Sample solutions (GT+VMM)

Final exam, Fall 2020: The legacy of "redlining"

> *Version 1.1 (added notes to the epilogue; no code changes)*

This problem builds on your knowledge of the Python data stack to do analyze data that contains geographic information. It has **6** exercises, nu **5**. There are **13 available points.** However, to earn 100%, the threshold is just **10 points.** (Therefore, once you hit **10** points, you can stop. Ther credit for exceeding this threshold.)

Each exercise builds logically on the previous one, but you may solve them in any order. That is, if you can't solve an exercise, you can still mov the next one. **However, if you see a code cell introduced by the phrase, "Sample result for ...", please run it.** Some demo cells in the notel depend on these precomputed results.

The point values of individual exercises are as follows:

- Exercise 0: 2 points
- Exercise 1: 3 points
- Exercise 2: 2 points
- Exercise 3: 2 points
- Exercise 4: 2 points
- Exercise 5: 2 points

Pro-tips.

- All test cells use **randomly generated inputs.** Therefore, try your best to write solutions that do not assume too much. To help you debug, test cell does fail, it will often tell you exactly what inputs it was using and what output it expected, compared to yours.
- If you need a complex SQL query, remember that you can define one using a triple-quoted (multiline) string (https://docs.python.org/3.7/tutorial/introduction.html#strings).
- If your program behavior seem strange, try resetting the kernel and rerunning everything.
- If you mess up this notebook or just want to start from scratch, save copies of all your partial responses and use `Actions` → `Reset Ass` to get a fresh, original copy of this notebook. *(Resetting will wipe out any answers you've written so far, so be sure to stash those somewhe you intend to keep or reuse them!)*
- If you generate excessive output (e.g., from an ill-placed `print` statement) that causes the notebook to load slowly or not at all, use `Acti` `Clear Notebook Output` to get a clean copy. The clean copy will retain your code but remove any generated output. **However**, it will a **rename** the notebook to `clean.xxx.ipynb`. Since the autograder expects a notebook file with the original name, you'll need to rename t notebook accordingly.

Good luck!

Background

During the economic Great Depression of the 1930s, the United States government began "rating" neighborhoods, on a letter-grade scale of "A "D" ("bad"). The purpose was to use such grades to determine which neighborhoods would qualify for new investments, in the form of resident business loans.

But these grades also reflected racial and ethnic bias toward the residents of their neighborhoods. Nearly 100 years later, the effects have taken environmental and economic disparaties.

In this notebook, you will get an idea of how such an analysis can come together using publicly available data and the basic computational dat techniques that appeared in this course. (And after you finish the exam, we hope you will try the optional exercise at the end and refer to the "e related reading.)

Goal and workflow. Your goal is to see if there is a relationship between the rating a neighborhood received in the 1930s and two attributes we today: the average temperature of a neighborhood and the average home price.

- Temperature tells you something about the local environment. Areas with more parks, trees, and green space tend to experience more mod temperatures.
- The average home price tells you something about the wealth or economic well-being of the neighborhood's residents.

Your workflow will consist of the following steps:

1. You'll start with neighborhood rating data, which was collected from public records as part of a University of Richmond study on redlining (https://dsl.richmond.edu/panorama/redlining)
2. You'll then combine these data with satellite images, which give information about climate. These data come from the US Geological Surve (https://usgs.gov/).
3. Lastly, you'll merge these data with home prices from the real estate website, Zillow (https://zillow.com).

> Note: The analysis you will perform is correlational, but the deeper research that inspired this problem tries to control for a variety of fac

Note: The analysis you will perform is correlational, but the deeper research that inspired this problem tries to control for a variety of fac and suggests causal effects.

Part 0: Setup

At a minimum, you will need the following modules in this problem. They include a new one we did not cover called `geopandas`. While it may b if you have mastered `pandas`, then you know almost everything you need to use `geopandas`. Anything else you need will be given to you as p problem, so don't be intimidated!

In [1]:
```
import sys
print(f"* Python version: {sys.version}")

# Standard packages you know and love:
import pandas as pd
import numpy as np
import scipy as sp
import matplotlib.pyplot as plt

import geopandas
print("* geopandas version:", geopandas.__version__)
```

```
* Python version: 3.7.5 (default, Dec 18 2019, 06:24:58)
[GCC 5.5.0 20171010]
* geopandas version: 0.6.2
```

Run the next code cell, which will load some tools needed by the test cells.

In [2]:
```
### BEGIN HIDDEN TESTS
%load_ext autoreload
%autoreload 2
### END HIDDEN TESTS

from testing_tools import data_fn, load_geopandas, load_df, load_pickle
from testing_tools import f_ex0__sample_result
from testing_tools import f_ex1__sample_result
from testing_tools import f_ex2__sample_result
from testing_tools import f_ex3__sample_result
from testing_tools import f_ex4__sample_result
from testing_tools import f_ex5__sample_result
```

Part 1: Neighborhood ratings

The neighborhood rating data is stored in a special extension of a pandas `DataFrame` called a `GeoDataFrame`. Let's load the data into a varia `neighborhood_ratings` and have a peek at the first few rows:

In [3]:
```
neighborhood_ratings = load_geopandas('fullDownload.geojson')
print(type(neighborhood_ratings))
neighborhood_ratings.head()
```

```
Opening geopandas data file, './resource/asnlib/publicdata/fullDownload.geojson' ...
<class 'geopandas.geodataframe.GeoDataFrame'>
```

Out[3]:

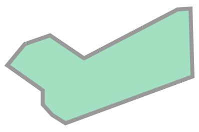
	state	city	name	holc_id	holc_grade	area_description_data	geometry
0	AL	Birmingham	Mountain Brook Estates and Country Club Garden...	A1	A	{'5': 'Both sales and rental prices in 1929 we...	MULTIPOLYGON ((33.49754, -86.756
1	AL	Birmingham	Redmont Park, Rockridge Park, Warwick Manor, a...	A2	A	{'5': 'Both sales and rental prices in 1929 we...	MULTIPOLYGON ((33.50933, -86.760
2	AL	Birmingham	Colonial Hills, Pine Crest (outside city limits)	A3	A	{'5': 'Generally speaking, houses are not buil...	MULTIPOLYGON ((33.49754, -86.751
3	AL	Birmingham	Grove Park, Hollywood, Mayfair, and Edgewood s...	B1	B	{'5': 'Both sales and rental prices in 1929 we...	MULTIPOLYGON ((33.48071, -86.800
4	AL	Birmingham	Best section of Woodlawn Highlands	B10	B	{'5': 'Both sales and rental prices in 1929 we...	MULTIPOLYGON ((33.53332, -86.749

Each row is a neighborhood. Its location is given by name, city, and a two-letter state abbreviation code (the `name`, `city`, and `state` columns, The rating assigned to a neighborhood is a letter, `'A'`, `'B'`, `'C'`, or `'D'`, given by the `holc_grade` column.

In addition, there is special column called `geometry`. It contains a geographic outline of the boundaries of this neighborhood. Let's take a look row shown above):

In [4]:
```
g4_example = neighborhood_ratings.loc[4, 'geometry']
print("* Type of `g4_example`:", type(g4_example))
print("\n* Contents of `g4_example`:", g4_example)
print("\n* A quick visual preview:")
display(g4_example)
```

```
* Type of `g4_example`: <class 'shapely.geometry.multipolygon.MultiPolygon'>

* Contents of `g4_example`: MULTIPOLYGON (((-86.749227 33.533325, -86.749156 33.530809, -86.7538
9 33.529075, -86.754373 33.529382, -86.754729 33.529769, -86.754729 33.530294, -86.7560480000000
25, -86.75539499999999 33.532008, -86.754456 33.532335, -86.753196 33.531483, -86.749714 33.5332
49227 33.533325)))

* A quick visual preview:
```



The output indicates that this boundary is stored a special object type called a `MultiPolygon`. It is usually a single connected polygon, but m union of multiple such polygons.

The coordinates of the multipolygon's corners are floating-point values, and correspond to longitude and latitude values (https://www.latlong.n this notebook, the exact format won't be important. Simply treat the shapes as being specified in some way via a collection of two-dimensiona coordinates measured in arbitrary units.

Lastly, observe that calling `display()` on a `MultiPolygon` renders a small picture of it.

Exercise 0: Filtering ratings (2 points)

Complete the function,

```
def filter_ratings(ratings, city_st, targets=None):
    ...
```

so that it filters ratings data by its city and state name, along with a set of targeted letter grades. In particular, the inputs are:

- `ratings`: A geopandas `GeoDataFrame` similar to the `neighborhood_ratings` example above.
- `city_st`: The name of a city and two-letter state abbreviation as a string, e.g., `city_st = 'Atlanta, GA'` to request only rows for Atl Georgia.
- `targets`: A Python set containing zero or more ratings, e.g., `targets = {'A', 'C'}` to request only rows having either an `'A'` grade c grade.

The function should return a copy of the input `GeoDataFrame` that has the same columns as `ratings` but only rows that match *both* the desi value *and* any one of the target ratings.

For example, suppose `ratings` is the following:

	city	state	holc_grade	holc_id	*(... other cols not shown ...)*	geometry
0	Chattanooga	TN	C	C4	...	MULTIPOLYGON(...)
1	Augusta	GA	C	C5	...	MULTIPOLYGON(...)
2	Chattanooga	TN	B	B7	...	MULTIPOLYGON(...)
3	Chattanooga	TN	A	A1	...	MULTIPOLYGON(...)
4	Augusta	GA	B	B4	...	MULTIPOLYGON(...)
5	Augusta	GA	D	D11	...	MULTIPOLYGON(...)
6	Augusta	GA	B	B1	...	MULTIPOLYGON(...)
7	Chattanooga	TN	D	D8	...	MULTIPOLYGON(...)
8	Chattanooga	TN	C	C7	...	MULTIPOLYGON(...)

Then `filter_ratings(ratings, 'Chattanooga, TN', {'A', 'C'})` would return

	city	state	holc_grade	holc_id	*(... other cols not shown ...)*	geometry
0	Chattanooga	TN	C	C4	...	MULTIPOLYGON(...)
3	Chattanooga	TN	A	A1	...	MULTIPOLYGON(...)
8	Chattanooga	TN	C	C7	...	MULTIPOLYGON(...)

