.20154	
54597	Buch-Muehle,Buch-Mühle	52.37377	15.30325	
54602	Grunower Muehle,Grunower Mühle	52.29722	15.27227	
54618	Schaeferei,Schäferei	52.28433	15.43927	
54648	NaN	52.11415	15.41433	
54686	NaN	52.28197	15.67062	
54717	NaN	52.35104	15.34610	
55695	Neuwitz	52.36865	15.71678	
55706	NaN	52.31629	15.71485	
55707	NaN	52.23151	15.34361	
55897	Grebiszew,Grębiszew	52.12157	21.50698	
57984	Gauerkow,Gurkow	53.72201	16.10879	

	feature_class	feature_code	country_code	cc2	admin1_code	admin2_code	\
21962	P	PPLL	PL	NaN	78.0	1411.0	
34858	P	PPLL	PL	NaN	76.0	807.0	
48723	P	PPLL	PL	NaN	77.0	1208.0	
49096	P	PPLL	PL	NaN	87.0	3217.0	
53638	P	PPLL	PL	NaN	72.0	210.0	
54438	P	PPLL	PL	NaN	72.0	222.0	
54440	P	PPLL	PL	NaN	78.0	1428.0	
54597	P	PPLL	PL	NaN	76.0	808.0	
54602	P	PPLL	PL	NaN	76.0	808.0	
54618	P	PPLL	PL	NaN	76.0	808.0	
54648	P	PPLL	PL	NaN	76.0	808.0	
54686	P	PPLL	PL	NaN	76.0	808.0	
54717	P	PPLL	PL	NaN	76.0	808.0	
55695	P	PPLL	PL	NaN	76.0	803.0	
55706	P	PPLL	PL	NaN	76.0	803.0	
55707	P	PPLL	PL	NaN	76.0	808.0	
55897	P	PPLL	PL	NaN	78.0	1412.0	
57984	P	PPLL	PL	NaN	87.0	3216.0	

	admin3_code	admin4_code	population	elevation	dem	timezone	\
21962	141108.0	NaN	0	NaN	95	Europe/Warsaw	
34858	80705.0	NaN	0	NaN	91	Europe/Warsaw	
48723	120805.0	NaN	0	275.0	266	Europe/Warsaw	
49096	321702.0	NaN	0	NaN	93	Europe/Warsaw	
53638	21002.0	NaN	0	NaN	516	Europe/Warsaw	

```
54438     22201.0         NaN            0        NaN  138  Europe/Warsaw
54440    142805.0         NaN            0        NaN   88  Europe/Warsaw
54597     80802.0         NaN            0        NaN  120  Europe/Warsaw
54602     80802.0         NaN            0        NaN  113  Europe/Warsaw
54618     80801.0         NaN            0        NaN   78  Europe/Warsaw
54648     80803.0         NaN            0        NaN   62  Europe/Warsaw
54686     80804.0         NaN            0        NaN   70  Europe/Warsaw
54717     80802.0         NaN            0        NaN  133  Europe/Warsaw
55695     80302.0         NaN            0        NaN   92  Europe/Warsaw
55706     80306.0         NaN            0        NaN   72  Europe/Warsaw
55707     80801.0         NaN            0        NaN  100  Europe/Warsaw
55897    141211.0         NaN            0        0.0  138  Europe/Warsaw
57984    321603.0         NaN            0        NaN  158  Europe/Warsaw

      modification_date
21962        2017-10-12
34858        2016-03-02
48723        2023-06-22
49096        2015-09-05
53638        2012-08-29
54438        2013-11-12
54440        2013-11-12
54597        2014-05-05
54602        2014-05-05
54618        2015-08-20
54648        2014-03-30
54686        2014-05-05
54717        2014-05-05
55695        2015-08-25
55706        2015-08-06
55707        2015-08-06
55897        2017-09-13
57984        2022-04-13
```

1.2.4 Czy sa hotele z populacja ponad 0?

Zadanie okresla aby znalezc miejsca zamieszkale, ale nie np. hotele czy latarnie morskie

[7]:
```python
df_pol[(df_pol.feature_code=="HTL") & (df_pol.population>0)]
```

[7]:
```
       geonameid   name asciiname           alternatenames  latitude  \
48726    6452689  Losie     Losie  Agroturystczny Dom Gosi  49.56586

       longitude feature_class feature_code country_code  cc2  admin1_code  \
48726   21.10783             S          HTL           PL  NaN         77.0

       admin2_code  admin3_code admin4_code  population  elevation  dem  \
```

```
48726       1205.0     120508.0         NaN         122       100.0  571

          timezone modification_date
48726  Europe/Warsaw        2015-09-05
```

1.2.5 Zostajemy przy miastach, miasteczkach, i wsiach (klasa P)

Ponieważ należa one zazwyczaj do jednostek administracyjnych (klasa A), czasem tez do obszarow (klasa L) oraz zawieraja w sobie miejsca jak budynki czy hotele (klasa S)

[8]:
```
df_pol[df_pol["feature_class"]=='P']
```

[8]:
```
       geonameid                     name                asciiname  \
5         620115                 Włodawka                 Wlodawka
6         688812             Vul’ka Ugruska           Vul'ka Ugruska
7         696099      Pshedmes’tse Vel’ke      Pshedmes'tse Vel'ke
8         698000                 Paportno                 Paportno
9         707872                    Gurne                    Gurne
…            …                        …                        …
58184   13118922                  Karpiny                  Karpiny
58185   13132183                Kostrzyca                Kostrzyca
58186   13132269              Trzebieradz              Trzebieradz
58187   13157303                  Żerdziny                 Zerdziny
58189   13192399  Nowa Wieś Goszczańska  Nowa Wies Goszczanska

                                          alternatenames  latitude  longitude  \
5                               Vlodavka,Wlodawka,Włodawka  51.53333   23.56667
6      Vul'ka Ugruska,Vul’ka Ugruska,Wolka Uhruska,Wó…  51.32150   23.62724
7      Bol'shoy Predmest'ye,Bol’shoy Predmest’ye,Pshe…  50.23333   23.06667
8                                               Paportno  49.59996   22.69709
9                                      Gorne,Gurne,Górne  50.04389   22.99222
…                                                    …        …         …
58184                                        Treugenkohl  53.64874   18.85904
58185                                                NaN  50.81906   15.80757
58186                                                NaN  54.02076   14.96106
58187                                                NaN  50.09702   18.15266
58189                  Goschuetz-Neudorf,Goschütz-Neudorf  51.41964   17.45134

      feature_class feature_code country_code  cc2  admin1_code  admin2_code  \
5                 P          PPL           PL  NaN         75.0        619.0
6                 P          PPL           PL  NaN          0.0          NaN
7                 P          PPL           PL  NaN          0.0          NaN
8                 P          PPL           PL  NaN         80.0       1813.0
9                 P          PPL           PL  NaN         80.0       1804.0
…               …           …          …   …          …            …
58184             P          PPL           PL  NaN         82.0       2207.0
58185             P          PPL           PL  NaN         72.0        206.0
```

```
58186              P          PPL           PL  NaN         87.0        3207.0
58187              P          PPL           PL  NaN         83.0        2411.0
58189              P          PPL           PL  NaN         72.0         214.0

      admin3_code admin4_code  population  elevation  dem       timezone  \
5         61906.0         NaN           0        NaN  154  Europe/Warsaw
6             NaN         NaN           0        NaN  173  Europe/Warsaw
7             NaN         NaN           0        NaN  243  Europe/Warsaw
8        181303.0         NaN           0        NaN  437  Europe/Warsaw
9        180405.0         NaN           0        NaN  207  Europe/Warsaw
…             …           …          …          …   …            …
58184    220706.0         NaN           0        NaN   57  Europe/Warsaw
58185     20607.0         NaN           0        NaN  403  Europe/Warsaw
58186    320705.0         NaN           0        NaN    9  Europe/Warsaw
58187    241107.0         NaN           0        NaN  247  Europe/Warsaw
58189     21408.0         NaN           0        NaN  142  Europe/Warsaw

      modification_date
5            2020-06-10
6            2021-07-27
7            2021-04-16
8            2019-05-18
9            2016-06-22
…                   …
58184        2024-11-14
58185        2024-11-27
58186        2024-11-28
58187        2025-01-08
58189        2025-01-28

[47583 rows x 19 columns]
```

