

Final Project for Data Wrangling with MongoDB

by Allan Reyes in fulfillment of Udacity's Data Analyst Nanodegree, Project 2

Project Summary

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Area of study:

- Location: Austin, TX
- [Open Street Map URL](<http://www.openstreetmap.org/relation/113314>)
- [Mapzen URL](https://s3.amazonaws.com/metro-extracts.mapzen.com/austin_texas.osm.bz2)

Objective: Audit and clean the data set, converting it from XML to JSON format.

References:

- Lesson 6 from Udacity course, "Data Wrangling with MongoDB"
- myDatamaster [US Street Suffixes and Abbreviations](<http://mydatamaster.com/wp-content/files/streetsuffix.zip>)
- zaiste.net [Importing JSON into MongoDB](http://zaiste.net/2012/08/importing_json_into_mongodb/)

Honor code statement:

"I, Allan Reyes, hereby confirm that this submission is my own 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 project report, 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."

Section 1: Problems Encountered in the Map

Unexpected Tags

``mapparser.py`` was used to count occurrences of each tag, with a result:

- ``bounds: 1``
- ``member: 12602``
- ``nd: 891530``
- ``node: 771167``
- ``osm: 1``
- ``relation: 1241``
- ``tag: 532159``
- ``way: 79357``

Additional functionality was added to `mapparser.py` to examine the keys stored in each `tag` element, in the `k` attribute. Unexpectedly, the 20 most common key values were:

```
`{'amenity': 7006, 'building': 12487, 'created_by': 8353, 'highway': 67137, 'name': 41954, 'odbl': 10223, 'oneway': 9506, 'ref': 3695, 'service': 5894, 'tiger:cfcc': 35037, 'tiger:county': 35058, 'tiger:name_base': 28536, 'tiger:name_type': 26254, 'tiger:reviewed': 32442, 'tiger:separated': 24167, 'tiger:source': 26710, 'tiger:tlid': 26725, 'tiger:upload_uuid': 7913, 'tiger:zip_left': 21001, 'tiger:zip_right': 19591}`
```

Using `tags.py`, I parsed through the tag data and sampled a maximum of 20 values for each key. Results were exported to `austin.osm-tag-data.json`. This gave insight on some inconsistent data formats (e.g. `25 mph` vs `25`), incorrect mappings (e.g. `78722` under `state`), and some minor misspellings (e.g. `construction`).

Extra Encoded Data and Systems

By examining what `tag` keys were present in the first 10 million lines, it was clear that at least two separate subsystems were encoded via `tag` elements: [Topologically Integrated Geographic Encoding and Referencing system (TIGER)](<http://wiki.openstreetmap.org/wiki/TIGER>) data and [USGS Geographic Names Information System (GNIS)](http://wiki.openstreetmap.org/wiki/USGS_GNIS) data. Due to both redundancy and significant information lacking in GNIS data, I chose to remit it from population into the database.

Specialized Tag Elements

At least 360 `tag` keys appeared only once. Many were extremely specialized, e.g. `recycling:glass_bottles` and several of these tags were name translations. As part of the cleaning process, I manually selected a list of `tag` keys to filter out prior to database population.

Multiple Zip Codes

Zip codes were presented in the data under various permutations of `tiger:zip_left` and `tiger:zip_right`, defined as semicolon delimited lists or colon delimited ranges. Given that zip codes are a common search criteria, I thought that it would be a good idea to collect and serialize all zipcodes from all sources into a single array, and populate this into the base of the node under `zipcodes`.

Phone Number Inconsistency

Phone numbers were formatted inconsistently. I used the Python module `phonenumbers` to parse all phone numbers and re-format them to the standard `(123) 456-7890`.

Abbreviated Street Names

There were inconsistencies with street name abbreviations. For consistency, I translated all abbreviations into the 'titleized' long forms, e.g. `EXPWY` to `Expressway`. Additionally, all `.` characters were removed. Standard street name suffixes were imported and parsed from a CSV of U.S. Street

Suffixes and Abbreviations (see References). Additional misspellings and special cases (e.g. `I 35`, `IH-35`, `IH 35` to `Interstate Highway 35`) were added to the translation table in `suffix.py`.