All of these rows match `'Chattanooga, TN'` and have a `holc_grade` value of either `'A'` or `'C'`. Other columns, such as `holc_id` and any shown, would be returned as-is from the original input.

Note 0: We will test your function on a randomly generated data frame. The input is guaranteed to have the columns, `'city'`, `'state` `'holc_grade'`, and `'geometry'`. However, it may have other columns with arbitrary names; your function should ensure these pass through unchanged, including the types.

Note 1: Observe that `targets` may be `None`, which is the default value if unspecified by the caller. In this case, you should *not* filter b rating, but only by `city_st`. The `targets` variable may be the empty set, in which case your function should return an empty `GeoDataFrame`.

Note 2: You may return the rows in any order. We will use a function similar to `tibbles_are_equivalent` from Notebook 7 to deter your output matches what we expect.

In [5]:
```
def filter_ratings(ratings, city_st, targets=None):
    assert isinstance(ratings, geopandas.GeoDataFrame)
    assert isinstance(targets, set) or (targets is None)
    assert {'city', 'state', 'holc_grade', 'geometry'} <= set(ratings.columns)
    ### BEGIN SOLUTION
    matches_city_st = (ratings['city'] + ', ' + ratings['state']) == city_st
    matches_targets = ratings['holc_grade'].isin(targets or set()) | (targets is None)
    return ratings[matches_city_st & matches_targets]
    ### END SOLUTION
```

In [6]:
```
# Demo cell
ex0_demo_result = filter_ratings(neighborhood_ratings, 'Atlanta, GA', targets={'A', 'C'})
print(type(ex0_demo_result), len(ex0_demo_result)) # Result: `<class 'geopandas.geodataframe.Ge
e'> 51`

ex0_demo_result.sample(5)
```

```
<class 'geopandas.geodataframe.GeoDataFrame'> 51
```

Out[6]:

	state	city	name	holc_id	holc_grade	area_description_data	geometry
1325	GA	Atlanta	Brookhaven and Brookhaven Heights (outside cit...	C2	C	{'0': 'Atlanta, Georgia', '5': 'Property if ac...	MULTIPOLYGON (((-33.85356, -84.3448
1327	GA	Atlanta	Melrose and Drexel Avenue section (in DeKalb C...	C21	C	{'0': 'Atlanta, Georgia', '5': 'Property if ac...	MULTIPOLYGON (((-33.77060, -84.3072
1318	GA	Atlanta	Hancock subdivision, Atkins Park, western edge...	C13	C	{'0': 'Atlanta, Georgia', '5': 'Property if ac...	MULTIPOLYGON (((-33.78501, -84.3432
1314	GA	Atlanta	Buckhead Section (outside city)	C1	C	{'0': 'Atlanta, Georgia', '5': 'Area contains ...	MULTIPOLYGON (((-33.83427, -84.3813
1333	GA	Atlanta	Federal Prison area	C27	C	{'0': 'Atlanta, Georgia. ', '5': 'Property if ...	MULTIPOLYGON (((-33.72186, -84.3771

In [7]:
```
# Test cell: f_ex0__filter_ratings (2 points)

### BEGIN HIDDEN TESTS
def f_ex0__gen_soln(grade=None, fn_base="atl", fn_ext="geojson", overwrite=False):
    from testing_tools import file_exists, load_geopandas, save_geopandas
    if grade is None:
        fn = f"{fn_base}.{fn_ext}"
        targets = None
    else:
        fn = f"{fn_base}-{grade}.{fn_ext}"
        targets = {grade}
    if file_exists(fn) and not overwrite:
        gdf = load_geopandas(fn)
    else: # not file_exists(fn) or overwrite
        gdf = filter_ratings(neighborhood_ratings, 'Atlanta, GA', targets=targets)
        save_geopandas(gdf, fn, overwrite=overwrite)
    return gdf

for g_ex0 in [None, 'A', 'B', 'C', 'D']:
    f_ex0__gen_soln(grade=g_ex0, overwrite=False)
### END HIDDEN TESTS

from testing_tools import f_ex0__check
print("Testing...")
for trial in range(125):
    f_ex0__check(filter_ratings)

filter_ratings__passed = True
print("\n(Passed!)")
```

```
Opening geopandas data file, './resource/asnlib/publicdata/atl.geojson' ...
Opening geopandas data file, './resource/asnlib/publicdata/atl-A.geojson' ...
Opening geopandas data file, './resource/asnlib/publicdata/atl-B.geojson' ...
Opening geopandas data file, './resource/asnlib/publicdata/atl-C.geojson' ...
Opening geopandas data file, './resource/asnlib/publicdata/atl-D.geojson' ...
Testing...
```

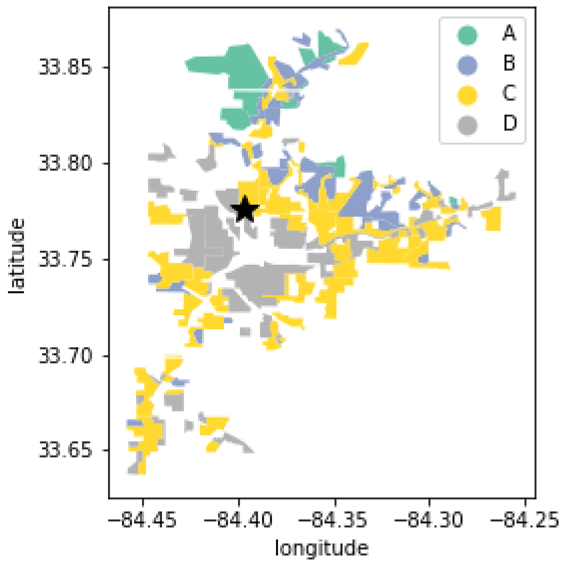
```
(Passed!)
```

Sample result of `filter_ratings` (Exercise 0) for Atlanta. If you had a working solution to Exercise 0, then in principle you could use it to v neighborhoods, color-coded by grade, as the following cell does for `'Atlanta, GA'`.

> **Run this cell even if you did not complete Exercise 0.**

In [8]:
```
f_ex0__sample_result(); # The black "star" is Georgia Tech!
```

```
Opening geopandas data file, './resource/asnlib/publicdata/atl.geojson' ...
```



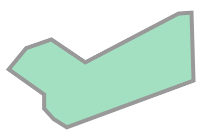
Bounding boxes

Recall that a geopandas dataframe includes a `'geometry'` column, which defines the geographic shape of each neighborhood using special r objects. To simplify some geometric calculations, a useful operation is to determine a multipolygon's *bounding box*, which is the smallest recta encloses it.

Getting a bounding box is easy! For example, recall the neighborhood in row 4 of the `neighborhood_ratings` geopandas dataframe:

In [9]:
```
g4_example = neighborhood_ratings.loc[4, 'geometry']
print("* Type of `g4_example`:", type(g4_example))
print("\n* Contents of `g4_example`:", g4_example)
print("\n* A quick visual preview:")
display(g4_example)
```

```
* Type of `g4_example`: <class 'shapely.geometry.multipolygon.MultiPolygon'>

* Contents of `g4_example`: MULTIPOLYGON (((-86.749227 33.533325, -86.749156 33.530809, -86.7538
9 33.529075, -86.754373 33.529382, -86.754729 33.529769, -86.754729 33.530294, -86.75604800000(
25, -86.75539499999999 33.532008, -86.754456 33.532335, -86.753196 33.531483, -86.749714 33.5332
49227 33.533325)))

* A quick visual preview:
```



The bounding box is given to you by the multipolygon's `.bounds` attribute. This attribute is a Python 4-tuple (tuple with four components) that the lower-left corner and the upper-right corner of the shape. Here is what that tuple looks like for the previous example:

In [10]:
```
print("* Recall: `g4_example` ==", g4_example)
print("\n* ==> `g4_example.bounds` ==", g4_example.bounds)
```

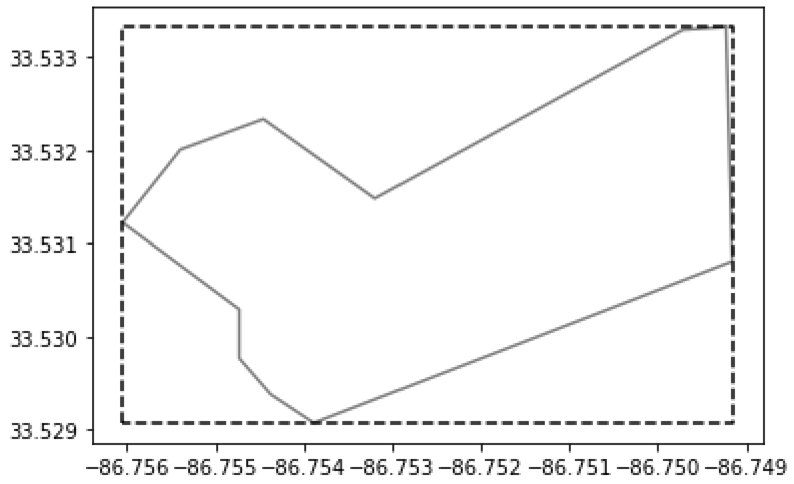
```
* Recall: `g4_example` == MULTIPOLYGON (((-86.749227 33.533325, -86.749156 33.530809, -86.75388
33.529075, -86.754373 33.529382, -86.754729 33.529769, -86.754729 33.530294, -86.75604800000001
5, -86.75539499999999 33.532008, -86.754456 33.532335, -86.753196 33.531483, -86.749714 33.5332
9227 33.533325)))

* ==> `g4_example.bounds` == (-86.756048, 33.529075, -86.749156, 33.533325)
```

The first two elements of the tuple are the smallest possible x-value and the smallest possible y-value among all points of the multipolygon. Th elements are the largest x-value and y-value.