2 Problemy z danymi i czyszczenie

2.0.1 Rzeka o tej samej nazwie występuje dwa razy

Raz jako rzeka, raz jako miejscowość.

Lokalizacja jest zbliżona, lecz nie taka sama.

Nazwa jest ta sama.

Kody administracyjne s te same.

Dem różni się o 1 jednostkę.

[15]:
```
df_pol[df_pol["asciiname"]=='Lagiewniki']
```

[15]:
```
       geonameid        name   asciiname  \
13833     766839  Łagiewniki  Lagiewniki
13834     766840  Łagiewniki  Lagiewniki
37831    3093992  Łagiewniki  Lagiewniki
37832    3093993  Łagiewniki  Lagiewniki
37833    3093994  Łagiewniki  Lagiewniki
37834    3093995  Łagiewniki  Lagiewniki
37835    3093996  Łagiewniki  Lagiewniki
37836    3093997  Łagiewniki  Lagiewniki
37837    3093998  Łagiewniki  Lagiewniki
37838    3093999  Łagiewniki  Lagiewniki
37839    3094000  Łagiewniki  Lagiewniki
37840    3094001  Łagiewniki  Lagiewniki
37841    3094002  Łagiewniki  Lagiewniki
37842    3094003  Łagiewniki  Lagiewniki
37843    3094004  Łagiewniki  Lagiewniki
37844    3094005  Łagiewniki  Lagiewniki
50695    7531984  Łagiewniki  Lagiewniki

                                             alternatenames  latitude  \
13833                                                   NaN  50.62300
13834                                 Lagiewniki,Łagiewniki  50.48619
37831                      Elvershagen,Lagiewniki,Łagiewniki  53.74378
37832                                                   NaN  52.56059
37833                                 Lagiewniki,Łagiewniki  52.53952
37834                                 Lagiewniki,Łagiewniki  52.50000
37835                                 Lagiewniki,Łagiewniki  52.15513
37836                                                   NaN  52.06215
37837    Lagiewniki,Lagiewniki Maly,Łagiewniki,Łagiewniki Mały  51.83732
37838                                 Lagiewniki,Łagiewniki  51.76490
37839                                                   NaN  51.54249
37840                                 Lagiewniki,Łagiewniki  51.27522
37841                                                   NaN  51.08433
37842                      Heidersdorf,Lagiewniki,Łagiewniki  50.79088
37843  Hohenlinde o/s,Lagiewniki,Lagiewniki Slaskie,Łagiewniki  50.32223
37844                                                   NaN  50.02561
50695                                 Lagiewniki,Łagiewniki  50.79300

       longitude feature_class feature_code country_code  cc2  admin1_code  \
13833   20.79987             P          PPL           PL  NaN         84.0
13834   20.74743             P          PPL           PL  NaN         84.0
37831   15.49559             P          PPL           PL  NaN         87.0
37832   19.05218             P          PPL           PL  NaN         73.0
37833   17.24990             P          PPL           PL  NaN         86.0
37834   16.86667             P          PPL           PL  NaN         86.0
37835   16.60473             P          PPL           PL  NaN         86.0
37836   18.03174             P          PPL           PL  NaN         86.0
```

37837	19.46401	P	PPL	PL	NaN	74.0
37838	17.23745	P	PPL	PL	NaN	86.0
37839	19.90791	P	PPL	PL	NaN	74.0
37840	18.51118	P	PPL	PL	NaN	74.0
37841	19.58107	P	PPL	PL	NaN	74.0
37842	16.84457	P	PPL	PL	NaN	72.0
37843	18.92871	P	PPL	PL	NaN	83.0
37844	19.93710	P	PPL	PL	NaN	77.0
50695	16.78300	A	ADM3	PL	NaN	72.0

	admin2_code	admin3_code	admin4_code	population	elevation	dem \
13833	2604.0	260404.0	NaN	0	NaN	251
13834	2601.0	260101.0	NaN	0	NaN	248
37831	3218.0	321804.0	NaN	0	NaN	74
37832	418.0	41813.0	NaN	0	NaN	72
37833	3021.0	302112.0	NaN	0	NaN	108
37834	3021.0	302115.0	NaN	0	NaN	98
37835	3011.0	301103.0	NaN	0	NaN	68
37836	3010.0	301002.0	NaN	0	NaN	99
37837	1061.0	106101.0	NaN	0	NaN	212
37838	3012.0	301202.0	NaN	0	NaN	116
37839	1016.0	101609.0	NaN	0	NaN	169
37840	1017.0	101702.0	NaN	0	NaN	183
37841	1012.0	101207.0	NaN	100	NaN	231
37842	202.0	20206.0	NaN	2900	NaN	177
37843	2462.0	246201.0	NaN	0	NaN	304
37844	1261.0	126101.0	NaN	0	NaN	223
50695	202.0	20206.0	NaN	7458	NaN	196

	timezone	modification_date
13833	Europe/Warsaw	2010-10-01
13834	Europe/Warsaw	2019-02-22
37831	Europe/Warsaw	2022-04-12
37832	Europe/Warsaw	2015-09-05
37833	Europe/Warsaw	2019-02-22
37834	Europe/Warsaw	2019-02-22
37835	Europe/Warsaw	2019-02-22
37836	Europe/Warsaw	2010-10-16
37837	Europe/Warsaw	2012-11-27
37838	Europe/Warsaw	2019-02-22
37839	Europe/Warsaw	2015-09-05
37840	Europe/Warsaw	2019-02-22
37841	Europe/Warsaw	2011-01-08
37842	Europe/Warsaw	2010-09-12
37843	Europe/Warsaw	2021-04-22
37844	Europe/Warsaw	2010-09-16
50695	Europe/Warsaw	2018-08-21

