OpenStreetMap Project for Data Wrangling with MongoDB

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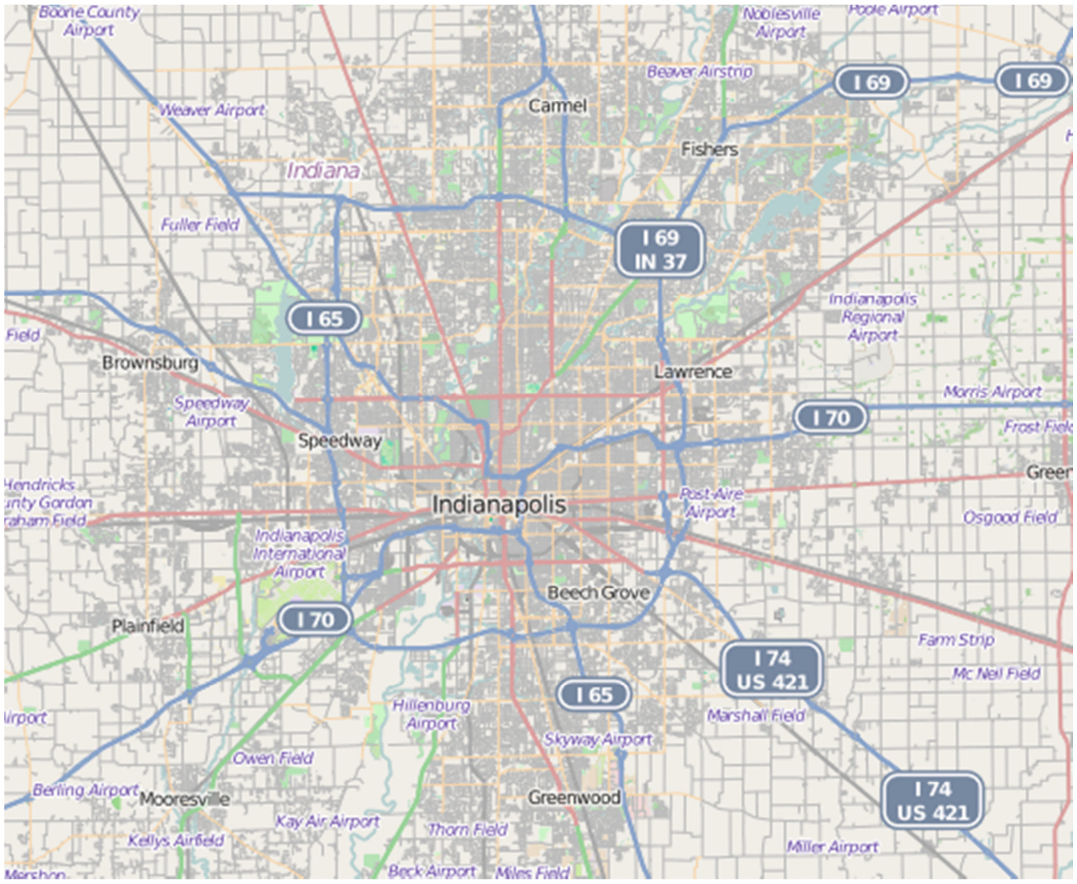
Map Area: Indianapolis, Indiana, United States

I chose this area because I attended high school in Carmel.

Map Zen:

https://s3.amazonaws.com/metro-extracts.mapzen.com/indianapolis_indiana.osm.bz2

https://www.openstreetmap.org/#map=10/39.7948/-86.3553



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1. Problems Encountered in the Map

Using a modified version of data.py, I discovered there were a few street names abbreviations unaccounted for and I added them to **mapping** array. Also, a few new valid regional names such as Circle, Crossing, Pass et al. were added to the **expected** array.

Zip codes I found were not consistent. A majority of them were 5 digits but a few were extended (8 digit) so I used a regex to remove the add-on code so we can aggregate easier in MongoDB.

# Sort zip codes by count, descending

```
db.indy.aggregate([{"$match":{"address.postcode":{"$exists":1}}},
                   {"$group":{"_id":"$address.postcode", "count":{"$sum":1}}},
                   {"$sort":{"count":-1}}])
```

Here are the top 5 most frequent zip codes:

```
{ "_id" : "46112", "count" : 111 }
{ "_id" : "46038", "count" : 49 }
{ "_id" : "46256", "count" : 35 }
{ "_id" : "46240", "count" : 32 }
{ "_id" : "46250", "count" : 23 }
```

Three out of the top 5 are in Castleton (46250, 46240, 46256), which is a densely populated area in the north, northwest of Indianapolis. It is close to many lakes and also has a large retail shopping mall, where I used to work. The second most frequent zip code is Fishers, IN (46038) a northwest suburb. The most used zip code is Brownsburg, IN (46112) a suburb west of the city. Before the regex, this would have been more difficult to produce.