If it's helpful, here is a plot that superimposes the bounding box on `g4_example`:

In [11]:
```
# Draw the multipolygon as a solid gray line:
from testing_tools import plot_multipolygon, plot_bounding_box
```

```
from testing_tools import plot_multipolygon, plot_bounding_box
plot_multipolygon(g4_example, color='gray')

# Add the bounding box as a dashed black line:
plot_bounding_box(g4_example.bounds, color='black', linestyle='--')
```



Exercise 1: Bounding box of *all* neighborhoods (3 points)

Complete the function, `get_bounds(gdf)`, below, so that it returns the coordinates of a single bounding box for *all* neighborhoods in a given

For example, suppose `gdf_ex1_demo` holds rows 3 and 4 of the `neighborhood_ratings` dataframe:

In [12]:
```
gdf_ex1_demo = neighborhood_ratings.loc[[3, 4]]
gdf_ex1_demo
```

Out[12]:

	state	city	name	holc_id	holc_grade	area_description_data	geometry
3	AL	Birmingham	Grove Park, Hollywood, Mayfair, and Edgewood s...	B1	B	{'5': 'Both sales and rental prices in 1929 we...	MULTIPOLYGON ((33.48071, -86.800
4	AL	Birmingham	Best section of Woodlawn Highlands	B10	B	{'5': 'Both sales and rental prices in 1929 we...	MULTIPOLYGON ((33.53332, -86.749

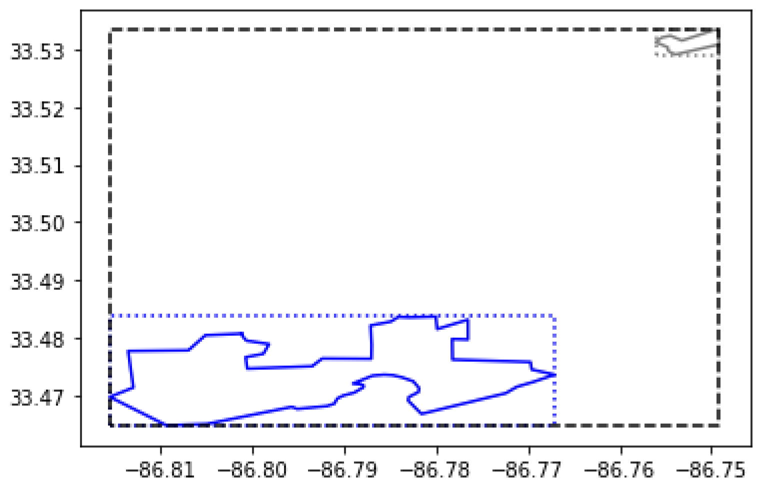
This dataframe has these bounds for each of the two rows:

In [13]:
```
print(gdf_ex1_demo.loc[3, 'geometry'].bounds)
print(gdf_ex1_demo.loc[4, 'geometry'].bounds)
```

```
(-86.815458, 33.464794, -86.767064, 33.483678)
(-86.756048, 33.529075, -86.749156, 33.533325)
```

Therefore, the bounding box for `gdf_ex1_demo` is the smallest rectangle that covers both neighborhoods, or `(-86.815458, 33.464794, - 33.533325)`. The next code cell illustrates the result.

In [14]:
```
plot_multipolygon(gdf_ex1_demo.loc[3, 'geometry'], color='blue')
plot_bounding_box(gdf_ex1_demo.loc[3, 'geometry'].bounds, color='blue', linestyle=':')
plot_multipolygon(gdf_ex1_demo.loc[4, 'geometry'], color='gray')
plot_bounding_box(gdf_ex1_demo.loc[4, 'geometry'].bounds, color='gray', linestyle=':')

gdf_ex1_demo_bounding_box = (-86.815458, 33.464794, -86.749156, 33.533325)
plot_bounding_box(gdf_ex1_demo_bounding_box, color='black', linestyle='--')
```



The plot shows two multipolygons, along with the bounding box around each one as dotted lines. Your function should return a single boundin multipolygons, which we show as the dashed black line that encloses both.

> **Note 0:** The test cell will use randomly generated input data frames. Per the example above, your solution should only depend on the presence of a column named `'geometry'`, and should return a correct result no matter what other columns are present in the input.
>
> **Note 1:** We've provided a partial solution that handles the corner-case of an empty input dataframe, so your solution can focus on dataframes having at least one row.

dataframes having at least one row.

In [15]:
```
def get_bounds(gdf):
    assert isinstance(gdf, geopandas.GeoDataFrame)
    if len(gdf) == 0:
        return None
    assert len(gdf) >= 1
    ### BEGIN SOLUTION
    return (gdf['geometry'].apply(lambda x: x.bounds[0]).min(),
            gdf['geometry'].apply(lambda x: x.bounds[1]).min(),
            gdf['geometry'].apply(lambda x: x.bounds[2]).max(),
            gdf['geometry'].apply(lambda x: x.bounds[3]).max())
    ### END SOLUTION
```

In [16]:
```
# Demo cell
your_gdf_ex1_demo_bounding_box = get_bounds(gdf_ex1_demo)
print("Your result on the demo dataframe:", your_gdf_ex1_demo_bounding_box)
print("Expected result:", gdf_ex1_demo_bounding_box)

assert all([np.isclose(a, b) for a, b in zip(your_gdf_ex1_demo_bounding_box,
                                             gdf_ex1_demo_bounding_box)]), \
       "*** Your result does not match our example! ***"
print("Great -- so far, your result matches our expected result.")
```

```
Your result on the demo dataframe: (-86.815458, 33.464794, -86.749156, 33.533325)
Expected result: (-86.815458, 33.464794, -86.749156, 33.533325)
Great -- so far, your result matches our expected result.
```

In [17]:
```
# Test cell: f_ex1__get_bounds (3 points)

### BEGIN HIDDEN TESTS
def f_ex1__gen_soln(fn_base="atl-bb", fn_ext="pickle", overwrite=False):
    from testing_tools import file_exists, load_pickle, save_pickle
    fn = f"{fn_base}.{fn_ext}"
    if file_exists(fn) and not overwrite:
        bounds = load_pickle(fn)
    else:
        gdf = f_ex0__gen_soln()
        bounds = get_bounds(gdf)
        save_pickle(bounds, fn)
    return bounds

f_ex1__gen_soln(overwrite=False)
### END HIDDEN TESTS

from testing_tools import f_ex1__check
print("Testing...")
for trial in range(250):
    f_ex1__check(get_bounds)

print("\n(Passed!)")
```

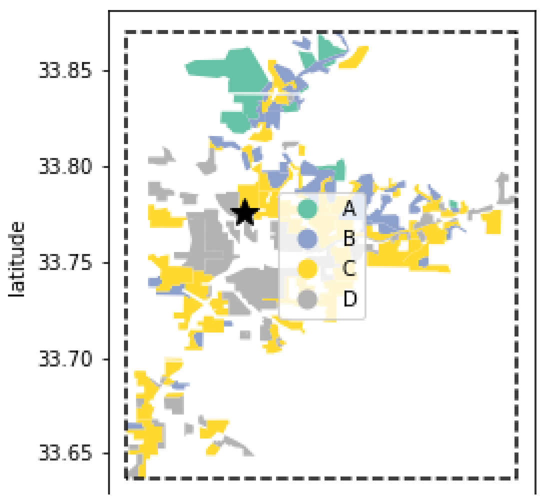
```
Opening pickle from './resource/asnlib/publicdata/atl-bb.pickle' ...
Testing...

(Passed!)
```

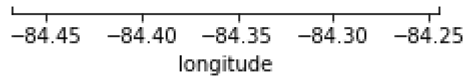
Sample result of `get_bounds` (Exercise 1) for Atlanta. If your function was working, then you could calculate the bounding box for Atlanta, w be the following.

Run this cell even if you did not complete Exercise 1.

In [18]:
```
_, _, f_ex1__atl_bounds = f_ex1__sample_result();
print(f"Bounding box for Atlanta: {f_ex1__atl_bounds}")
```

```
Opening geopandas data file, './resource/asnlib/publicdata/atl.geojson' ...
Opening pickle from './resource/asnlib/publicdata/atl-bb.pickle' ...
Bounding box for Atlanta: (-84.457945, 33.637042, -84.254692, 33.869701)
```





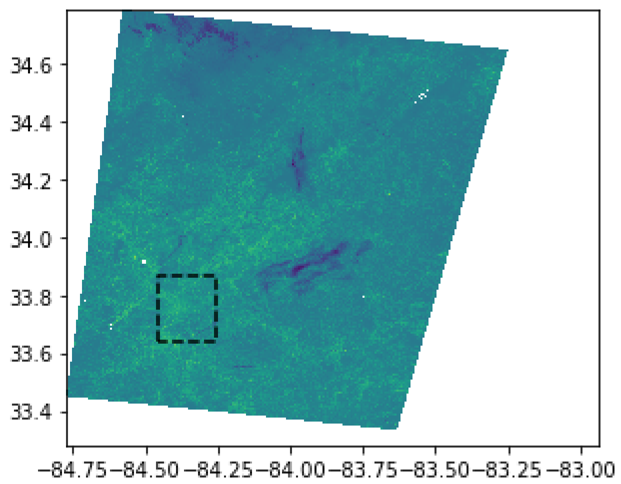
Part 2: Temperature analysis

We have downloaded satellite images that cover some of the cities in the `neighborhood_ratings` dataset. Each pixel of an image is the esti temperature at the earth's surface. The images we downloaded were taken by the satellite on a summer day.

Here is an example of a satellite image that includes the Atlanta, Georgia neighborhoods used in earlier examples. The code cell below loads th draws it, and superimposes the Atlanta bounding box. The image is stored in the variable `sat_demo`. The geopandas dataframe for Atlanta is s `gdf_sat_demo`, and its bounding box in `bounds_sat_demo`.

In [19]:
```
from testing_tools import load_satellite_image, plot_satellite_image

# Load a satellite image that includes the Atlanta area
sat_demo = load_satellite_image('LC08_CU_024013_20190808_20190822_C01_V01_ST--EPSG_4326.tif')

fig = plt.figure()
plot_satellite_image(sat_demo, ax=fig.gca())

# Add the bounding box for Atlanta
_, gdf_sat_demo, bounds_sat_demo = f_ex1__sample_result(do_plot=False);
plot_bounding_box(bounds_sat_demo, color='black', linestyle='dashed')
```

```
Opening satellite image, './resource/asnlib/publicdata/LC08_CU_024013_20190808_20190822_C01_V01_
4326.tif' ...
Opening geopandas data file, './resource/asnlib/publicdata/atl.geojson' ...
Opening pickle from './resource/asnlib/publicdata/atl-bb.pickle' ...
```



Masked images: *merging the satellite and neighborhood data.* A really cool feature of a geopandas dataframe is that you can "intersect" its po image!

