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Turn Web Content Into Useful Data

SCRAPY, MATPLOTLIB AND MYSQL: REAL ESTATE DATA ANALYSIS

November 07, 2019 Attila Tóth 2 Comments

In today's article we will extract real estate listings from one of the biggest real estate sites and then analyze the data. Similar to our previous web data analysis blogpost, I will show you a simple way to extract web data with python and then perform descriptive analysis on the dataset.

Tech stack and methodology

We are going to use python as a programming language.

Tools and libraries:

- Scrapy for web scraping
- MySQL to store data
- Pandas to query and structure data in code
- Matplotlib to visualize data

Although this could be a really complex project as it involves web scraping and data analysis as well, we are going to make it simple by using this process:

1. Define data requirements
2. Implement data extraction
3. Perform data analysis (query database + visualization)

Let's start!

Data requirements

For every web scraping project the first question we need to answer is this - What data do we exactly need? When it comes to real-estate listings, there are so many data points we could scrape that we would have to really narrow them down based on our needs. For now, I'm going to choose these fields:

- listing type
- price
- house size
- city
- year built

These data fields will give us freedom to look at the listings from different perspectives.

Data extraction

Now that we know what data to extract from the website we can start working on our spider.

Installing Scrapy

We are using Scrapy, the web scraping framework for this project. It is recommended to install Scrapy in a virtual environment so it doesn't conflict with other system packages.

Create a new folder and install virtualenv:

```
mkdir real_estate
cd real_estate
pip install virtualenv
virtualenv env
source env/bin/activate
```

Install Scrapy:

```
pip install scrapy
```

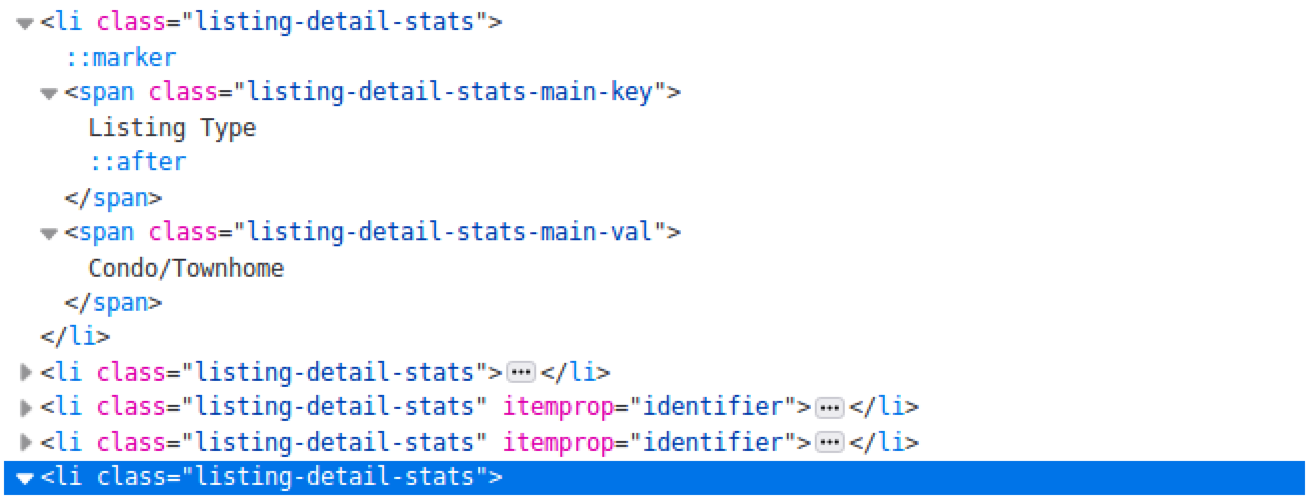
If you're having trouble with installing scrapy check out the installation guide.

