## OpenStreetMap Project in Data Wrangling with MongoDB

Name: Anna Li

Email: annax.li10@gmail.com

Map Area: Auckland, New Zealand

URL: <http://www.openstreetmap.org/export#map=12/-36.8612/174.7839>

I chose my hometown, Auckland, New Zealand, for project 2 because I grew up in this city, and I know the area well. New Zealand is also far away from the rest of the world, and there is little OpenStreetMaps data. I want to contribute to improve the quality of the Auckland map.

The area I chose to wrangle includes the central Auckland city (I live in Epsom) and the greater suburban region, such the North Shore (Takapuna, Birkenhead, and Devonport), all the way west to Henderson and Te Atau and as far south as Mangere Bridge. I have friends living in all of these areas

I downloaded the data in two steps: 1. I found the area I was interested in using OpenStreetMap (<http://www.openstreetmap.org/export#map=12/-36.8612/174.7839>) and made sure it was over 50MB using this website, 2. I ran a mapping query from Overpass API (<http://overpass-api.de/query_form.html>) to download the xml data.

**Table of Contents**

OpenStreetMap Project in Data Wrangling with MongoDB 1

Problems/Points of Interest 1

*Standardization* 1

Appendix 2

## Problems in the OSM Auckland Data

After downloading and auditing the original dataset, I discovered three problems in the data set that required wrangling and cleaning as well as two interesting points that merit investigation. The three problems:

* Lack of standardization in street types (e.g. ‘Queen St.' and ‘Queen st’)
* Incorrect values in fields (e.g. ‘Newmarket’ suburb is misplaced in the street)
* Missing values (city was often missing from the address)

Command line function to import OSM Auckland json data into MongoDB

mongoimport --db auckland --collection full --file osm-auckland.json --jsonArray

## Standardization

Inconsistent street types

Using the aklaudit.py script, which is modified from the auditing exercise in lesson 6, I discovered inconsistent street types that required cleaning. For example, “Queen St.” and “Queen st” needed to be standardized to “Queen Street”. I updated inconsistent street types to match the standardized format and removed leading and trailing whitespaces, for example:

Gillies Ave => Gillies Avenue

Erson Ave => Erson Avenue

Queen st => Queen Street

Queen St. => Queen Street

New North Rd => New North Road

Note: New Zealand streets frequently have the street direction appended at the end of the street name, such as “Customs Street West”. I decided not to remove the direction because they are meaningful. This happens because very long streets stretch across the city and “90 Green Lane East” is in a different suburb (Remuera) than “90 Green Lane West” (Epsom).

After importing the JSON-formatted data into MongoDB, I wrote queries with the pymongo connector to retrieve the street names and cities from the Auckland data.

db.full.aggregate( [{'$match': {'address.street': {'$exists': 1}}},'$group': {'\_id': '$address.street','count': { '$sum': 1} }},

{'$sort': {'count': -1}}, {'$limit': 100}] )

I was able to look at the different street names to find incorrect values, such as “Hurstmere” which is missing “Road” or “Waverley” which is missing “Avenue” (I fixed this in aklaudit.py). I noticed some streets have unusual names and types, such as “The Strand”. But this is a correct street name (The Strand is an arcade-style square in the Auckland city center so its street type is an unusual exception) and does not require cleaning.

## Incorrect values in fields

City values frequently contain additional data like housenumber and street

After exploring the addresses, I audited the city data to determine where what kinds of inconsistent formatting and values occurred, and therefore what needed cleaning. I modified the MongoDB aggregation pipeline query for street to work on city:

db.full.aggregate( {'$match': {'address.city': {'$exists': 1}}}, {'$group': {'\_id': '$address.city', 'count': { '$sum': 1} }}, {'$sort': {'count': -1}}] )

The city field had two main problems:

* Inconsistent or incorrect spellings of “Auckland”, such as “auckland”, “1 Auckland”, and “Auckalnd”
* Most of the city values were suburbs in Auckland, such as “Parnell”, “Takapuna”, and “Morningside”. Sometimes there was a suburb concatenated with the city, such as “Birkenhead, Auckland” and “New Lynn, Auckland”.

The city ‘Auckland’ appears correctly 460 times in the OSM data set. The instances where it requires cleaning are listed below:

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| 'Waterview' | 1 | 'North Shore': | 3 | 'Kelston, Auckland' | 1 | 'Takapuna' | 5 |
| 'auckland' | 1 | 'Royal Oak' | 1 | 'Birkenhead, Auckland' | 1 | 'Mt Wellington' | 1 |
| 'Waitemata' | 5 | 'Morningside' | 2 | 'New Lynn, Auckland' | 3 | 'Auckalnd' | 1 |
| 'St Heliers' | 1 | '1 Auckland' | 1 | 'Glen Eden' |  |  |  |

## Missing values

City is missing from address data that has at least a street

Realizing that many city values were actually suburbs made me wonder how many city fields were missing data. I wrote a query to uncover how many address documents that had at least a street were missing a city:

db.full.aggregate ( [{'$match': {'address': {'$exists': 1}}}, {'$match': {'address.street': {'$exists': 1}}}, {'$match': {'address.city': {'$exists': False}}}, {'$group': {'\_id': '$address.city','count': {'$sum': 1}}}] )

The result showed there were 801 address documents missing a city.