We wrote a function called `mask_image_by_geodf(img, gdf)` that does this merging for you. It takes as input a satellite image, `img`, and a dataframe, `gdf`. It then clips the image to the bounding box of `gdf`, and masks out all the pixels. By "masking," we mean that pixels falling with multipolygon regions of `gdf` retain their original value; everything outside those regions gets a special "undefined" value.

Here is an example. First, let's call `mask_image_by_geodf` to generate the Numpy array, stored as `sat_demo_masked`:

In [20]:
```
def mask_image_by_geodf(img, gdf):
    from json import loads
    from rasterio.mask import mask
    gdf_json = loads(gdf.to_json())
    gdf_coords = [f['geometry'] for f in gdf_json['features']]
    out_img, _ = mask(img, shapes=gdf_coords, crop=True)
    return out_img[0]

sat_demo_masked = mask_image_by_geodf(sat_demo, gdf_sat_demo)
print(sat_demo_masked.shape)
sat_demo_masked
```

```
(798, 698)
```

Out[20]:
```
array([[-9999, -9999, -9999, ..., -9999, -9999, -9999],
       [-9999, -9999, -9999, ..., -9999, -9999, -9999],
       [-9999, -9999, -9999, ..., -9999, -9999, -9999],
       ...,
       [-9999, -9999,  3167, ..., -9999, -9999, -9999],
       [-9999, -9999, -9999, ..., -9999, -9999, -9999],
       [-9999, -9999, -9999, ..., -9999, -9999, -9999]], dtype=int16)
```

The output shows the clipped result has a shape of 798 x 698 pixels, and the values are 16-bit integers (`dtype=int16`). The first thing you mig bunch of values equal to -9999. That is the special value indicating that the given pixel falls *outside* of any neighborhood polygon.

Any other integer is the estimated surface temperature **in [degrees Kelvin (https://en.wikipedia.org/wiki/Kelvin#2019_redefinition)](https://en.wikipedia.org/wiki/Kelvin#2019_redefinition) multiplie** instance, suppose a pixel has the value `3167` embedded in the sample output above. That is 3167 / 10 = 316.7 degrees Kelvin, which in degree would be 316.7 - 273.15 = 43.55 degrees Celsius. (That, in turn, is approximately (316.7 – 273.15) * 9/5 + 32 = 110.39 degrees Farenheit.)

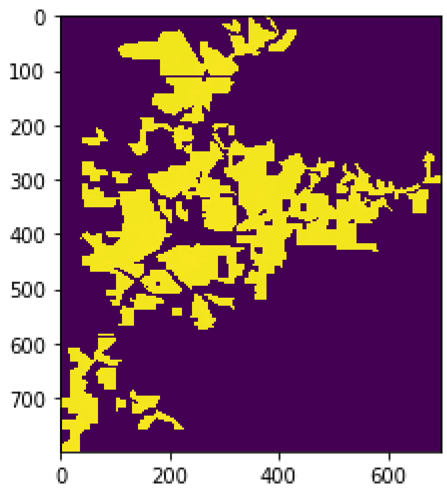
In our analysis, we'd like to inspect the average temperatures of the neighborhoods, **ignoring** the -9999 values.

If it's helpful, here is a picture of that Numpy array. The dark regions correspond to the -9999 values that fall outside the neighborhoods of `gdf`, the bright ones indicate the presence of valid temperatures.

> If they appear to have the same color or shade, it's because the -9999 values make other "real" temperatures look nearly the same.

In [21]:
```
plt.imshow(sat_demo_masked)
```

Out[21]: <matplotlib.image.AxesImage at 0x7fa501179ad0>



Exercise 2: Cleaning masked images (2 points)

To help our analysis, your next task is to clean a masked image, converting its values to degrees Celsius.

In particular, let `masked_array` be any Numpy array holding `int16` values, where the value `-9999` represents masked or missing values, and integer is a temperature in degrees Kelvin times 10. You should complete the function, `masked_to_degC(masked_array)`, so that it returns array having the same shape as `masked_array`, but with the following properties:

- The new array should hold **floating-point** values, not integers. That is, the new Numpy array should have `dtype=float`.
- Every `-9999` value should be converted into a **not-a-number (NaN)** value.
- Any other integer value should be converted to **degrees Celsius.**

For instance, suppose `masked_array` is the following 2-D Numpy array:

```
[[-9999  2950 -9999]
 [-9999  3167  2014]
 [-9999  3075  3222]
 [ 2801 -9999  2416]]
```

Then the output array should have the following values:

```
[[   nan  21.85    nan]
 [   nan  43.55 -71.75]
 [   nan  34.35  49.05]
 [  6.95    nan -31.55]]
```

> **Note 0:** The simplest way to use a NaN value is through the predefined constant, `np.nan` (https://numpy.org/doc/stable/user/misc.htm
>
> **Note 1:** There are three demo cells. Two of them show plots in addition to input/output pairs, in case you work better with visual representations. In the plots, any NaN entries will appear as blanks (white space).
>
> **Note 2:** Your function must work for an input array of *any* dimension greater than or equal to 1. That is, it could be a 1-D array, a 2-D ar (e.g., like true images), or 3-D or higher. Solutions that only work on 2-D arrays will only get half credit (one point instead of two).

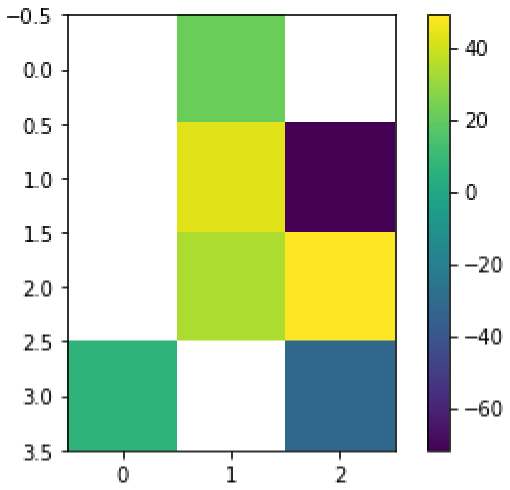
In [22]:
```
# Note:
print(np.nan) # a single NaN value
```

```
nan
```

In [23]:
```
def masked_to_degC(masked_array):
    assert isinstance(masked_array, np.ndarray)
    assert masked_array.ndim >= 1
    assert np.issubdtype(masked_array.dtype, np.integer)
    ### BEGIN SOLUTION
    new_array = masked_array.astype(float)
    new_array[new_array == -9999] = np.nan
    new_array *= 0.1
    new_array -= 273.15
    return new_array
    ### END SOLUTION
```

In [24]:
```
# Demo cell 0:
img_ex2_demo = np.array([[-9999,  2950, -9999],
                         [-9999,  3167, 2014],
                         [-9999,  3075, 3222],
                         [ 2801, -9999, 2416]], dtype=np.int16)

img_ex2_demo_clean = masked_to_degC(img_ex2_demo)

print(img_ex2_demo)
print()
print(img_ex2_demo_clean)
plt.imshow(img_ex2_demo_clean)
plt.colorbar();
```

```
[[-9999  2950 -9999]
 [-9999  3167  2014]
 [-9999  3075  3222]
 [ 2801 -9999  2416]]

[[   nan  21.85    nan]
 [   nan  43.55 -71.75]
 [   nan  34.35  49.05]
 [  6.95    nan -31.55]]
```

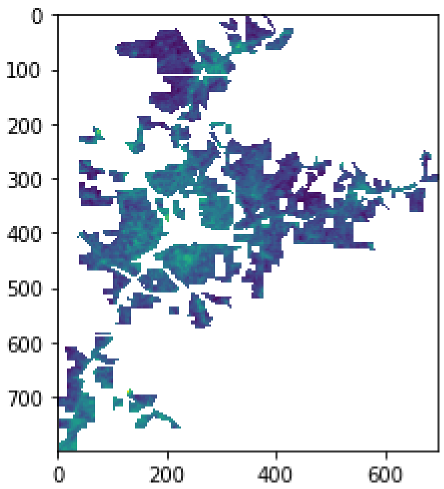


In [25]:
```
# Demo cell 1: Try a 1-D array. Expected output: array([-260.85, nan, -227.55, -194.25, nan])
masked_to_degC(np.array([123, -9999, 456, 789, -9999], dtype=np.int16))
```

Out[25]:
```
array([-260.85,     nan, -227.55, -194.25,     nan])
```

In [26]:
```
# Demo cell 2: Apply to the example satellite image
sat_demo_clean_ex2 = masked_to_degC(sat_demo_masked)
print(sat_demo_clean_ex2)
plt.imshow(sat_demo_clean_ex2);
```

```
[[  nan   nan   nan ...   nan   nan   nan]
 [  nan   nan   nan ...   nan   nan   nan]
 [  nan   nan   nan ...   nan   nan   nan]
 ...
 [  nan   nan 43.55 ...   nan   nan   nan]
 [  nan   nan   nan ...   nan   nan   nan]
 [  nan   nan   nan ...   nan   nan   nan]]
```



In [27]:
```
# Test cell 0: f_ex2__masked_to_degC_2d (1 point)

### BEGIN HIDDEN TESTS
def f_ex2__gen_soln(fn_base="atl-masked-cleaned", fn_ext="pickle", overwrite=False):
    from testing_tools import file_exists, load_pickle, save_pickle
    fn = f"{fn_base}.{fn_ext}"
    if file_exists(fn) and not overwrite:
        img_clean = load_pickle(fn)
    else: # not file_exists(fn) or overwrite
        gdf = f_ex0__gen_soln()
        img = load_satellite_image('LC08_CU_024013_20190808_20190822_C01_V01_ST--EPSG_4326.tif'
        img_masked = mask_image_by_geodf(img, gdf)
        img_clean = masked_to_degC(img_masked)
        save_pickle(img_clean, fn)
    return img_clean
```

```
f_ex2__gen_soln(overwrite=False)
### END HIDDEN TESTS

from testing_tools import f_ex2__check
print("Testing...")
for trial in range(250):
    f_ex2__check(masked_to_degC, ndim=2)

masked_to_degC__passed_2d = True
print("\n(Passed the 2-D case!)")
```

```
Opening pickle from './resource/asnlib/publicdata/atl-masked-cleaned.pickle' ...
Testing...

(Passed the 2-D case!)
```

In [28]:
```
# Test cell 1: f_ex2__masked_to_degC_nd (1 point)

from testing_tools import f_ex2__check
print("Testing...")
for trial in range(250):
    f_ex2__check(masked_to_degC, ndim=None)

print("\n(Passed the any-D case!)")
```

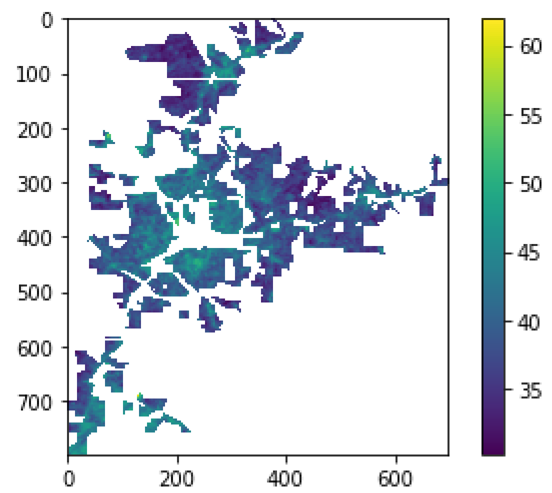
```
Testing...

(Passed the any-D case!)
```

Sample result of `masked_to_degC` (Exercise 2) on the Atlanta data. A correct implementation of `masked_to_degC` would, when applied tc data, produce a masked image resembling what follows.