Create a new Scrapy project:

```
scrapy startproject real_estate
```

Inspection

Now that we have scrapy installed, let's inspect the website we are trying to get data from. For this you can use your browser's inspector. Our goal here is to find all the data fields on the page, in the html, and write a selector/xpath for them.



```
▾<li class="listing-detail-stats">
   ::marker
  ▾<span class="listing-detail-stats-main-key">
     Listing Type
     ::after
   </span>
  ▾<span class="listing-detail-stats-main-val">
     Condo/Townhome
   </span>
 </li>
▸<li class="listing-detail-stats">⋯</li>
▸<li class="listing-detail-stats" itemprop="identifier">⋯</li>
▸<li class="listing-detail-stats" itemprop="identifier">⋯</li>
▾<li class="listing-detail-stats">
```

This html snippet above contains many list elements. Inside each *<li>* tag we can find many of the fields we're looking for, for example, the listing_type field. As different listings have different details defined we cannot select data solely based on html tags or css selectors. (Some listings have *house size* defined others don't) So for example, if we want to extract the *listing type* from the code above, we can use xpath to choose the one html element which has the "Listing Type" in its text then extract its first sibling.

Xpath for *listing_type*:

"//span[@class='listing-detail-stats-main-key'][contains(text(),'ListingType')]/following-sibling::span"

Then, we can do the same thing for house size, etc…

"//span[@class='listing-detail-stats-main-key'][contains(text(),HouseSize)]/following-sibling::span"

After finding all the selectors, this is our spider code:

```
def parse(self, response):
        item_loader = ItemLoader(item=RealEstateItem(), response=response)
        item_loader.default_input_processor = MapCompose(remove_tags)
        item_loader.default_output_processor = TakeFirst()

        item_loader.add_value("url", response.url)
        item_loader.add_xpath("listing_type", "")
        item_loader.add_css("price", "")
        item_loader.add_css("price", "")
        item_loader.add_xpath("house_size", "")
        item_loader.add_css("city", "")
        item_loader.add_xpath("year_built","")

        return item_loader.load_item()
```

As you can see, I'm using an ItemLoader. The reason for this is that for some of the fields the extracted data is messy. For example, this is what we get as the raw house size value:

```
2,100 sq.ft.
```

This value is not usable in its current form because we need a number as the house size. Not a string. So we need to remove the unit and the comma. In scrapy, we can use input processors for this. This is the *house_size* field with a cleaning input processor:

```
house_size = Field(
      input_processor=MapCompose(remove_tags, strip, lambda value: float(value.re
      )
```

What this processor does, in order:

1. Removes html tags
2. Removes unnecessary whitespaces
3. Removes "sqft"
4. Removes comma

The output becomes a numeric value which can be easily inserted into any database:

```
2100
```

After writing the cleaning functions for each field, this is what our item class looks like:

```
class RealEstateItem(Item):
       listing_type = Field(
       input_processor=MapCompose(remove_tags, strip)
       )
       price = Field(
       input_processor=MapCompose(remove_tags, lambda value: int(value.replace(",
       )
       house_size = Field(
       input_processor=MapCompose(remove_tags, strip,  lambda value: float(value
       )
       year_built = Field(
       input_processor=MapCompose(remove_tags, strip, lambda value: int(value))
       )
       city = Field()
       url = Field()
```