[10]:
```
df = df_pol
print(df[df["feature_code"] == "PPLA"][['name','population']].head(20))
# print(df[df["feature_code"] == "AREA"][['name','population']].head(20))
```

```
                      name  population
6769               Rzeszów      158382
10179              Olsztyn      171803
12875               Lublin      360044
16231               Kielce      208598
23009            Białystok      291855
24090          Zielona Góra     118433
25289              Wrocław      634893
27734             Szczecin      407811
32048               Poznań      570352
33910                Opole      127676
36978                 Łódź      768755
38636               Kraków      755050
40301             Katowice      317316
42538  Gorzów Wielkopolski      124430
43243               Gdańsk      461865
45803            Bydgoszcz      366452
```

[11]:
```
df_pol[df_pol["feature_class"] == 'P']['name'].duplicated()
```

[11]:
```
5        False
6        False
7        False
8        False
9        False
         …
58184    False
58185    False
58186    False
58187     True
58189    False
Name: name, Length: 47583, dtype: bool
```

[12]:
```
df_pol[df_pol["feature_code"] == 'PPLX']
```

[12]:
```
       geonameid                 name            asciiname  \
29        752954        Żywawoda Szury       Zywawoda Szury
30        752955        Żywawoda Stara       Zywawoda Stara
31        752956       Żywawoda Pieńki      Zywawoda Pienki
89        753014   Zwierzyniec Wielki   Zwierzyniec Wielki
90        753015     Zwierzyniec Mały     Zwierzyniec Maly
…            …                    …                    …
58043   12523044           Węgrzynowo           Wegrzynowo
```

```
58050  12557472              Klonownica Plac              Klonownica Plac
58051  12557473             Kolonownica Plac             Kolonownica Plac
58146  13100477  Orunia Górna-Gdańsk Południe  Orunia Gorna-Gdansk Poludnie
58183  13118921                         Glina                        Glina

                                        alternatenames  latitude  longitude  \
29                                                 NaN  54.16643   22.86944
30                                                 NaN  54.17962   22.86025
31                                                 NaN  54.17471   22.88062
89                                  Zwierzyniec Wielki  53.66370   23.19968
90                     Zwierzyniec Maly,Zwierzyniec Mały  53.66225   23.21715
…                                                    …         …          …
58043                                              NaN  52.76309   19.69901
58050                                              NaN  52.14290   23.17299
58051                                              NaN  52.13532   23.16006
58146  Higher Orunia and Gdansk South,Higher Orunia a…  54.32491   18.61567
58183                                       Stangendorf  53.62368   18.76817

      feature_class feature_code country_code  cc2  admin1_code  admin2_code  \
29                P         PPLX           PL  NaN         81.0       2012.0
30                P         PPLX           PL  NaN         81.0       2012.0
31                P         PPLX           PL  NaN         81.0       2012.0
89                P         PPLX           PL  NaN         81.0       2011.0
90                P         PPLX           PL  NaN         81.0       2011.0
…                 …            …            …    …            …            …
58043             P         PPLX           PL  NaN         78.0       1427.0
58050             P         PPLX           PL  NaN         75.0        601.0
58051             P         PPLX           PL  NaN         75.0        601.0
58146             P         PPLX           PL  NaN         82.0       2261.0
58183             P         PPLX           PL  NaN         82.0       2207.0

       admin3_code admin4_code  population  elevation  dem       timezone  \
29        201203.0         NaN           0        NaN  233  Europe/Warsaw
30        201203.0         NaN           0        NaN  215  Europe/Warsaw
31        201203.0         NaN           0        NaN  243  Europe/Warsaw
89        201101.0         NaN           0        NaN  154  Europe/Warsaw
90        201101.0         NaN           0        NaN  159  Europe/Warsaw
…                …           …           …          …    …              …
58043     142702.0         NaN           0        NaN  127  Europe/Warsaw
58050      60105.0         NaN           0        NaN  166  Europe/Warsaw
58051      60105.0         NaN           0        NaN  178  Europe/Warsaw
58146     226101.0         NaN       19807        NaN   49  Europe/Warsaw
58183     220706.0         NaN           0        NaN   20  Europe/Warsaw

      modification_date
29           2015-09-05
30           2015-09-05
```

```
31           2015-09-05
89           2015-09-05
90           2015-09-05
…                 …
58043        2023-04-16
58050        2023-08-25
58051        2023-08-25
58146        2024-10-08
58183        2024-11-14

[2249 rows x 19 columns]
```

[13]:

```python
df_p = df_pol[df_pol["feature_class"] == 'P']  # Filtrujemy tylko miejsca␣
↪zamieszkane
duplikaty = df_p[df_p["name"].duplicated(keep=False)]  # Filtrujemy duplikaty

# Grupujemy po nazwie i zbieramy geonameid w listę
duplikaty["duplicate_geonameids"] = duplikaty.groupby("name")["geonameid"].
↪transform(lambda x: list(x))

import pandas as pd
pd.set_option("display.max_colwidth", None)  # Aby widzieć pełne listy ID w␣
↪kolumnie

duplikaty
```

```
/var/folders/kd/qh5jdc_d3bv65018mk4x4mw80000gn/T/ipykernel_29488/653814563.py:5:
SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  duplikaty["duplicate_geonameids"] =
duplikaty.groupby("name")["geonameid"].transform(lambda x: list(x))
```