{u'ok': 1.0, u'result': [{u'\_id': None, u'count': 801}]}

## Appendix

For a list of sources, please refer to the Resources Used.txt file in the Project2 folder in Github (relative path in Github is ../NanoDA/DataWranglingMongoDB/Project2/Resources Used.txt)

“I hereby confirm that this submission is my work. I have cited above the origins of any parts of the submission that were taken from Websites, books, forums, blog posts, github repositories, etc. By including this in my email, I understand that I will be expected to explain my work in a video call with a Udacity coach before I can receive my verified certificate.”

Is there any other important information that you would want your project evaluator to know?

Use this space to communicate with your project evaluator. Is there anything you would like to communicate? Feedback or suggestions?

[*https://www.openstreetmap.org/relation/177415*](https://www.google.com/url?q=https%3A%2F%2Fwww.openstreetmap.org%2Frelation%2F177415&sa=D&sntz=1&usg=AFQjCNHfumZldEV08ImbcbWHb0Xg3Ejlmg)

[*http://metro.teczno.com/#charlotte*](http://www.google.com/url?q=http%3A%2F%2Fmetro.teczno.com%2F%23charlotte&sa=D&sntz=1&usg=AFQjCNGCsHL2If59bTZ7McZVY_nEgQR40A)

[1. Problems Encountered in the Map](https://docs.google.com/document/d/1F0Vs14oNEs2idFJR3C_OPxwS6L0HPliOii-QpbmrMo4/pub#h.ueey7dly83g7)

[Over-­abbreviated Street Names](https://docs.google.com/document/d/1F0Vs14oNEs2idFJR3C_OPxwS6L0HPliOii-QpbmrMo4/pub#h.l5zk1sr6iqsy)

[Postal Codes](https://docs.google.com/document/d/1F0Vs14oNEs2idFJR3C_OPxwS6L0HPliOii-QpbmrMo4/pub#h.1gvukyc8hthj)

[2. Data Overview](https://docs.google.com/document/d/1F0Vs14oNEs2idFJR3C_OPxwS6L0HPliOii-QpbmrMo4/pub#h.ql5hndj5vh2a)

[3. Additional Ideas](https://docs.google.com/document/d/1F0Vs14oNEs2idFJR3C_OPxwS6L0HPliOii-QpbmrMo4/pub#h.30qfugxkfikk)

[Contributor statistics and gamification suggestion](https://docs.google.com/document/d/1F0Vs14oNEs2idFJR3C_OPxwS6L0HPliOii-QpbmrMo4/pub#h.vtjnh5x9putq)

[Additional data exploration using MongoDB](https://docs.google.com/document/d/1F0Vs14oNEs2idFJR3C_OPxwS6L0HPliOii-QpbmrMo4/pub#h.7ygo1ggwcb7)

[Conclusion](https://docs.google.com/document/d/1F0Vs14oNEs2idFJR3C_OPxwS6L0HPliOii-QpbmrMo4/pub#h.rc7ls9o2vj3)

**1. Problems Encountered in the Map**

After initially downloading a small sample size of the Charlotte area and running it against a provisional data.py file, I noticed three main problems with the data, which I will discuss in the following order:

* Over­-abbreviated street names (“S Tryon St Ste 105”)
* Inconsistent postal codes (“NC28226”, “28226­0783”, “28226”)
* “Incorrect” postal codes (*Charlotte area zip codes all begin with “282” however a large portion of all* *documented zip codes were outside this region.*)

**Over-­abbreviated Street Names**



Once the data was imported to MongoDB, some basic querying revealed street name abbreviations and postal code inconsistencies. I updated all substrings in problematic address strings, such that “S Tryon St Ste 105” becomes “South Tryon Street Suite 105”.

**Postal Codes**

Postal code strings posed a different sort of problem, forcing a decision to strip all leading and trailing characters before and after the main 5-­digit zip code. This effectually dropped all leading state characters (as in “NC28226”) and 4­-digit zip code extensions following a hyphen (“28226­0783”). This 5­-digit constriction benefits MongoDB aggregation calls on postal codes.