> **Run this cell even if you did not complete Exercise 2.**

In [29]:
```
sat_demo_clean = f_ex2__sample_result();
```

```
Opening pickle from './resource/asnlib/publicdata/atl-masked-cleaned.pickle' ...
```



Exercise 3: Average temperature (2 points)

Suppose you are given `masked_array`, a Numpy array of masked floating-point temperatures like that *produced* by `masked_to_degC` in Exe is, it has floating-point temperature values *except* at "masked" entries, which are marked by NaN values. Complete the function `mean_temperature(masked_array)` so that it returns the mean temperature value over all pixels, **ignoring any NaNs.**

For example, suppose `masked_array` equals the Numpy array,

```
[[   nan  21.85    nan]
 [   nan  43.55 -71.75]
 [   nan  34.35  49.05]
 [  6.95    nan -31.55]]
```

where the values are in degrees Celsius. Then `mean_temperature(masked_array)` would equal (21.85+43.55-71.75+34.35+49.05+6.95-31 is approximately 7.49 degrees Celsius.

> **Note 0:** Your approach should work for an input array of *any* dimension. You'll get partial credit (1 point) if it works for 2-D input arrays, full credit (2 points) if it works for arrays of *all* dimensions.
>
> **Note 1:** If all input values are NaN values, then your function should return NaN.

In [30]:
```
def mean_temperature(masked_array):
    assert isinstance(masked_array, np.ndarray)
    assert np.issubdtype(masked_array.dtype, np.floating)
    ### BEGIN SOLUTION
    return np.nanmean(masked_array)
```

```
    ### END SOLUTION
```

In [31]:
```
# Demo cell 0:
img_ex3_demo_clean = np.array([[np.nan,  21.85, np.nan],
                               [np.nan,  43.55, -71.75],
                               [np.nan,  34.35,  49.05],
                               [  6.95, np.nan, -31.55]])
mean_temperature(img_ex3_demo_clean) # Expected result: ~ 7.49
```

Out[31]: 7.492857142857143

In [32]:
```
# Demo cell 1: Check the 1-D case, as an example (expected output is roughly -277.55)
mean_temperature(np.array([-260.85, np.nan, -227.55, -194.25, np.nan]))
```

Out[32]: -227.55000000000004

In [33]:
```
# Demo cell 2: Mean temperature in Atlanta (a.k.a., "Hotlanta!")
mean_temperature(sat_demo_clean)
```

Out[33]: 39.24372126540902

In [34]:
```
# Test cell 0: f_ex3__mean_temperature_2d (1 point)

### BEGIN HIDDEN TESTS
def f_ex3__gen_soln(grade=None, fn_base="atl-temp", fn_ext="pickle", overwrite=False):
    from testing_tools import file_exists, load_pickle, save_pickle
    if grade is None:
        fn = f"{fn_base}.{fn_ext}"
    else:
        fn = f"{fn_base}-{grade}.{fn_ext}"
    if file_exists(fn) and not overwrite:
        temperature = load_pickle(fn)
    else: # not file_exists(fn) or overwrite
        gdf = f_ex0__gen_soln(grade=grade)
        img = load_satellite_image('LC08_CU_024013_20190808_20190822_C01_V01_ST--EPSG_4326.tif')
        img_masked = mask_image_by_geodf(img, gdf)
        img_clean = clean_masked_image(img_masked)
        temperature = mean_temperature(img_clean)
        save_pickle(temperature, fn)
    return temperature

for g_ex2 in [None, 'A', 'B', 'C', 'D']:
    f_ex3__gen_soln(grade=g_ex2, overwrite=False)
### END HIDDEN TESTS

from testing_tools import f_ex3__check
print("Testing...")
for trial in range(250):
    f_ex3__check(mean_temperature, ndim=2)

mean_temperature__passed_2d = True
print("\n(Passed the 2-D case!)")
```

```
Opening pickle from './resource/asnlib/publicdata/atl-temp.pickle' ...
Opening pickle from './resource/asnlib/publicdata/atl-temp-A.pickle' ...
Opening pickle from './resource/asnlib/publicdata/atl-temp-B.pickle' ...
Opening pickle from './resource/asnlib/publicdata/atl-temp-C.pickle' ...
Opening pickle from './resource/asnlib/publicdata/atl-temp-D.pickle' ...
Testing...

(Passed the 2-D case!)

/usr/lib/python3.7/site-packages/ipykernel_launcher.py:5: RuntimeWarning: Mean of empty slice
  """
```

In [35]:
```
# Test cell 1: f_ex3__mean_temperature_nd (1 point)

from testing_tools import f_ex3__check
print("Testing...")
for trial in range(250):
    f_ex3__check(mean_temperature, ndim=None)

print("\n(Passed the N-D case!)")
```

```
Testing...

(Passed the N-D case!)

/usr/lib/python3.7/site-packages/ipykernel_launcher.py:5: RuntimeWarning: Mean of empty slice
  """
```

Sample result of `mean_temperature` (Exercise 3) for Atlanta. If all of your code were working up until now, you could analyze the average t each type of neighborhood by rating. You would see the result below. It shows that there is an observable difference in temperature based on tl the neighborhood -- a difference of 5 to 6 degrees Celsius is about 10 degrees Fahrenheit.

Run this cell even if you did not complete Exercise 3.

In [36]:
```
f_ex3__sample_result();
```

```
Average temperatures in Atlanta during some summer day:
*  Overall: ~ 39.2 degrees Celsius (~ 102.6 deg F)
*  In 1930s 'A'-rated neighborhoods: ~ 35.3 degrees Celsius (~ 95.6 deg F)
*  In 1930s 'B'-rated neighborhoods: ~ 37.6 degrees Celsius (~ 99.7 deg F)
*  In 1930s 'C'-rated neighborhoods: ~ 39.3 degrees Celsius (~ 102.8 deg F)
*  In 1930s 'D'-rated neighborhoods: ~ 41.5 degrees Celsius (~ 106.7 deg F)
```

Part 3: Real estate data

The last piece of data we'll incorporate is real estate data. Here is the raw data:

In [37]:
```
home_prices = load_df("Zip_zhvi_uc_sfrcondo_tier_0.33_0.67_sm_sa_mon.csv") # From Zillow
print("\nColumns:\n", home_prices.columns, "\n")
home_prices.head(3)
```

```
Reading a regular pandas dataframe from './resource/asnlib/publicdata/Zip_zhvi_uc_sfrcondo_tier_
_sm_sa_mon.csv' ...

Columns:
 Index(['RegionID', 'SizeRank', 'RegionName', 'RegionType', 'StateName',
       'State', 'City', 'Metro', 'CountyName', '1996-01-31',
       ...
       '2020-01-31', '2020-02-29', '2020-03-31', '2020-04-30', '2020-05-31',
       '2020-06-30', '2020-07-31', '2020-08-31', '2020-09-30', '2020-10-31'],
      dtype='object', length=307)
```

Out[37]:

	RegionID	SizeRank	RegionName	RegionType	StateName	State	City	Metro	CountyName	1996-01-31	...
0	61639	0	10025	Zip	NY	NY	New York	New York-Newark-Jersey City	New York County	223469.0	...
1	84654	1	60657	Zip	IL	IL	Chicago	Chicago-Naperville-Elgin	Cook County	205864.0	...
2	61637	2	10023	Zip	NY	NY	New York	New York-Newark-Jersey City	New York County	227596.0	...

3 rows × 307 columns

This dataframe has a lot of information, but here are the elements you need:

- Each row gives historical average home price estimates for different areas of the United States. The areas are uniquely identified by their 5 code, stored as integers in the `'RegionName'` column. Zip codes are areas that are *different* from the neighborhoods you'd been conside previously.
- The city and two-letter state abbreviations are given by the `'City'` and `'State'` columns. Their values match the city and state abbrevia you've seen in the other data.
- The home price estimates appear in the columns given by numeric dates, in the string format `'yyyy-mm-dd'`.

Exercise 4: Cleaning the dataframe (2 points)

Given a regular pandas dataframe `df` formatted like `home_prices` above, complete the function `clean_zip_prices(df)` so that it returns a dataframe containing the following columns:

- `'ZipCode'`: The 5-digit zip code, taken from the `'RegionName'` column and stored as integers.
- `'City'`: The city name, taken directly from `'City'`.
- `'State'`: The two-letter state abbreviation, taken directly from `'State'`.
- `'Price'`: The home price, taken as the **latest** (most recent) date column and stored as floating-point values. In `home_prices`, the latest recent date is `'2020-10-31'`; therefore, the `'Price'` column of the output would contain the values from this column.

For example, suppose `df` is the following:

	RegionID	SizeRank	RegionName	RegionType	StateName	State	City	Metro	CountyName	1996-01-31	2(0(
0	98046	6533	95212	Zip	CA	CA	Stockton	Stockton-Lodi	San Joaquin County	nan	424

1	68147	16308	24445	Zip	VA	VA	Hot Springs	nan	Bath County	nan	138
2	84364	3748	60110	Zip	IL	IL	Carpentersville	Chicago-Naperville-Elgin	Kane County	138980	178

Then your function would return:

	ZipCode	City	State	Price
0	95212	Stockton	CA	430334.0
1	24445	Hot Springs	VA	138496.0
2	60110	Carpentersville	IL	179852.0

Note 0: We will test your code on randomly generated input dataframes. Therefore, your solution should only depend on the existence columns `'RegionName'`, `'City'`, `'State'`, and at least one column whose name is formatted as a date-string (`yyyy-mm-dd`). Any c columns may have different names from what is shown above and, in any case, are immaterial to your solution.