[13]:

```
       geonameid       name   asciiname  \
12        752937   Zastawie   Zastawie
15        752940  Parszywka  Parszywka
16        752941  Małszewko  Malszewko
17        752942      Poraj      Poraj
20        752945     Żyznów     Zyznow
…          …          …        …
58175   13118913     Łączno     Laczno
58178   13118916   Jakubowo   Jakubowo
58179   13118917   Dąbrówka   Dabrowka
58183   13118921      Glina      Glina
```

```
58187   13157303   Żerdziny   Zerdziny

                                                    alternatenames  \
12                Krasniczyn-Zastawie,Kraśniczyn-Zastawie,Zastawie
15                                             Parszywa,Parszywka
16       Malschowen,Malschöwen,Malshofen,Malshöfen,Malszewko,Małszewko
17                                              Kolonia Poraj,Poraj
20                                                             NaN
…                                                             …
58175                                                       Lanzen
58178                                                   Jacobsdorf
58179                                                    Dombrowka
58183                                                  Stangendorf
58187                                                          NaN

       latitude  longitude feature_class feature_code country_code  cc2  \
12     50.93755   23.34217             P          PPL           PL  NaN
15     50.41667   20.41667             P          PPL           PL  NaN
16     53.58333   20.71667             P          PPL           PL  NaN
17     50.89962   23.99191             P          PPL           PL  NaN
20     50.61667   23.28333             P          PPL           PL  NaN
…           …          …             …            …            …  …
58175  53.63215   16.53295             P          PPL           PL  NaN
58178  53.58646   17.48628             P          PPL           PL  NaN
58179  53.65337   17.87497             P          PPL           PL  NaN
58183  53.62368   18.76817             P         PPLX           PL  NaN
58187  50.09702   18.15266             P          PPL           PL  NaN

       admin1_code  admin2_code  admin3_code admin4_code  population  \
12            75.0        606.0      60606.0         NaN           0
15            84.0       2608.0     260804.0         NaN           0
16            85.0       2817.0     281703.0         NaN           0
17            75.0        604.0      60403.0         NaN         266
20            75.0        620.0      62001.0         NaN           0
…               …            …            …           …           …
58175         87.0       3215.0     321504.0         NaN           0
58178         73.0        413.0      41301.0         NaN           0
58179         73.0        416.0      41606.0         NaN           0
58183         82.0       2207.0     220706.0         NaN           0
58187         83.0       2411.0     241107.0         NaN           0

       elevation  dem       timezone modification_date  duplicate_geonameids
12           NaN  198  Europe/Warsaw        2010-10-16                752937
15           NaN  320  Europe/Warsaw        2015-09-05                752940
16           NaN  130  Europe/Warsaw        2015-09-05                752941
17           NaN  196  Europe/Warsaw        2010-09-06                752942
20           NaN  300  Europe/Warsaw        2015-09-05                752945
```

```
…          …  …            …               …                   …
58175        NaN  166  Europe/Warsaw        2024-11-14           13118913
58178        NaN  157  Europe/Warsaw        2024-11-14           13118916
58179        NaN  141  Europe/Warsaw        2024-11-14           13118917
58183        NaN   20  Europe/Warsaw        2024-11-14           13118921
58187        NaN  247  Europe/Warsaw        2025-01-08           13157303

[19593 rows x 20 columns]
```

3 Mapa

[ ]:
```python
import folium
import pandas as pd

# Filtrujemy lokalizacje zamieszkane
df_p = df_pol[df_pol["feature_class"].isin(['PPL', 'PPLA', 'PPLA2', 'PPLA'])]
# df_p = df_p[df_p['admin3_code'] == 220401]

# Definiujemy kolory dla różnych typów feature_code
feature_colors = {
    'PPL': 'blue',     # Populated place
    'PPLA': 'red',     # Seat of admin division
    'PPLA2': 'red',
    'PPLA3': 'red',
    'PPLA4': 'red',
    'PPLC': 'purple', # Capital city
    'PPLX': 'green',  # Section of populated place
    'PPLF': 'orange', # Farm village
    'PPLH': 'black',  # Historical populated place
    'PPLW': 'gray'    # Destroyed populated place
}

# Tworzymy mapę centrowaną na Polskę
mapa = folium.Map(location=[52.0, 19.0], zoom_start=6)

# Iterujemy po rekordach i dodajemy markery
for _, row in df_p.iterrows():
    lat, lon = row['latitude'], row['longitude']
    feature_code = row['feature_code']
    color = feature_colors.get(feature_code, 'cadetblue')  # Domyślny kolor

    popup_text = f"""
    <b>Nazwa:</b> {row['name']}<br>
    <b>Feature Code:</b> {row['feature_code']}<br>
    <b>Populacja:</b> {row['population']}<br>
    <b>Geoname ID:</b> {row['geonameid']}<br>
```

```
    <b>Współrzędne:</b> ({lat}, {lon})<br>
    <b>Admin1 code:</b> {row['admin1_code']} <br>
    <b>Admin2 code:</b> {row['admin2_code']} <br>
    <b>Admin3 code:</b> {row['admin3_code']}
    """

    folium.CircleMarker(
        location=[lat, lon],
        radius=5,
        color=color,
        fill=True,
        fill_color=color,
        fill_opacity=0.7,
        popup=folium.Popup(popup_text, max_width=300)
    ).add_to(mapa)

# Zapisujemy mapę do pliku HTML i otwieramy w przeglądarce
mapa.save("mapa_miejscowosci.html")
print("Mapa została zapisana jako 'mapa_miejscowosci.html'. Otwórz ją w␣
 ↪przeglądarce.")
```

```
Mapa została zapisana jako 'mapa_miejscowosci.html'. Otwórz ją w przeglądarce.
```

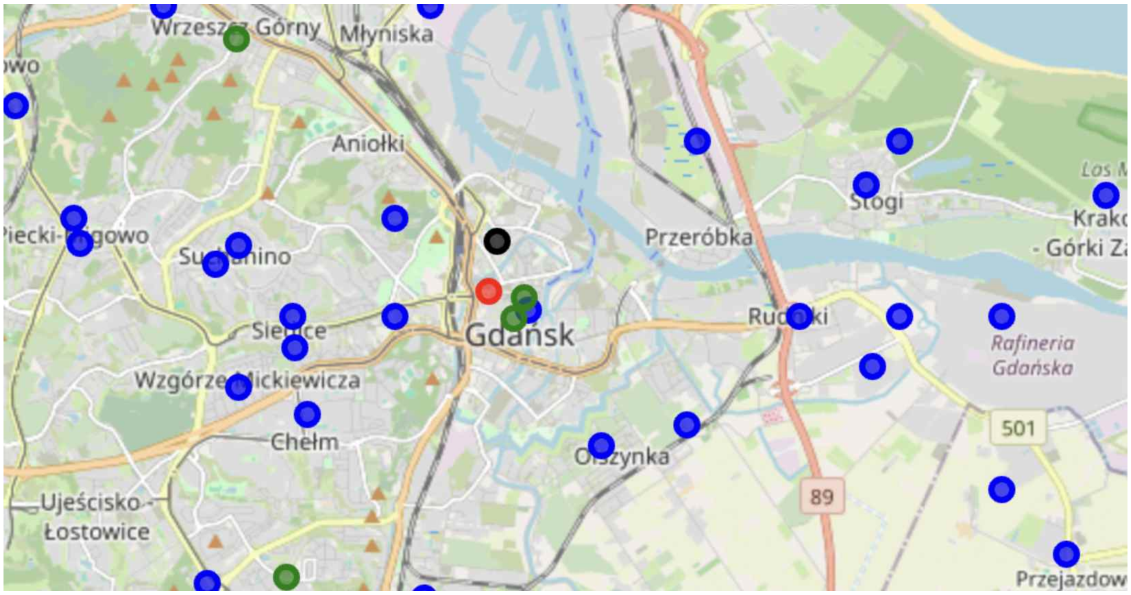
3.0.1 Wnioski z mapy Gdańska i okolic

- PPL (niebieski) - dzielnice i obszary Gdańska
- PPLA (czerwony) - stolica województwa / Gdańsk
- PPLX (zielony) - niektore obszary, nie do konca dzielnice - np. Westerplatte, Wisłoujście, Orunia Górna-Gdańsk Płd
- PPLH (czerwony) - miejsca historyczne - np stare miasto
- PPLA2 - np Pruszcz Gdański, czyli stolica powiatu?
- PPLA3 - mniejsza miescina - stolica gimny

Wyglada na to, że dana lokalizacja nie będzie jednocześnie PPLA% oraz PPL.