Database pipeline

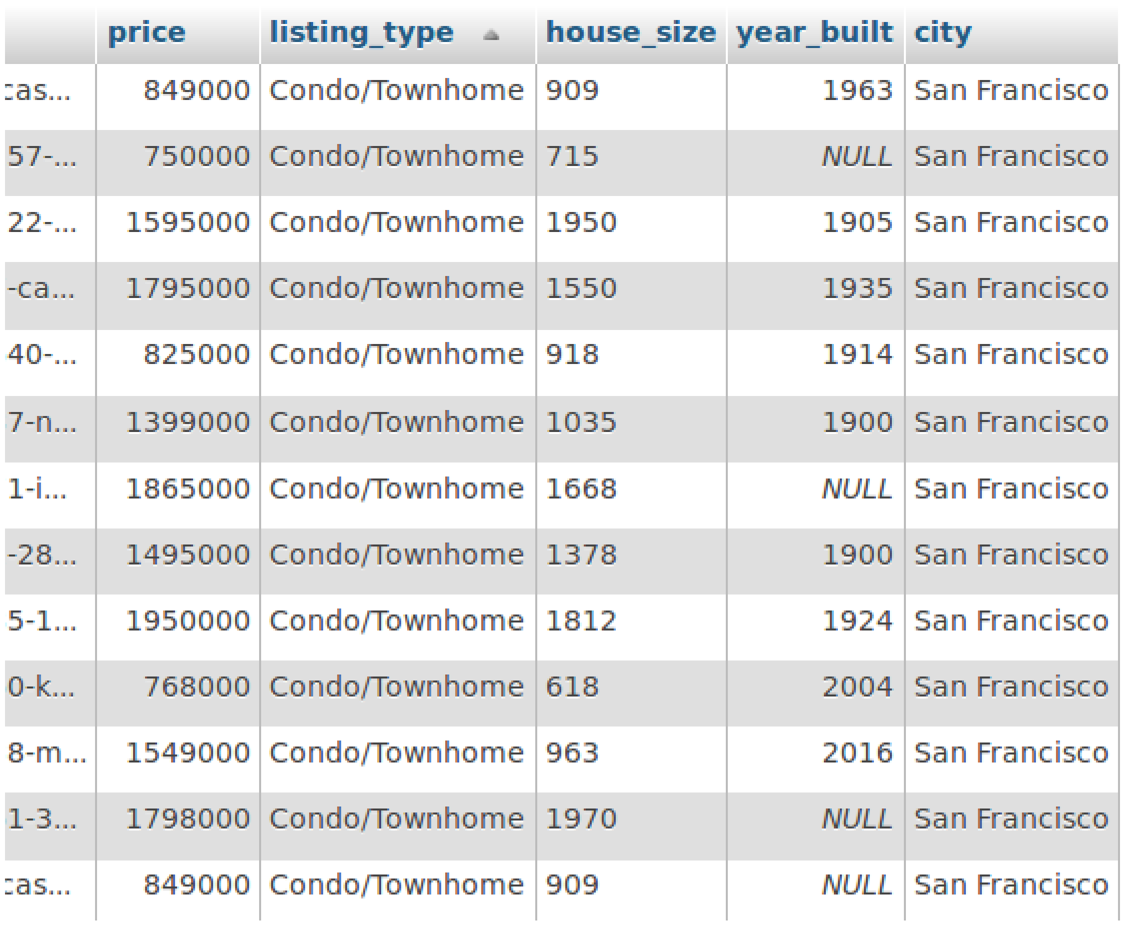
At this point we have the data extraction part handled. To prepare the data for analysis we need to store it in a database. For this, we create a custom scrapy pipeline. If you are not sure how a database pipeline works in scrapy, have a look at this article.

```
class DatabasePipeline(object):

   def __init__(self, db, user, passwd, host):
     self.db = db
     self.user = user
     self.passwd = passwd
     self.host = host

    @classmethod
    def from_crawler(cls, crawler):
      db_settings = crawler.settings.getdict("DB_SETTINGS")
      if not db_settings:
         raise NotConfigured
      db = db_settings['db']
      user = db_settings['user']
      passwd = db_settings['passwd']
      host = db_settings['host']
      return cls(db, user, passwd, host)

    def open_spider(self, spider):
      self.conn = MySQLdb.connect(db=self.db,
                     user=self.user, passwd=self.passwd,
                    host=self.host,
                    charset='utf8', use_unicode=True)
        self.cursor = self.conn.cursor()

    def process_item(self, item, spider):
        sql = "INSERT INTO Listing (url, price, listing_type, house_size, year_bui
        self.cursor.execute(sql,
                    (
                     item.get("url"),
                     item.get("price"),
                     item.get("listing_type"),
                     item.get("house_size"),
                     item.get("year_built"),
                     item.get("city")
                    )
                    )
        self.conn.commit()
        return item

   def close_spider(self, spider):
        self.conn.close()
```