Note 1: A helpful function for searching for column names matching a given pattern is [`df.filter` (https://pandas.pydata.org/pandas-docs/stable/reference/api/pandas.DataFrame.filter.html)](https://pandas.pydata.org/pandas-docs/stable/reference/api/pandas.DataFrame.filter.html).

Note 2: Row ordering does not matter, since we will use an `tibbles_are_equivalent`-type function to check for dataframe equival

In [38]:
```
def clean_zip_prices(df):
    assert isinstance(df, pd.DataFrame)
    ### BEGIN SOLUTION
    last_date = sorted(df.filter(regex='\d{4}-\d{2}-\d{2}', axis=1).columns)[-1]
    df_new = df[['RegionName', 'City', 'State', last_date]]
    df_new = df_new.rename(columns={'RegionName': 'ZipCode', last_date: 'Price'})
    df_new['ZipCode'] = df_new['ZipCode'].astype(int)
    df_new['Price'] = df_new['Price'].astype(float)
    return df_new
    ### END SOLUTION
```

In [39]:
```
# Demo cell
clean_zip_prices(home_prices)
```

Out[39]:

	ZipCode	City	State	Price
0	10025	New York	NY	1073416.0
1	60657	Chicago	IL	492585.0
2	10023	New York	NY	1152889.0
3	77494	Katy	TX	347871.0
4	60614	Chicago	IL	629989.0
...	...	...	...	...
30225	47865	Carlisle	IN	44241.0
30226	20052	Washington	DC	1343080.0
30227	801	Charlotte Amalie	UT	30100.0
30228	820	Choudrant	LA	191183.0
30229	822	Choudrant	LA	190667.0

30230 rows × 4 columns

In [40]:
```
# Test cell: f_ex4__clean_zip_prices (2 points)

### BEGIN HIDDEN TESTS
def f_ex4__gen_soln(fn_base="zip-prices", fn_ext="pickle", overwrite=False):
    from testing_tools import file_exists, load_df, load_pickle, save_pickle
    fn = f"{fn_base}.{fn_ext}"
    if file_exists(fn) and not overwrite:
        df_clean = load_pickle(fn)
    else: # not file_exists(fn) or overwrite
        df = load_df("Zip_zhvi_uc_sfrcondo_tier_0.33_0.67_sm_sa_mon.csv") # From Zillow
        df_clean = clean_zip_prices(df)
        save_pickle(df_clean, fn)
    return df_clean

f_ex4__gen_soln(overwrite=False)
### END HIDDEN TESTS

from testing_tools import f_ex4__check
print("Testing...")
for trial in range(250):
```

```
    f_ex4__check(clean_zip_prices)

print("\n(Passed!)")
```

```
Opening pickle from './resource/asnlib/publicdata/zip-prices.pickle' ...
Testing...

(Passed!)
```

Sample result of `clean_zip_prices` (Exercise 4). A successful implementation of Exercise 4 would produce a cleaned dataframe for `home_` shown below.

> **Run this cell even if you did not complete Exercise 4.**

In [41]:
```
home_prices_clean = f_ex4__sample_result()
home_prices_clean.head()
```

```
Opening pickle from './resource/asnlib/publicdata/zip-prices.pickle' ...
```

Out[41]:

	ZipCode	City	State	Price
0	10025	New York	NY	1073416.0
1	60657	Chicago	IL	492585.0
2	10023	New York	NY	1152889.0
3	77494	Katy	TX	347871.0
4	60614	Chicago	IL	629989.0

Zip code boundaries

To merge the home prices with the neighborhood rating information, we need the geographic boundaries of the zip codes. The following code l geopandas dataframe with this information:

In [42]:
```
zip_geo = load_pickle('tl_2017_us_zcta510.pickle')
zip_geo.head(3)
```

```
Opening pickle from './resource/asnlib/publicdata/tl_2017_us_zcta510.pickle' ...
```

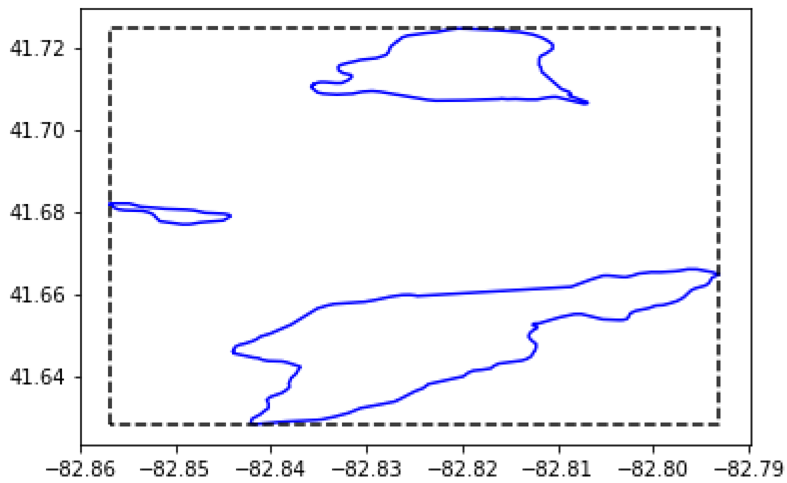
Out[42]:

	GEOID10	geometry
0	43451	POLYGON ((-83.70873 41.32733, -83.70815 41.327...
1	43452	POLYGON ((-83.08698 41.53780, -83.08256 41.537...
2	43456	MULTIPOLYGON (((-82.83558 41.71082, -82.83515 ...

This dataframe has just two columns: the zip code, stored as a **string** in the column named `'GEOID10'`, and `'geometry'`, which holds the sh code's area. Being stored in a geopandas dataframe, each zip code's boundary can be visualized easily and a bounding box computed, as the below demonstrates.

> **Note 0:** Zip codes in this dataframe are stored as strings, rather than integers as in the pricing dataframe.
>
> **Note 1:** The sample zip code visualized by the following code cell is a bit unusual in that it consists of three spatially disconnected regi However, that won't matter. Just note that each zip code is associated with some shape, just like the neighborhoods of the 1930s ratin data.

In [43]:
```
plot_multipolygon(zip_geo.loc[2, 'geometry'], color='blue')
plot_bounding_box(zip_geo.loc[2, 'geometry'].bounds, color='black', linestyle='dashed')
```



Exercise 5 (last one!): Merging price and geographic boundaries (2 points)

Complete the function, `merge_prices_with_geo(prices_clean, zip_gdf)`, so that it merges price information stored in `prices_clea` geographic boundaries stored in `zip_gdf`.

- The `prices_clean` object is a **pandas** dataframe that will have four columns, `'ZipCode'`, `'City'`, `'State'`, and `'Price'`, as would b produced by `clean_home_prices` (Exercise 4).
- The `zip_gdf` input is a **geopandas** dataframe with two columns, `'GEOID10'` and `'geometry'`.
- Your function should return a new **geopandas** dataframe with five columns: `'ZipCode'`, `'City'`, `'State'`, `'Price'`, and `'geometry'`

> **Note 0:** Recall that the `'ZipCode'` column of `prices_clean` stores values as integers, whereas the `'GEOID10'` column of `zip_gdf` values as strings. In your final result, store the `'ZipCode'` column using integer values.
>
> **Note 1:** We are only interested in zip codes with *both* price information *and* known geographic boundaries. That is, if a zip code is miss either `prices_clean` or `zip_gdf`, you should ignore and omit it from your output.
>
> **Note 2:** If `df` is a pandas dataframe, you can convert it to a geopandas one simply by calling `geopandas.GeoDataFrame(df)`.

In [44]:
```
def merge_prices_with_geo(prices_clean, zip_gdf):
    assert isinstance(prices_clean, pd.DataFrame)
    assert isinstance(zip_gdf, geopandas.GeoDataFrame)
    ### BEGIN SOLUTION
    zip_gdf_int = zip_gdf.copy()
    zip_gdf_int['ZipCode'] = zip_gdf_int['GEOID10'].astype(int)
    prices_gdf = geopandas.GeoDataFrame(prices_clean)
    return prices_gdf.merge(zip_gdf_int[['ZipCode', 'geometry']], on='ZipCode')
    ### END SOLUTION
```

In [45]:
```
# Demo cell
merge_prices_with_geo(home_prices_clean, zip_geo).head(3)
```

Out[45]:

	ZipCode	City	State	Price	geometry
0	10025	New York	NY	1073416.0	POLYGON ((-73.97701 40.79281, -73.97695 40.792...
1	60657	Chicago	IL	492585.0	POLYGON ((-87.67850 41.94504, -87.67802 41.945...
2	10023	New York	NY	1152889.0	POLYGON ((-73.99015 40.77231, -73.98992 40.773...

In [46]:
```
merge_prices_with_geo(home_prices_clean, zip_geo).head(3)
```

Out[46]:

	ZipCode	City	State	Price	geometry
0	10025	New York	NY	1073416.0	POLYGON ((-73.97701 40.79281, -73.97695 40.792...
1	60657	Chicago	IL	492585.0	POLYGON ((-87.67850 41.94504, -87.67802 41.945...
2	10023	New York	NY	1152889.0	POLYGON ((-73.99015 40.77231, -73.98992 40.773...

In [47]:
```
# Test cell: f_ex5__merge_prices_with_geo (2 points)

### BEGIN HIDDEN TESTS
def f_ex5__gen_soln(fn_base="prices-geo", fn_ext="pickle", overwrite=False):
    from testing_tools import file_exists, load_df, load_pickle, save_pickle
    fn = f"{fn_base}.{fn_ext}"
    if file_exists(fn) and not overwrite:
        result = load_pickle(fn)
    else: # not file_exists(fn) or overwrite
        prices = f_ex4__sample_result()
        geo = load_pickle('tl_2017_us_zcta510.pickle')
        prices_geo = merge_prices_with_geo(prices, geo)
        neighborhood_ratings = load_geopandas('fullDownload.geojson')
        result = geopandas.overlay(neighborhood_ratings,
                                   prices_geo[['ZipCode', 'Price', 'geometry']],
                                   how='intersection')
        save_pickle(result, fn)
    return result

f_ex5__gen_soln(overwrite=False)
### END HIDDEN TESTS

from testing_tools import f_ex5__check
print("Testing...")
for trial in range(250):
    f_ex5__check(merge_prices_with_geo)

print("\n(Passed!)")
```

```
Opening pickle from './resource/asnlib/publicdata/prices-geo.pickle' ...
Testing...

(Passed!)
```

Part 4: Fin! (Epilogue and *optional* wrap-up)

There are no additional required exercises — you've reached the end of the final exam and, therefore, of the class! Don't forget to restart and ru
again to make sure it's all working when run in sequence; and make sure your work passes the submission process. Good luck!