DODATKOWO, admin_code 1-3 wskazuja na wspolna przynaleznosc lokalizacji do jednostek administracyjnych

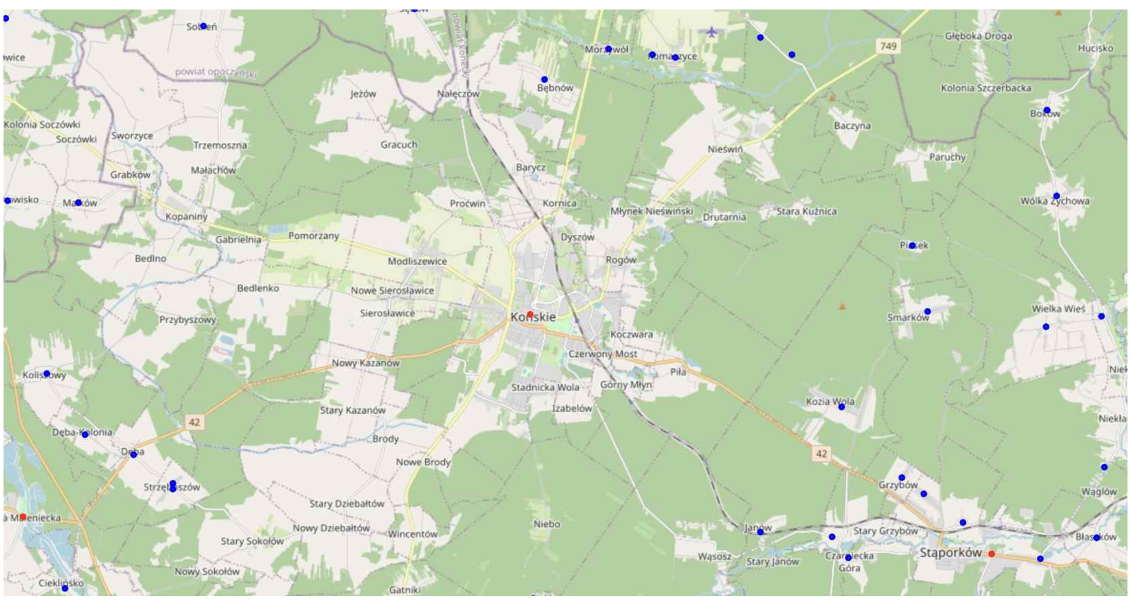
Np. wszystkie dzielnice w Gdansku beda mialy przydzial do tego samego powiatu co sam Gdansk, co pozwala je wyeliminowac. Konieczne jest wyeliminowanie dzielnic, ponieważ niektóre w większych miastach maja znaczaca populacje, i moglyby byc traktowane jak osobne miejscowosci.



3.1 Podejście oparte na admin_codes

Jednak dla mniejszych miejscowości admin2_code lub admin3_code beda takie same jak u pobliskich małych miejscowości.

Czyli eliminowanie ze wzgledu na admin_code moze usunac pelnoprawne, oddzielne miejscowosci, natomiast brak filtrowania moze skutkowac traktowaniem dzielnic jak miejscowosci (szczegolnie jak maja niezerowa populacje).




```
[ ]: import pandas as pd
     import folium

     # Creating DataFrame with only places (P)
```

```python
df = df_pol[df_pol['feature_class'] == 'P']

# Filtering out PPLH and PPLX
df = df[~df["feature_code"].isin(["PPLH", "PPLX"])]

# Step 1: Filtering based on admin2_code (handling PPLA and PPLC)
admin2_groups = df.groupby("admin2_code")

filtered_admin2 = []
for _, group in admin2_groups:
    if "PPLA" in group["feature_code"].values:
        filtered_admin2.append(group[group["feature_code"] == "PPLA"])
    elif "PPLC" in group["feature_code"].values:
        filtered_admin2.append(group[group["feature_code"] == "PPLC"])
    else:
        filtered_admin2.append(group)

df_filtered_admin2 = pd.concat(filtered_admin2)

# Step 2: Filtering based on admin3_code (handling PPLA2)
admin3_groups = df_filtered_admin2.groupby("admin3_code")

filtered_admin3 = []
for _, group in admin3_groups:
    if "PPLA2" in group["feature_code"].values:
        filtered_admin3.append(group[group["feature_code"] == "PPLA2"])
    else:
        filtered_admin3.append(group)

df_final = pd.concat(filtered_admin3)

# Filtrujemy lokalizacje zamieszkane
df_p = df_final
# df_p = df_p[df_p['admin3_code'] == 220401]

# Definiujemy kolory dla różnych typów feature_code
feature_colors = {
    'PPL': 'blue',     # Populated place
    'PPLA': 'red',     # Seat of admin division
    'PPLA2': 'red',
    'PPLA3': 'red',
    'PPLA4': 'red',
    'PPLC': 'purple', # Capital city
    'PPLX': 'green',  # Section of populated place
    'PPLF': 'orange', # Farm village
    'PPLH': 'black',  # Historical populated place
    'PPLW': 'gray'    # Destroyed populated place
```

```
}

# Tworzymy mapę centrowaną na Polskę
mapa = folium.Map(location=[52.2298, 21.0122], zoom_start=10)

# Iterujemy po rekordach i dodajemy markery
for _, row in df_p.iterrows():
    lat, lon = row['latitude'], row['longitude']
    feature_code = row['feature_code']
    color = feature_colors.get(feature_code, 'cadetblue')  # Domyślny kolor

    popup_text = f"""
    <b>Nazwa:</b> {row['name']}<br>
    <b>Feature Code:</b> {row['feature_code']}<br>
    <b>Populacja:</b> {row['population']}<br>
    <b>Geoname ID:</b> {row['geonameid']}<br>
    <b>Współrzędne:</b> ({lat}, {lon})<br>
    <b>Admin1 code:</b> {row['admin1_code']} <br>
    <b>Admin2 code:</b> {row['admin2_code']} <br>
    <b>Admin3 code:</b> {row['admin3_code']}
    """

    folium.CircleMarker(
        location=[lat, lon],
        radius=2,
        color=color,
        fill=True,
        fill_color=color,
        fill_opacity=0.3,
        popup=folium.Popup(popup_text, max_width=300)
    ).add_to(mapa)

# Zapisujemy mapę do pliku HTML i otwieramy w przeglądarce
mapa.save("mapa_miejscowosci1.html")
print("Mapa została zapisana jako 'mapa_miejscowosci1.html'. Otwórz ją w␣
 ↪przeglądarce.")
```