Now we can run our spider:

```
scrapy crawl real_estate
```

If we've done everything correctly we should see the extracted records in the database, nicely formatted.



	price	listing_type	house_size	year_built	city
cas...	849000	Condo/Townhome	909	1963	San Francisco
57-...	750000	Condo/Townhome	715	*NULL*	San Francisco
22-...	1595000	Condo/Townhome	1950	1905	San Francisco
-ca...	1795000	Condo/Townhome	1550	1935	San Francisco
40-...	825000	Condo/Townhome	918	1914	San Francisco
7-n...	1399000	Condo/Townhome	1035	1900	San Francisco
1-i...	1865000	Condo/Townhome	1668	*NULL*	San Francisco
-28...	1495000	Condo/Townhome	1378	1900	San Francisco
5-1...	1950000	Condo/Townhome	1812	1924	San Francisco
0-k...	768000	Condo/Townhome	618	2004	San Francisco
8-m...	1549000	Condo/Townhome	963	2016	San Francisco
1-3...	1798000	Condo/Townhome	1970	*NULL*	San Francisco
cas...	849000	Condo/Townhome	909	*NULL*	San Francisco

Data analysis

Now we are going to visualize the data. Hoping to get a better understanding of it. The process we are going to follow to draw charts:

1. Query the database to get the required data
2. Put it into a pandas dataframe
3. Clean, manipulate data if necessary
4. Use panda's plot() function to draw charts

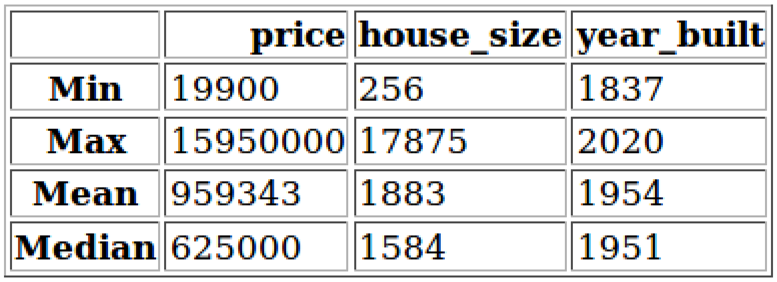
A few important things to point out before drawing far-reaching conclusions while analyzing the dataset:

- We have only ~3000 records (I did not scrape the whole website only part of it)
- I removed the land listings (without a building)
- I scraped listings from only 9 cities in the US

Descriptive reports

Starting off, let's "get to know" our database a little bit. We will query the whole database into a dataframe and create a new dictionary to get min, max, mean and median values for all numeric data fields. Then create a new dataframe from the dict to be able to display it as a table.

```
query = ("SELECT price, house_size, year_built FROM Listing")
df = pd.read_sql(query, self.conn)
d = {'Mean': df.mean(),
     'Min': df.min(),
     'Max': df.max(),
     'Median': df.median()}
return pd.DataFrame.from_dict(d, dtype='int32')[["Min", "Max", "Mean", "Median"]
```



	price	house_size	year_built
Min	19900	256	1837
Max	15950000	17875	2020
Mean	959343	1883	1954
Median	625000	1584	1951

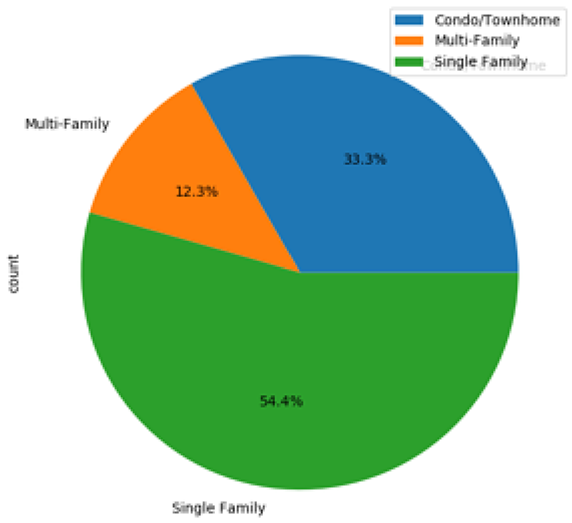
This table shows us some information:

- The oldest house was built in 1837
- The cheapest house is $19 900, the most expensive is $15 950 000
- The smallest house is 256 sq ft, the largest one is 17 875 sq ft
- The average house was built in the 1950s
- The average house size is 1883 sq ft (174 m2)

Ratio of house types

Overall, we have three types of listings: Condo/Townhome, Multi-Family and Single-family. Let’s see which are the more popular among the listings.

```
query = ("SELECT listing_type, COUNT(*) AS 'count' FROM Listing GROUP BY listing_
df = pd.read_sql(query, self.conn, index_col="listing_type")
df.plot.pie(y="count", autopct="%1.1f%%", figsize=(7, 7))
plt.show()
```

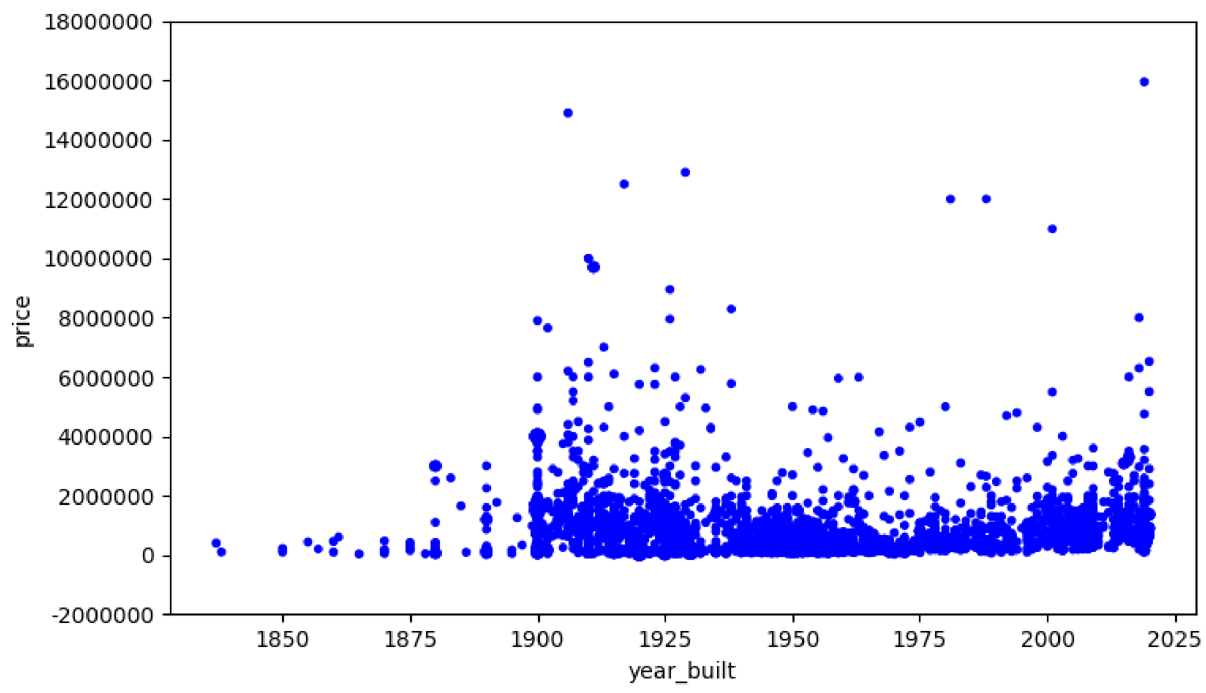


A little more than half of the listings are Single family homes. About a third of them are considered Condo/Townhome. And only 12.3% is a Multi-family home.