The code cells below provide a bit more supplementary information and analysis. If you've finished early and want to try an interesting analysis
optional "Exercise 6," below, a shot!

Sample result of `merge_prices_with_geo` (Exercise 5). One incredibly cool feature of geopandas is that it can do spatial (geographic) que
For instance, let's merge the neighborhood rating data with the housing price data. The geopandas merging routines will account for how the g
zones in one dataframe intersect with the other.

Visually, imagine laying the two "geographies" on top of one another, as illustrated below. (The shading corresponds with house prices by zip c
and the hollow polygons correspond to neighborhoods.)

Overlaying neighborhoods and zip code boundaries

If a neighborhood overlaps with two zip codes, the merge can create two rows in the output for each combination of (neighborhood, zip code).
you to run subsequent queries, like examining the relationship between rating and price.

We have carried out this merge for you. Run the cell below to load that precomputed result into a geopandas dataframe named `neighborhoo`
opposed to the original, `neighborhood_ratings`).

In [48]:
```
neighborhood_prices = f_ex5__sample_result()
neighborhood_prices.head()
```

```
Opening pickle from './resource/asnlib/publicdata/prices-geo.pickle' ...
```

Out[48]:

	state	city	name	holc_id	holc_grade	area_description_data	ZipCode	Price	geon
0	AL	Birmingham	Mountain Brook Estates and Country Club Garden...	A1	A	{'5': 'Both sales and rental prices in 1929 we...	35223	610462.0	MUL (((-86 33.49 -86.7
1	AL	Birmingham	Redmont Park, Rockridge Park, Warwick Manor, a...	A2	A	{'5': 'Both sales and rental prices in 1929 we...	35223	610462.0	MUL (((-86 33.49 -86.7
2	AL	Birmingham	Colonial Hills, Pine Crest (outside city limits)	A3	A	{'5': 'Generally speaking, houses are not buil...	35223	610462.0	POLY ((-86. 33.48 -86.7 33.48
3	AL	Birmingham	Grove Park, Hollywood, Mayfair, and Edgewood s...	B1	B	{'5': 'Both sales and rental prices in 1929 we...	35223	610462.0	MUL (((-86 33.47 -86.7
4	AL	Birmingham	First Addition to South Highlands	B3	B	{'5': 'Both sales and rental prices in 1929 we...	35223	610462.0	POLY ((-86. 33.49 -86.7 33.49

If we consider just the Atlanta area, here is how today's average house price varies by that original 1930s neighborhood rating.

> This code cell requires a working solution to Exercise 0.

In [49]:
```
from testing_tools import f_ex5b__sample_result

if 'filter_ratings__passed' in globals() and filter_ratings__passed:
    f_ex5b__sample_result(neighborhood_prices, 'Atlanta, GA', filter_ratings) # Try other citie
else:
    print("This code cell was not run because it needs a working version of `filter_ratings` fro
0.")
```

```
Average house price in Atlanta, GA:
*  Overall: ~ $398,127.40
*  In 1930s 'A'-rated neighborhoods: ~ $589,818.12
*  In 1930s 'B'-rated neighborhoods: ~ $445,985.37
*  In 1930s 'C'-rated neighborhoods: ~ $393,349.46
*  In 1930s 'D'-rated neighborhoods: ~ $317,403.05
```

OPTIONAL Exercise 6: Put it all together (no points)

We've provided satellite images for not just Atlanta, but all the cities defined in the dictionary below. Use all of your code from earlier exercises Atlanta analysis for all other neighborhoods.

In particular, construct a table that shows, for each city, the percent differences in mean temperature and house price among the A/B/C/D-ratec neighborhoods. Then try running a multiple regression (Notebook 12) to see how the 1930s rating predicts them.

> *Hint:* To conduct the regression analysis, you'll want to "dummy-code" the ratings variable, since it is categorical (A, B, C, and D values this explanation (https://stats.idre.ucla.edu/spss/faq/coding-systems-for-categorical-variables-in-regression-analysis-2/#DUMMYCOD you aren't familiar with this practice. When you construct the data matrix, pandas's `pd.get_dummies()` (https://pandas.pydata.org/p docs/stable/reference/api/pandas.get_dummies.html) function is a good tool.