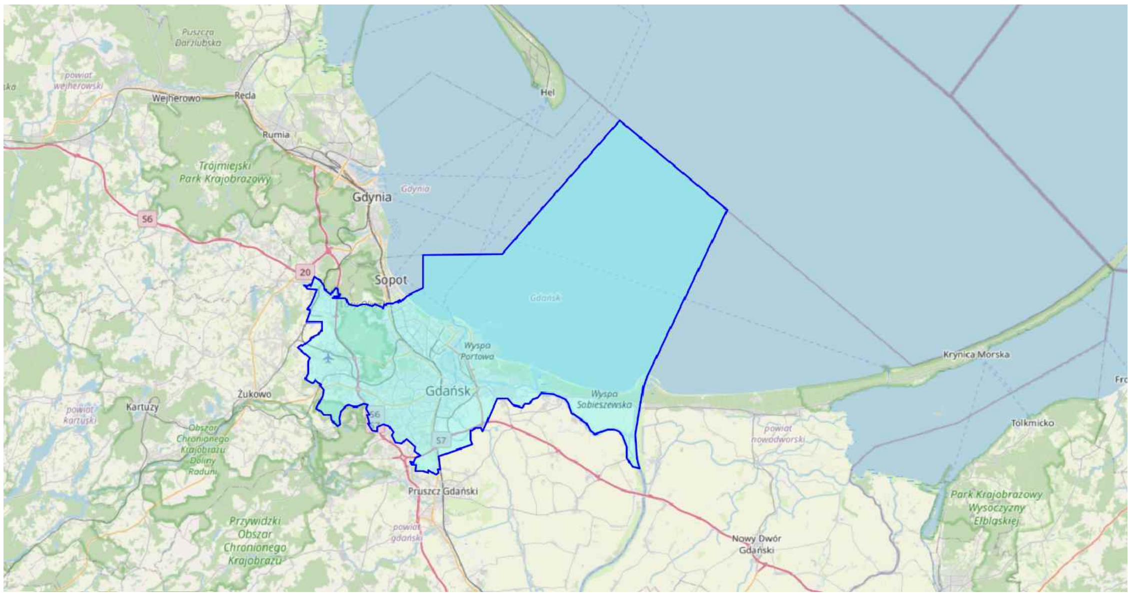
4 GEOAPIFY approach

Nakladanie granic wiekszych miejscowosci, aby pozbyc sie zbednych pinezek jak np dzielnice W ten sposób wyelminowane będa tylko pinezki zawierajace się w innych miejscowościach.

4.0.1 Testing Gdansk borders on map

[ ]:
```
import requests
import folium

API_KEY = "75c3d3b386d541dc8513254d3ec79539"
city_name = "Gdańsk, Poland"

geocode_url = f"https://api.geoapify.com/v1/geocode/search?
↪text={city_name}&type=city&format=json&apiKey={API_KEY}"
response = requests.get(geocode_url)
data = response.json()

if "results" in data and len(data["results"]) > 0:
    place_id = data["results"][0]["place_id"]
    print("Place ID:", place_id)
else:
    print("City not found!")

# url = f"https://api.geoapify.com/v1/boundaries"
url = f"https://api.geoapify.com/v2/place-details"

params = {
    "id": place_id,
    # "lat": "50.93755",
    # "lon": "23.34217",
    "geometry": "geometry_1000",
    "apiKey": "75c3d3b386d541dc8513254d3ec79539"
}

response = requests.get(url, params=params)

print(response.json())

# Reverse longitude and latitude for folium
polygon_coords = [(lat, lon) for lon, lat in response.
↪json()["features"][0]["geometry"]["coordinates"][0]]


print('Polygon: %s' % polygon_coords[:10])

# Add the polygon to the map
borders_map = folium.Map(location=[52.0, 19.0], zoom_start=6)

folium.Polygon(
    locations=polygon_coords,
    color="blue",
```

```
    weight=2,
    fill=True,
    fill_color="cyan",
    fill_opacity=0.4,
).add_to(borders_map)

# Save and display the map
borders_map.save("gdansk_polygon_map.html")
```



4.1 Experimenting with different Geoapify endpoint

[108]:
```
import requests
import folium
import pandas as pd

API_KEY = "75c3d3b386d541dc8513254d3ec79539"

# List of PPLA and PPLC cities
cities = ["Warsaw", "Gdańsk", "Kraków", "Łódź", "Wrocław", "Poznań"]  # Add␣
↪more cities as needed

# Function to get city boundary using v2/place-details
def get_city_boundary(city_name):
    # Step 1: Get the Place ID for the city
    geocode_url = f"https://api.geoapify.com/v1/geocode/search?
↪text={city_name}&type=city&format=json&apiKey={API_KEY}"
    response = requests.get(geocode_url)
    data = response.json()
```

```python
    if "results" in data and len(data["results"]) > 0:
        place_id = data["results"][0]["place_id"]
    else:
        print(f"City {city_name} not found!")
        return None

    # Step 2: Fetch city boundary using v2/place-details
    boundary_url = f"https://api.geoapify.com/v2/place-details?
↪id={place_id}&apiKey={API_KEY}"
    response = requests.get(boundary_url)
    boundary_data = response.json()

    if "features" in boundary_data and len(boundary_data["features"]) > 0:
        geometry = boundary_data["features"][0]["geometry"]
        if geometry["type"] == "MultiPolygon":
            polygons = [[(lat, lon) for lon, lat in poly[0]] for poly in␣
↪geometry["coordinates"]]
        else:
            polygons = [[(lat, lon) for lon, lat in geometry["coordinates"][0]]]
        return polygons
    else:
        print(f"No boundary data found for {city_name}")
        return None

# Create map centered on Poland
borders_map = folium.Map(location=[52.0, 19.0], zoom_start=6)

# Store boundaries in a DataFrame
boundaries = []

# Fetch and overlay city boundaries
for city in cities:
    city_polygons = get_city_boundary(city)
    if city_polygons:
        for polygon in city_polygons:
            folium.Polygon(
                locations=polygon,
                color="blue",
                weight=2,
                fill=True,
                fill_color="cyan",
                fill_opacity=0.4,
                tooltip=city
            ).add_to(borders_map)
        boundaries.append({"City": city, "Polygons": city_polygons})

# Save boundaries as DataFrame
```

```
df_boundaries = pd.DataFrame(boundaries)

# Save and display the map
borders_map.save("poland_cities_boundaries.html")
```