Regardless, after standardizing inconsistent postal codes, some altogether “incorrect” (or perhaps misplaced?) postal codes surfaced when grouped together with this aggregator:

# Sort postcodes by count, descending

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

Here are the top two results, beginning with the highest count:

[ {"\_id" : "29732", "count" : 103},

{"\_id" : "28134", "count" : 27}, ...

Considering the relatively few documents that included postal codes, of those, it appears that out of the top ten, seven aren’t even in Charlotte. That struck me as surprisingly high to be a blatant error, and found that the number one postal code and all others starting with “297” lie in Rock Hill, SC. So, I performed another aggregation to verify a certain suspicion...

# Sort cities by count, descending

> db.char.aggregate([{"$match":{"address.city":{"$exists":1}}}, {"$group":{"\_id":"$address.city", "count":{"$sum":1}}}, {"$sort":{"count":­1}}])

And, the results, edited for readability:

[ {"\_id" : "Rock Hill", "count" : 111},...

These results confirmed my suspicion that this metro extract would perhaps be more aptly named “Metrolina” or the “Charlotte Metropolitan Area” for its inclusion of surrounding cities in the sprawl.

So, these postal codes aren’t “incorrect,” but simply unexpected.

**2. Data Overview**

This section contains basic statistics about the dataset and the MongoDB queries used to gather them.

File sizes

charlotte.osm ......... 294 MB

charlotte.osm.json .... 322 MB

# Number of documents

> db.char.find().count()

1555851

# Number of nodes

> db.char.find({"type":"node"}).count()

1471349

# Number of ways

> db.char.find({"type":"way"}).count()

84502

# Number of unique users

> db.char.distinct({"created.user"}).length

336

# Top 1 contributing user

> db.char.aggregate([{"$group":{"\_id":"$created.user", "count":{"$sum":1}}}, sort":{"count":­1}}, {"$limit":1}])

[ { "\_id" : "jumbanho", "count" : 823324 } ]

# Number of users appearing only once (having 1 post)

> db.char.aggregate([{"$group":{"\_id":"$created.user", "count":{"$sum":1}}}, {"$group":{"\_id":"$count", "num\_users":{"$sum":1}}}, {"$sort":{"\_id":1}}, {"$limit":1}])

[ {"\_id":1,"num\_users":56} ]

# “\_id” represents postcount

**3. Additional Ideas**

**Contributor statistics and gamification suggestion**

The contributions of users seems incredibly skewed, possibly due to automated versus manual map editing (*the word “bot” appears in some usernames*). Here are some user percentage statistics:

* Top user contribution percentage (“jumbanho”) - 52.92%
* Combined top 2 users' contribution (“jumbanho” and “woodpeck\_fixbot”) - 83.87%
* Combined Top 10 users contribution - 94.3%
* Combined number of users making up only 1% of posts - 287 (about 85% of all users)

Thinking about these user percentages, I’m reminded of “gamification” as a motivating force for contribution. In the context of the OpenStreetMap, if user data were more prominently displayed, perhaps others would take an initiative in submitting more edits to the map. And, if everyone sees that only a handful of power users are creating more than 90% a of given map, that might spur the creation of more efficient bots, especially if certain gamification elements were present, such as rewards, badges, or a leaderboard.

**Additional data exploration using MongoDB queries**

# Top 10 appearing amenities

> db.char.aggregate([{"$match":{"amenity":{"$exists":1}}}, {"$group":{"\_id":"$amenity",

"count":{"$sum":1}}}, {"$sort":{"count":­1}}, {"$limit":10}])

[ {"\_id":"place\_of\_worship","count":587},

{"\_id" : "school", "count" : 416}, ….

# Biggest religion (no surprise here)

> db.char.aggregate([{"$match":{"amenity":{"$exists":1}, "amenity":"place\_of\_worship"}},

{"$group":{"\_id":"$religion", "count":{"$sum":1}}},

{"$sort":{"count":­1}}, {"$limit":1}])

[ {"\_id":"christian","count":577} ]

# Most popular cuisines

> db.char.aggregate([{"$match":{"amenity":{"$exists":1}, "amenity":"restaurant"}}, {"$group":{"\_id":"$cuisine", "count":{"$sum":1}}},        {"$sort":{"count":­1}}, {"$limit":2}])

[ { "\_id" : "pizza", "count" : 9},

{ "\_id" : "american", "count" : 9} ...

**Conclusion**

After this review of the data it’s obvious that the Charlotte area is incomplete, though I believe it has been well cleaned for the purposes of this exercise. It interests me to notice a fair amount of GPS data makes it into OpenStreetMap.org on account of users’ efforts, whether by scripting a map editing bot or otherwise. With a rough GPS data processor in place and working together with a more robust data processor similar to data.py think it would be possible to input a great amount of cleaned data to OpenStreetMap.org.