In [50]:

```
satellite_image_data = {
    'Birmingham, AL': 'LC08_CU_022014_20200614_20200628_C01_V01_ST--EPSG_4326.tif'
    , 'Los Angeles, CA': 'LC08_CU_003012_20200703_20200709_C01_V01_ST--EPSG_4326.tif'
    , 'Denver, CO': 'LC08_CU_012009_20200812_20200824_C01_V01_ST--EPSG_4326.tif' # incomplete
    , 'New Haven, CT': 'LC08_CU_029006_20200613_20200627_C01_V01_ST--EPSG_4326.tif' # incomplete
    , 'Jacksonville, FL': 'LC08_CU_026016_20160709_20190430_C01_V01_ST--EPSG_4326.tif' # mostly
    , 'Atlanta, GA': 'LC08_CU_024013_20190808_20190822_C01_V01_ST--EPSG_4326.tif'
    , 'Chicago, IL': 'LC08_CU_021007_20160624_20181205_C01_V01_ST--EPSG_4326.tif' # incomplete
e)
    , 'Indianapolis, IN': 'LC08_CU_022009_20200824_20200907_C01_V01_ST--EPSG_4326.tif'
    , 'Louisville, KY': 'LC08_CU_023010_20200817_20200825_C01_V01_ST--EPSG_4326.tif' # incomple
ile)
    , 'New Orleans, LA': 'LC08_CU_020016_20200612_20200627_C01_V01_ST--EPSG_4326.tif'
    , 'Boston, MA': 'LC08_CU_030006_20180719_20190614_C01_V01_ST--EPSG_4326.tif' # incomplete (
    , 'Baltimore, MD': 'LC08_CU_028008_20190812_20190822_C01_V01_ST--EPSG_4326.tif'  # mostly c
    , 'Detroit, MI': 'LC08_CU_024007_20190714_20190723_C01_V01_ST--EPSG_4326.tif'  # mostly com
    , 'Minneapolis, MN': 'LC08_CU_018005_20190613_20190621_C01_V01_ST--EPSG_4326.tif'
    , 'St.Louis, MO': 'LC08_CU_020010_20180723_20190614_C01_V01_ST--EPSG_4326.tif'
    , 'Charlotte, NC': 'LC08_CU_026012_20180823_20190614_C01_V01_ST--EPSG_4326.tif'
    , 'Bergen Co., NJ': 'LC08_CU_029007_20190830_20190919_C01_V01_ST--EPSG_4326.tif'
    , 'Manhattan, NY': 'LC08_CU_029007_20190830_20190919_C01_V01_ST--EPSG_4326.tif' # same tile
 Co., NJ!
    , 'Brooklyn, NY': 'LC08_CU_029007_20190830_20190919_C01_V01_ST--EPSG_4326.tif' # same tile
o., NJ!
    , 'Columbus, OH': 'LC08_CU_024009_20190824_20190908_C01_V01_ST--EPSG_4326.tif' # partial
    , 'Portland, OR': 'LE07_CU_003003_20190813_20190910_C01_V01_ST--EPSG_4326.tif'
    , 'Philadelphia, PA': 'LC08_CU_028008_20190720_20190803_C01_V01_ST--EPSG_4326.tif'
    , 'Nashville, TN': 'LC08_CU_022012_20190603_20190621_C01_V01_ST--EPSG_4326.tif'
    , 'Dallas, TX': 'LC08_CU_016014_20190816_20190906_C01_V01_ST--EPSG_4326.tif'
    , 'Richmond, VA': 'LC08_CU_027010_20190727_20190803_C01_V01_ST--EPSG_4326.tif'
    , 'Seattle, WA': 'LC08_CU_003002_20190828_20190905_C01_V01_ST--EPSG_4326.tif' # partial
    , 'Milwaukee Co., WI': 'LC08_CU_021007_20180801_20190614_C01_V01_ST--EPSG_4326.tif'
    , 'Charleston, WV': 'LC08_CU_025010_20190817_20190905_C01_V01_ST--EPSG_4326.tif'
}

### BEGIN SOLUTION

# Merges neighborhood ratings, satellite image with temperatures, and Zillow data
# for a given city and (optionally) target rating. Returns the mean temperature
# and house price.
def merge_city(neighborhood_ratings, satimg, neighborhood_prices, city_st, targets=None):
    ratings = filter_ratings(neighborhood_ratings, city_st, targets)
    satimg_clean = mask_image_by_geodf(satimg, ratings)
    degC = mean_temperature(masked_to_degC(satimg_clean))
    prices = filter_ratings(neighborhood_prices, city_st, targets)
    price = prices['Price'].mean()
    return degC, price

# Merges data for every city having ratings, a temperature satellite image, and prices
def merge_all_data(ratings, images, prices):
    all_rows = []
    for city_st, satimg_filename in images.items():
        print(f"Processing {city_st} [image={satimg_filename}] ...")
        satimg = load_satellite_image(satimg_filename, verbose=False)
        degC_overall, price_overall = merge_city(ratings, satimg, prices, city_st)
        for rating in ['A', 'B', 'C', 'D']:
            degC_r, price_r = merge_city(ratings, satimg, prices, city_st, targets={rating})
            delta_degC = round(degC_r - degC_overall, 1)
            price_percent = round((price_r - price_overall) / price_overall * 100.0, 1)
            all_rows.append((city_st, rating, delta_degC, price_percent))
    return pd.DataFrame(all_rows, columns=['city_st', 'ratings', 'delta_degC', '%price'])

# Construct a data matrix from a table with a single categorical predictor
def build_matrix_dataframe(df, continuous=[], categorical=[], standardize=False, add_bias_term=
    df_data = df[continuous] if continuous else pd.DataFrame()
    if standardize:
        for col in continuous:
            mu = df[col].mean(skipna=True)
            df_data[col] = (df[col] - mu) / mu
    for col in categorical:
```

```
        df_cat_col = pd.get_dummies(df[col], prefix=col)
        df_data = pd.concat([df_data, df_cat_col], axis=0)
    if add_bias_term:
        df_data['__ones__'] = np.ones(len(df))
    return df_data

# ========== Analysis begins here ==========

# First, verify that dependent functions work:
if not ('filter_ratings__passed' in globals() and filter_ratings__passed \
        and 'mean_temperature__passed_2d' in globals() and mean_temperature__passed_2d \
        and 'masked_to_degC__passed_2d' in globals() and masked_to_degC__passed_2d \
        ):
    print("This code cell was not run because it needs working solutions from earlier exercises.
    assert False, "*** Stopping execution here. ***"

summary_tibble = merge_all_data(neighborhood_ratings, satellite_image_data, neighborhood_prices)
summary_df = summary_tibble.pivot(index='city_st', values=['delta_degC', '%price'], columns=['ra
eset_index()
display(summary_df)

from numpy.linalg import lstsq
print(f"Regressing on neighborhood ratings {tuple(summary_tibble['ratings'].unique())}:")
X = build_matrix_dataframe(summary_tibble, categorical=['ratings']).values
for response in ['delta_degC', '%price']:
    y = summary_tibble[response]
    theta, _, _, _ = lstsq(X, y, rcond=None)
    print(f"* Response '{response}' has these weights: {theta.T}")

### END SOLUTION
```

```
Processing Birmingham, AL [image=LC08_CU_022014_20200614_20200628_C01_V01_ST--EPSG_4326.tif] ...
Processing Los Angeles, CA [image=LC08_CU_003012_20200703_20200709_C01_V01_ST--EPSG_4326.tif] ..
Processing Denver, CO [image=LC08_CU_012009_20200812_20200824_C01_V01_ST--EPSG_4326.tif] ...
Processing New Haven, CT [image=LC08_CU_029006_20200613_20200627_C01_V01_ST--EPSG_4326.tif] ...
Processing Jacksonville, FL [image=LC08_CU_026016_20160709_20190430_C01_V01_ST--EPSG_4326.tif] .
Processing Atlanta, GA [image=LC08_CU_024013_20190808_20190822_C01_V01_ST--EPSG_4326.tif] ...
Processing Chicago, IL [image=LC08_CU_021007_20160624_20181205_C01_V01_ST--EPSG_4326.tif] ...
Processing Indianapolis, IN [image=LC08_CU_022009_20200824_20200907_C01_V01_ST--EPSG_4326.tif] .
Processing Louisville, KY [image=LC08_CU_023010_20200817_20200825_C01_V01_ST--EPSG_4326.tif] ...
Processing New Orleans, LA [image=LC08_CU_020016_20200612_20200627_C01_V01_ST--EPSG_4326.tif] ..
Processing Boston, MA [image=LC08_CU_030006_20180719_20190614_C01_V01_ST--EPSG_4326.tif] ...
Processing Baltimore, MD [image=LC08_CU_028008_20190812_20190822_C01_V01_ST--EPSG_4326.tif] ...
Processing Detroit, MI [image=LC08_CU_024007_20190714_20190723_C01_V01_ST--EPSG_4326.tif] ...
Processing Minneapolis, MN [image=LC08_CU_018005_20190613_20190621_C01_V01_ST--EPSG_4326.tif] ..
Processing St.Louis, MO [image=LC08_CU_020010_20180723_20190614_C01_V01_ST--EPSG_4326.tif] ...
Processing Charlotte, NC [image=LC08_CU_026012_20180823_20190614_C01_V01_ST--EPSG_4326.tif] ...
Processing Bergen Co., NJ [image=LC08_CU_029007_20190830_20190919_C01_V01_ST--EPSG_4326.tif] ...
Processing Manhattan, NY [image=LC08_CU_029007_20190830_20190919_C01_V01_ST--EPSG_4326.tif] ...
Processing Brooklyn, NY [image=LC08_CU_029007_20190830_20190919_C01_V01_ST--EPSG_4326.tif] ...
Processing Columbus, OH [image=LC08_CU_024009_20190824_20190908_C01_V01_ST--EPSG_4326.tif] ...
Processing Portland, OR [image=LE07_CU_003003_20190813_20190910_C01_V01_ST--EPSG_4326.tif] ...
Processing Philadelphia, PA [image=LC08_CU_028008_20190720_20190803_C01_V01_ST--EPSG_4326.tif] .
Processing Nashville, TN [image=LC08_CU_022012_20190603_20190621_C01_V01_ST--EPSG_4326.tif] ...
Processing Dallas, TX [image=LC08_CU_016014_20190816_20190906_C01_V01_ST--EPSG_4326.tif] ...
Processing Richmond, VA [image=LC08_CU_027010_20190727_20190803_C01_V01_ST--EPSG_4326.tif] ...
Processing Seattle, WA [image=LC08_CU_003002_20190828_20190905_C01_V01_ST--EPSG_4326.tif] ...
Processing Milwaukee Co., WI [image=LC08_CU_021007_20180801_20190614_C01_V01_ST--EPSG_4326.tif]
Processing Charleston, WV [image=LC08_CU_025010_20190817_20190905_C01_V01_ST--EPSG_4326.tif] ...
```

	city_st	**delta_degC**				**%price**			
ratings		**A**	**B**	**C**	**D**	**A**	**B**	**C**	**D**
0	Atlanta, GA	-3.9	-1.6	0.1	2.3	48.1	12.0	-1.2	-20.3
1	Baltimore, MD	-2.7	-1.2	1.2	2.8	11.1	10.6	-4.7	-14.8
2	Bergen Co., NJ	-2.9	-1.0	0.2	2.3	22.4	3.3	-1.1	-10.3
3	Birmingham, AL	-3.6	0.1	1.6	-0.2	166.6	52.9	-27.6	-35.2
4	Boston, MA	-5.4	-0.9	-0.2	2.3	17.9	3.4	-5.6	6.1
5	Brooklyn, NY	-0.0	-0.2	-0.2	0.3	-32.8	-4.9	-2.0	5.5
6	Charleston, WV	-2.8	0.6	1.1	-1.0	21.5	-3.6	-5.0	3.8
7	Charlotte, NC	-2.4	-0.6	0.5	1.1	38.5	27.2	-17.6	-7.4
8	Chicago, IL	-5.3	-1.9	0.8	0.8	103.7	23.7	-11.5	-24.1
9	Columbus, OH	-1.6	-0.1	0.3	0.8	27.5	5.5	-4.0	-10.9
10	Dallas, TX	-3.0	-1.1	1.0	1.9	57.8	-3.8	-20.1	-20.3
11	Denver, CO	11.6	1.5	-2.8	0.2	12.2	10.4	-0.5	-11.8
12	Detroit, MI	-3.0	-0.8	0.0	1.0	59.1	14.9	-1.4	-19.9
13	Indianapolis, IN	-1.7	-0.5	-0.3	1.2	15.5	-1.4	-3.2	1.1
14	Jacksonville, FL	-3.7	-0.6	0.1	0.9	32.5	7.7	-7.8	-10.0

15	Los Angeles, CA	-5.2	-0.8	1.2	1.1	40.5	7.9	-6.9	-22.2
16	Louisville, KY	-2.5	-0.4	0.3	1.9	46.7	10.0	-12.7	-15.3
17	Manhattan, NY	-1.0	-1.0	0.0	0.6	1.0	-12.3	-12.9	7.5
18	Milwaukee Co., WI	-2.9	0.4	-0.2	0.7	29.8	12.0	-5.4	-10.3
19	Minneapolis, MN	-2.8	-0.7	1.0	2.0	4.5	6.0	-4.7	-6.0
20	Nashville, TN	-2.2	-0.3	-0.2	1.3	20.7	5.3	0.5	-11.2
21	New Haven, CT	-3.2	-1.5	0.8	1.8	8.2	-1.5	-4.9	5.9
22	New Orleans, LA	-1.9	-0.7	0.2	0.2	16.6	13.7	2.0	-10.7
23	Philadelphia, PA	-4.4	-1.2	1.6	2.9	34.9	4.9	-15.0	-10.5
24	Portland, OR	-5.8	0.0	0.7	2.1	13.2	1.7	-7.8	7.6
25	Richmond, VA	-3.0	-0.3	0.2	1.6	18.9	11.8	-5.6	-20.7
26	Seattle, WA	-3.2	-0.6	1.0	-0.2	8.1	3.0	-1.0	-8.9
27	St.Louis, MO	-2.0	0.2	0.1	1.2	40.6	-11.2	-12.6	-14.2

```
Regressing on neighborhood ratings ('A', 'B', 'C', 'D')):
* Response 'delta_degC' has these weights: [-2.51785714 -0.54285714  0.36071429  1.21071429]
* Response '%price' has these weights: [31.61785714  7.47142857 -7.15357143 -9.91071429]
```

Epilogue. The analysis in this notebook is inspired by a New York Times article (https://www.nytimes.com/interactive/2019/08/09/climate/city-h islands.html) about the disproportionate affects of climate on different racial and socioeconomic groups. What you've done in this notebook jus the surface of that analysis, available in this paper (https://www.mdpi.com/2225-1154/8/1/12/htm), but we hope you can appreciate how remar with just a semester's worth of experience, this kind of data analysis is well within your grasp!

Indeed, although we ended up cutting it out of the problem, you could easily imagine applying any number of the analyses from Notebooks 12- with simple regression models that relate ratings with temperature and home prices.

Data sources for this notebook:

- Redlining data: The *Mapping Inequality* website (dsl.richmond.edu/panorama/redlining)
- Satellite data: The US Geological Survey (USGS) Earth Explorer (https://earthexplorer.usgs.gov) (we used the "provisional land surface tem images)
- Real estate data: Zillow Home Price Forecast Data for Researchers (https://www.zillow.com/research/data)
- Geographic boundaries for zip codes: this blog post (https://n8henrie.com/uploads/2017/11/plotting-us-census-data-with-python-and-geopandas.html), which derives this information from US Census Data (see the post for details)

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