4.2 Fetching city borders for all selected cities

[ ]:
```
import requests
import folium
import pandas as pd
import time

API_KEY = "75c3d3b386d541dc8513254d3ec79539"

# Filter cities that are PPLC, PPLA, or PPLA2
df_cities = df_pol[df_pol["feature_code"].isin(["PPLC", "PPLA", "PPLA2"])]

# Function to get city boundary using v2/place-details
def get_city_boundary(city_name):
    try:
        # Step 1: Get the Place ID for the city
        geocode_url = f"https://api.geoapify.com/v1/geocode/search?
↪text={city_name}&type=city&format=json&apiKey={API_KEY}"
        response = requests.get(geocode_url)
        data = response.json()

        if "results" in data and len(data["results"]) > 0:
            place_id = data["results"][0]["place_id"]
        else:
            print(f"  City {city_name} not found!")
            return None

        # Step 2: Fetch city boundary using v2/place-details
        boundary_url = f"https://api.geoapify.com/v2/place-details?
↪id={place_id}&apiKey={API_KEY}"
        response = requests.get(boundary_url)
        boundary_data = response.json()

        if "features" in boundary_data and len(boundary_data["features"]) > 0:
            geometry = boundary_data["features"][0]["geometry"]
            if geometry["type"] == "MultiPolygon":
                polygons = [[(lat, lon) for lon, lat in poly[0]] for poly in␣
↪geometry["coordinates"]]
            else:
                polygons = [[(lat, lon) for lon, lat in␣
↪geometry["coordinates"][0]]]
```

```
            return polygons
        else:
            print(f"  No boundary data found for {city_name}")
            return None
    except Exception as e:
        print(f"  Error fetching {city_name}: {e}")
        return None

# Create map centered on Poland
borders_map = folium.Map(location=[52.0, 19.0], zoom_start=6)

# Store boundaries in a DataFrame
boundaries = []

# Fetch and overlay city boundaries
for index, row in df_cities.iterrows():
    city_name = row["name"]
    print(f"  Fetching boundary for: {city_name}...")

    city_polygons = get_city_boundary(city_name)

    if city_polygons:
        for polygon in city_polygons:
            folium.Polygon(
                locations=polygon,
                color="blue",
                weight=2,
                fill=True,
                fill_color="cyan",
                fill_opacity=0.4,
                tooltip=city_name
            ).add_to(borders_map)

        boundaries.append({"City": city_name, "Polygons": city_polygons})

    time.sleep(1)  # Avoid exceeding API rate limits

# Save boundaries as DataFrame
df_boundaries = pd.DataFrame(boundaries)

df_boundaries.to_csv('df_boundaries.csv')

# Save and display the map
borders_map.save("poland_cities_boundaries.html")
```

4.2.1 Połaczenie mapy z df_pol oraz df_boundaries

```
[ ]: # Create map centered on Poland
borders_map = folium.Map(location=[52.0, 19.0], zoom_start=6)
df_cities = df_pol[df_pol["feature_code"].isin(["PPLC", "PPLA", "PPLA2"])].
 ↪copy()
df_boundaries = pd.read_csv('df_boundaries.csv')
```

```
[ ]: # Merge only with PPLC, PPLA, and PPLA2
df_cities = df_cities.merge(df_boundaries, on="name", how="left")

# Filter out cities that were in df_cities from df_pol_copy
df_remaining = df_pol[~df_pol["feature_code"].isin(["PPLC", "PPLA", "PPLA2"])]

# Concatenate back the updated df_cities with the rest of df_pol_copy
df_pol = pd.concat([df_remaining, df_cities])

# Save the updated dataframe
df_pol.to_csv('df_pol_with_boundaries.csv', index=False)

# Save and display the map
borders_map.save("poland_cities_boundaries.html")

print("  Updated df_pol saved as 'df_pol_with_boundaries.csv'")
print("  Map saved as 'poland_cities_boundaries.html'")
```

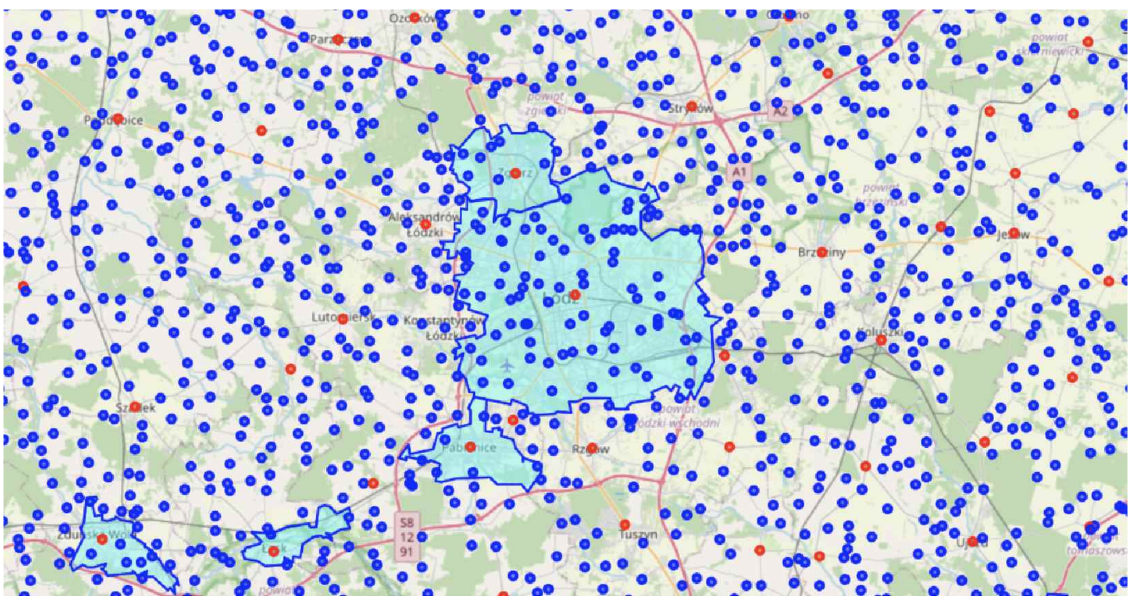
4.3 Mapowanie pinezek i granic

```
[ ]: import folium
import pandas as pd
import math
import ast

def get_marker_radius(population):
    if population is None or population <= 0:
        return 3
    if population < 1000:
        return 3
    elif population < 50000:
        return 3 + (population - 1000) / (50000 - 1000) * (8 - 3)
    elif population < 200000:
        return 8 + (population - 50000) / (200000 - 50000) * (12 - 8)
    else:
        return 12


def generate_map(df, output_html="map.html", draw_lines=False):
```

```python
    """
    Generates a Folium map with:
      - A background layer for connection lines (if draw_lines is True)
      - Markers for each city (colored and sized by feature_code/population)
      - Polygons if available in the 'polygons' column
      - Optionally, if draw_lines is True, draws assigned connection lines
        from non-metro towns to their assigned metros in a separate␣
↪FeatureGroup.
    """
    # Build a lookup dictionary: geonameid -> (latitude, longitude)
    geonameid_to_coords = {}
    for _, row in df.iterrows():
        try:
            key = int(row["geonameid"])
        except ValueError:
            continue
        geonameid_to_coords[key] = (row["latitude"], row["longitude"])

    # Create the base map, centered on the average lat/lon
    mean_lat = df["latitude"].mean()
    mean_lon = df["longitude"].mean()
    m = folium.Map(location=[mean_lat, mean_lon], zoom_start=6)


    # Plot markers and polygons for each city.
    for idx, row in df.iterrows():
        lat = row["latitude"]
        lon = row["longitude"]
        feature_code = str(row["feature_code"])
        name = row["name"]
        population = row.get("population", 0)
        admin1_code = row.get("admin1_code", "")
        admin2_code = row.get("admin2_code", "")
        admin3_code = row.get("admin3_code", "")

        # Determine marker color
        if feature_code.startswith("PPLA"):
            color = "red"
        elif feature_code == "PPLC":
            color = "green"
        else:
            color = "blue"

        radius_value = get_marker_radius(population)

        # Build basic tooltip text.
        tooltip_text = (
```