Correlation between price and year

Next, let’s have a look at the prices. It would be good to see if there’s any correlation between price and age of the building.

```
query = "SELECT price, year_built FROM Listing"
df = pd.read_sql(query, self.conn)
x = df["year_built"].tolist()
y = df["price"].tolist()
c = Counter(zip(x, y))
s = [10 * c[(xx, yy)] for xx, yy in zip(x, y)]
df.plot(kind="scatter", x="year_built", y="price", s=s, color="blue")
yy, locs = plt.yticks()
ll = ['%.0f' % a for a in yy]
plt.yticks(yy, ll)
plt.show()
```

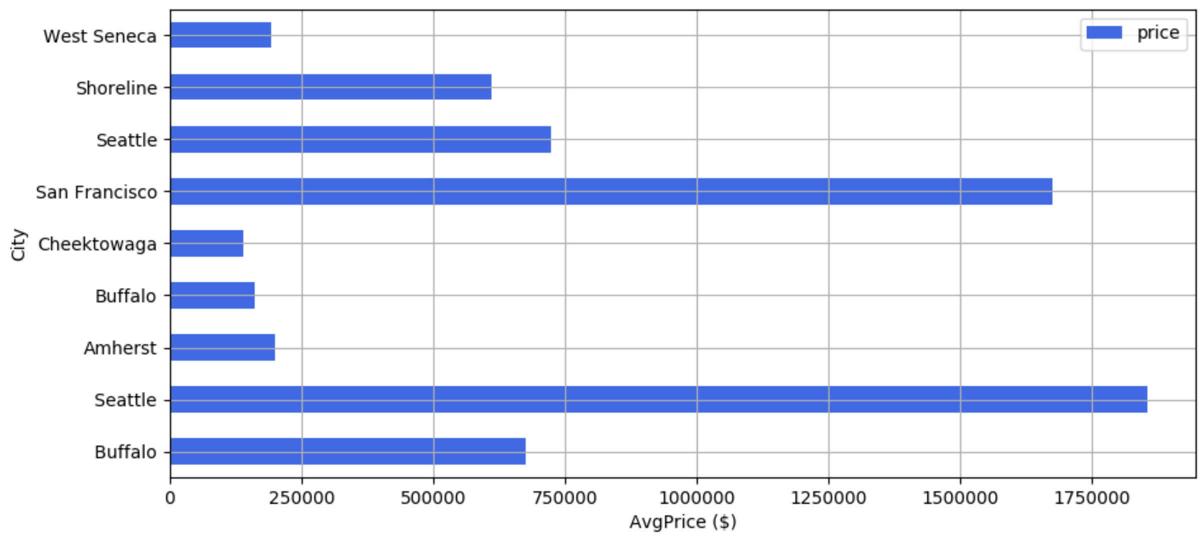


What we see here is that we have a listing for pretty much every year. But there's not really a clear conclusion we can draw from this. It looks like there are quite a few houses that were built in the first half of the 20th century and they are more expensive than recently built ones.

Average price per city

In this one we look at the price tags for each city.

```
query = "SELECT FLOOR(AVG(price)) AS 'price', city, COUNT(city) AS 'count' FROM I
df = pd.read_sql(query, self.conn)
df = df.drop(df.index[1])
ax = plt.gca()
ax.get_yaxis().get_major_formatter().set_useOffset(False)
ax.get_yaxis().get_major_formatter().set_scientific(False)
df.plot.barh(x="city", y="price", color="royalblue", ax=ax, grid=True)
plt.xlabel("AvgPrice ($)")
plt.ylabel("City")
plt.show()
```