Phone numbers were also in a variety of formats. I Googled a regex online[1] and applied it to the **phone** field.

2. Data Overview

This section contains statistical summary of the dataset and the respective MongoDB queries used.

File sizes

```
indy.osm ......... 268 MB
indy.osm.json .... 300 MB
```

# Number of documents

```
> db.indy.find().count()
1356221
```

# Number of nodes

```
> db.indy.find({"type":"node"}).count()
1231835
```

```
# Number of ways
> db.indy.find({"type":"way"}).count()
124386

# Number of unique users
> db.indy.distinct("created.user").length
552

# Top 5 contributing users
> db.indy.aggregate( [{"$group" : {"_id":"$created.user",  "count": {"$sum":1} }},
                              {“$sort":{"count":-1}},
                              {"$limit":5} ] )

{ "_id" : "woodpeck_fixbot", "count" : 401279 }  33%
{ "_id" : "rama_ge", "count" : 360319 }  29%
{ "_id" : "debutterfly", "count" : 154934 }  13%
{ "_id" : "Dr Centerline", "count" : 75155 }  6%
{ "_id" : "svance92", "count" : 62162 }  5%

# Number of users appearing only once (having 1 post)
> db.indy.aggregate([{"$group":{"_id":"$created.user", "count":{"$sum":1}}},
                           {"$group":{"_id":"$count", "num_users":{"$sum":1}}},
                           {"$sort":{"_id":1}}, {"$limit":1}])

{ "_id" : 1, "num_users" : 103 }
# “_id” represents postcount
```

3. Additional Ideas

Similar to the sample project, it seems the contribution of data has been skewed towards a few users. The top 5 users comprise 85% of all documents in this collection. This leads me to conclude that this open source tool hasn’t crowd sourced a lot of its data but done so via select users or bots. “Gamification” could help but the Google maps product has more information and a richer dataset. This is a useful tool to explore and study with but as a viable tool maybe they could focus on a particular segment of their users. For example, they could gear information to find public schools, day care centers, parking lots.

Additional data exploration using MongoDB queries

```
# Top 5 appearing amenities
> db.indy.aggregate([{"$match":{"amenity":{"$exists":1}}},
                              {"$group":{"_id":"$amenity",
                              "count":{"$sum":1}}},
                              {"$sort":{"count":-1}},
                              {"$limit":5}])
```

```
{ "_id" : "parking", "count" : 6981 }
{ "_id" : "place_of_worship", "count" : 756 }
{ "_id" : "school", "count" : 513 }
{ "_id" : "grave_yard", "count" : 326 }
{ "_id" : "restaurant", "count" : 231 }
```

# Biggest religion

```
> db.indy.aggregate([ {"$match":{"amenity":{"$exists":1},
                        "amenity":"place_of_worship"}},
                        {"$group":{"_id":"$religion",
                        "count":{"$sum":1}}},
                        {"$sort":{"count":-1}},
                        {"$limit":1}])

{ "_id" : "christian", "count" : 721 }
```

# Most popular cuisines

```
> db.indy.aggregate([{"$match":{"amenity":{"$exists":1}, "amenity":"restaurant"}},
                        {"$group":{"_id":"$cuisine", "count":{"$sum":1}}},
                        {"$sort":{"count":-1}}, {"$limit":2}])
 { "_id" : null, "count" : 93 }
{ "_id" : "pizza", "count" : 22 }
```

A closer look at the restaurants with null cuisine reveals they are mainly chain restaurants.

```
db.indy.aggregate([{"$match":{"amenity":{"$exists":1}, "amenity":"restaurant", "cuisine": null}},
                        {"$project" : {"_id" :"$name"}}])

{ "_id" : "Hard Rock Cafe" }
{ "_id" : "TGI Fridays" }
{ "_id" : "Steak 'n Shake" }
{ "_id" : "Donato's" }
{ "_id" : "The Cheesecake Factory" }
{ "_id" : "Jersey Mike's Subs" }
{ "_id" : "Panera Bread" }
{ "_id" : "Noodles & Company" }
```

4. Conclusion

The OSM dataset has been fun to play with and explore. The Indianapolis data is pretty clean but has obvious gaps. I chose NYC before that because that's where I live and I found that the Map Zen data set was too large to process for my computer (over 2 GB) and one I selected from Overpass API, although more manageable(Manhattan, BK, Queens only), was mostly done by scripts or bots. I guess NYers can't be bothered. Overall, I enjoyed this project and hope to explore more datasets.

5. References

1. Regex deal with phone numbers

http://www.diveintopython.net/regular_expressions/phone_numbers.html

http://www.tutorialspoint.com/python/python_reg_expressions.htm