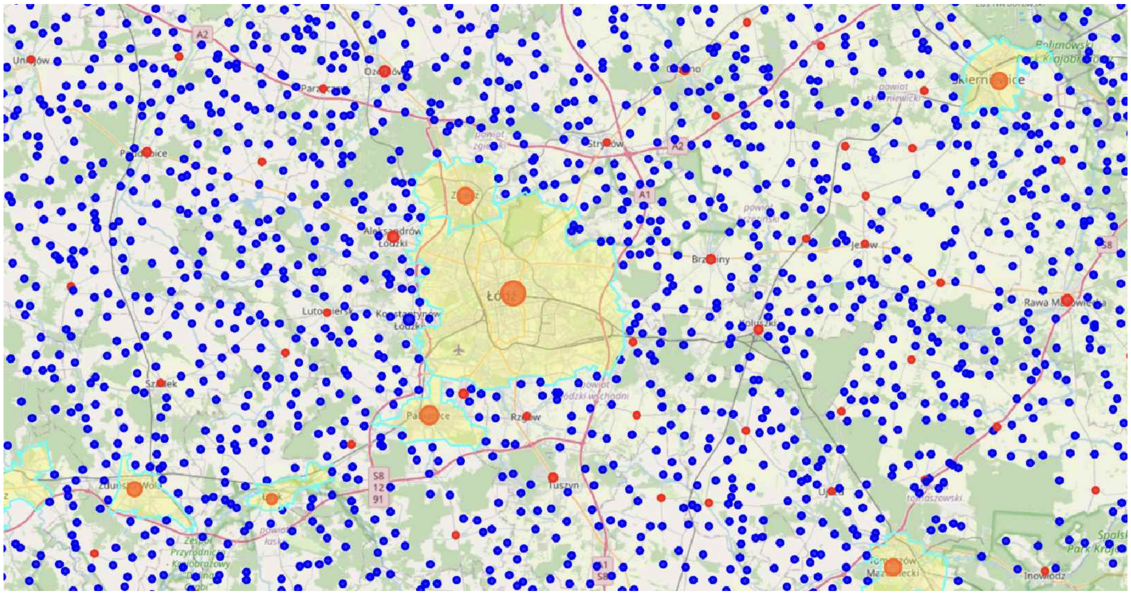
```
            f"City: {name}<br>"
            f"Population: {population}<br>"
            f"Feature: {feature_code}<br>"
            f"Admin1: {admin1_code}, Admin2: {admin2_code}, Admin3: {admin3_code}"
        )

        # Add the marker.
        folium.CircleMarker(
            location=[lat, lon],
            radius=radius_value,
            color=color,
            fill=True,
            fill_color=color,
            fill_opacity=0.8,
            tooltip=tooltip_text
        ).add_to(m)

        # Overlay polygons if present.
        polygons = row.get("polygons", None)
        if isinstance(polygons, list) and len(polygons) > 0:
            for poly in polygons:
                folium.Polygon(
                    locations=poly,
                    color="cyan",
                    weight=2,
                    fill=True,
                    fill_color="yellow",
                    fill_opacity=0.3,
                    tooltip=tooltip_text
                ).add_to(m)

    m.save(output_html)
    print(f"Map saved to {output_html}")


def safe_parse_polygons(val):
    """
    Safely parse the 'polygons' column from the CSV.
    Returns a list of polygon coordinates or an empty list if parsing fails.
    """
    # If it's NaN or empty
    if pd.isna(val):
        return []
    # If it's already a list (rare in CSV, but possible if it was saved in some way)
    if isinstance(val, list):
```

```python
        return val
    # If it's a string, try literal_eval
    if isinstance(val, str):
        try:
            parsed = ast.literal_eval(val)
            # Ensure parsed is a list of polygon coords
            if isinstance(parsed, list):
                return parsed
            else:
                return []
        except Exception:
            return []
    # If none of the above, return empty
    return []

if __name__ == "__main__":
    df = pd.read_csv(
        "data/processed/final_with_metropolis_assignment.csv",
        converters={
            "polygons": safe_parse_polygons
        }
    )

    # Generate the map with draw_lines enabled.
    generate_map(df, output_html="data/cities_map_nolines.html")
```



4.4 Usuwanie pinezek w obrebie granic

[ ]:
```python
# scripts/remove_nested_points.py

import os
import sys
import pandas as pd

# Make sure Python can see the src folder
BASE_DIR = os.path.dirname(os.path.dirname(__file__))
sys.path.append(BASE_DIR)

from src.pipeline.polygon_utils import create_multipolygon_from_borders,␣
↪filter_points_outside_polygons


# 1. Read the CSV with boundaries, e.g. final_PL_with_boundaries.csv
csv_path = os.path.join(BASE_DIR, "data", "processed",␣
↪"final_PL_with_boundaries.csv")
df = pd.read_csv(csv_path)
print(f"Loaded {len(df)} rows from {csv_path}")

# 2. Split into df_borders (has polygons) and df_rest
df_borders = df[df["polygons"].notna()].copy()
df_rest = df[df["polygons"].isna()].copy()
print(f"{len(df_borders)} rows have polygon data.")
print(f"{len(df_rest)} rows have no polygon data.")

# 3. Create a MultiPolygon
mpoly = create_multipolygon_from_borders(df_borders)

# 4. Filter out df_rest points that are inside polygons
df_rest_filtered = filter_points_outside_polygons(df_rest, mpoly)
print(f"{len(df_rest_filtered)} rows remain after removing those inside␣
↪polygons.")

# 5. Combine them back if you like, or just keep df_rest_filtered
df_final = pd.concat([df_borders, df_rest_filtered], ignore_index=True)
print(f"Final DataFrame has {len(df_final)} rows.")

# 6. Save result
output_path = os.path.join(BASE_DIR, "data", "processed", "final_without_nested.
↪csv")
df_final.to_csv(output_path, index=False)
print(f"Saved final data to {output_path}")
```



A2
A1
S8
12
91
Aleksandrów
Łódzki
Tuszyn
Jeżów
Inowłódz