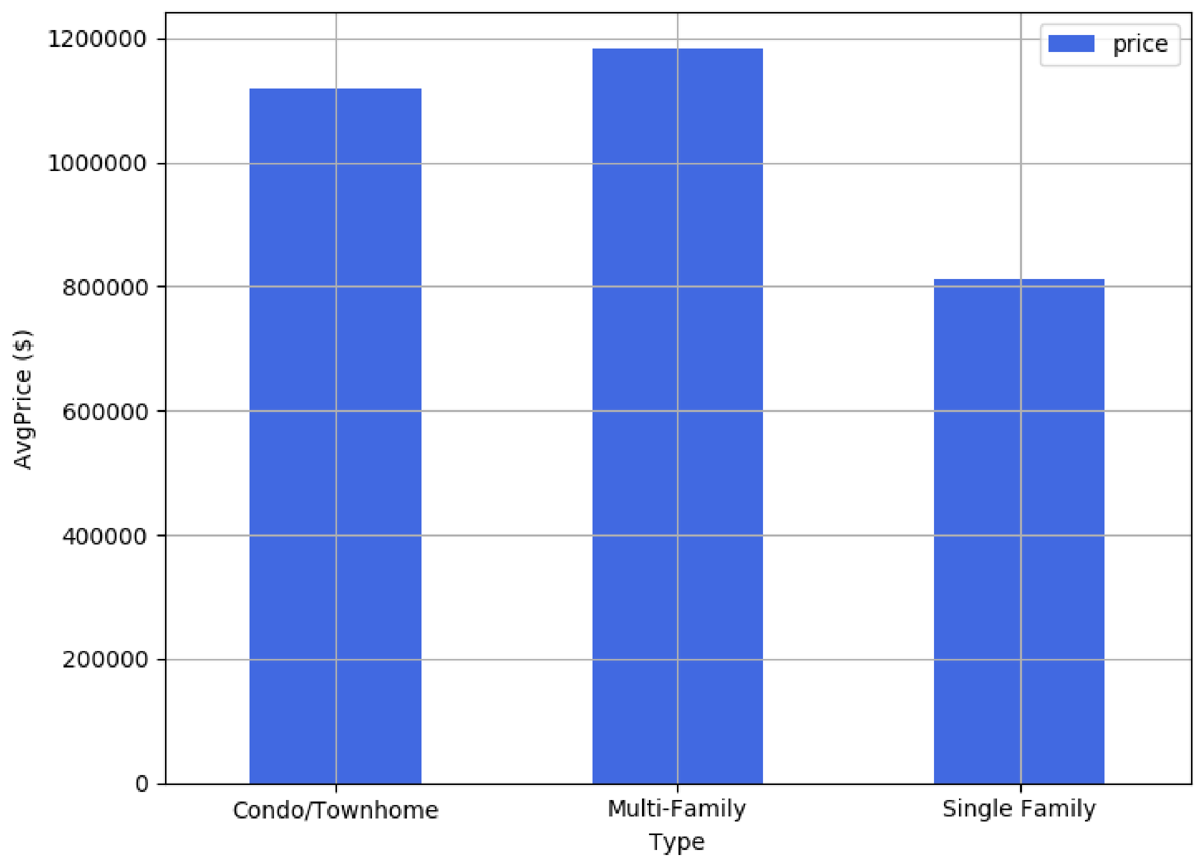


Among the cities we analyzed, San Francisco and Seattle are the most expensive ones. San Francisco has an average house price of ~$1 650 000. For Seattle, it's ~$1 850 000. The cheapest cities to buy a house are Cheektowaga and Buffalo, the average price is about $250 000 for both.

Average price per house type

In the next analysis we examine the average price for different house types. Out of the three house types, which one is the most expensive and the cheapest one?

```
query = "SELECT FLOOR(AVG(price)) AS 'price', listing_type FROM Listing GROUP BY
df = pd.read_sql(query, self.conn)
ax = plt.gca()
df.plot(kind="bar", x="listing_type", y="price", color="royalblue", ax=ax, grid=
plt.xlabel("Type")
plt.ylabel("AvgPrice ($)")
plt.show()
```



As we can see, there's not much of a difference between Condo/Townhome and Multi-Family Type houses. Both are between $1,000,000 - $ 1,200,000. Single Family homes are considerably cheaper, with an average price of $800,000.

Wrapping up

As I said at the beginning, the data sample I used to create these charts is really small. Thus, the results of this analysis cannot be considered reliable to generalize to the whole real estate market. The goal of this article is just to show you how you can make use of web data and turn it into actual insights. If you are interested in how to analyze ecommerce prices, check out this article here.

If you have a data-driven product which is fueled by web data, read more about how Scrapinghub can help you!

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