Relation and Member Elements

There was the additional presence of `relation` and `member` tags. According to the [OSM wiki](<http://wiki.openstreetmap.org/wiki/Relation>), the `relation` tags are used to define logical or geographical groups. For the purposes of populating a document database of `node` and `way` tags, I concluded that the best option was to parse these tags out.

Section 2: Data Overview

This section contains basic statistics about the dataset and the MongoDB queries used to gather them. The queries are included in `query.py`.

File sizes:

- `austin.osm: 177 MB`
- `austin.osm.json: 194 MB`

Number of documents:

```
...  
> db.austin.count()  
850524  
...
```

Number of nodes and ways:

```
...  
> db.austin.find({'type':'node'}).count()  
771167  
> db.austin.find({'type':'way'}).count()  
79357  
...
```

Number of unique users:

```
...  
db.austin.distinct("created.user").length  
874  
...
```

Top contributing user:

```
...  
> db.austin.aggregate([  
...     '$group': {  
...         '_id': '$created.user',  
...         'count': {  
...             '$sum': 1  
...         }  
...     }, {  
...         '$sort': {  
...             'count': -1  
...         }  
...     }, {
```



```

...     }
...     })
{ "_id" : "Zip Codes in Austin", "count" : 402, "zipcodes": [ "76577",
... # truncated
"78469", "78721", "78612", "78645", "78715", "78735", "78426" ] }
` ``

```

Most common building types/entries:

```

> db.austin.aggregate([
...     '$match': {
...         'building': {
...             '$exists': 1
...         }
...     }, {
...         '$group': {
...             '_id': '$building',
...             'count': {
...                 '$sum': 1
...             }
...         }
...     }, {
...         '$sort': {
...             'count': -1
...         }
...     }, {
...         '$limit': 10
...     })
{ "_id" : "yes", "count" : 8384 }
{ "_id" : "house", "count" : 2080 }
{ "_id" : "detached", "count" : 555 }
{ "_id" : "school", "count" : 308 }
{ "_id" : "apartments", "count" : 213 }
{ "_id" : "university", "count" : 170 }
{ "_id" : "commercial", "count" : 147 }
{ "_id" : "retail", "count" : 121 }
{ "_id" : "roof", "count" : 84 }
{ "_id" : "residential", "count" : 81 }

```

Most common street address:

```

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

```

```

...         '$sort': {
...             'count': -1
...         }
...     }, {
...         '$limit': 1
...     }
... ])
{ "_id" : "Research Boulevard", "count" : 53 }

```

Nodes without addresses:

```

> db.austin.aggregate([
...     '$match': {
...         'type': 'node',
...         'address': {
...             '$exists': 0
...         }
...     }, {
...         '$group': {
...             '_id': 'Nodes without addresses',
...             'count': {
...                 '$sum': 1
...             }
...         }
...     }
... ])
{ "_id" : "Nodes without addresses", "count" : 770002 }

```

Section 3: Conclusion

Additional Ideas

With the queries conducted, there was more of a focus on the study of node ‘places’ rather than ways and their respective node ‘waypoints’. Given that an overwhelming number of nodes (90.5%) do not include addresses and the large number (891530) of ‘nd’ reference tags, an interesting exercise would be to compress this data by removing any ‘way’ tags and waypoint-like nodes. Naturally, this decision falls on the application. This could potentially reduce the database size by a factor of 10. Furthermore, if ways were still needed, it would still be possible to remove any ‘orphaned’ nodes that were only referenced in the removed ‘relation’ and ‘member’ tags.

There are still several opportunities for cleaning and validation that I left unexplored. Of note, the data set is populated only from one source: OpenStreetMaps. While this crowdsourced repository pulls from multiple sources, some of data is potentially outdated. According to the [OSM Tiger Wiki](<http://wiki.openstreetmap.org/wiki/TIGER>), the most recent data pulled was from 2005. It would have been an interesting exercise to validate and/or pull missing information (i.e. names) from the Google Maps API, since every node has latitude-longitude coordinates.

Comments

This review of this data is cursory. While there are many additional opportunities for cleaning and validation, I believe the data set was well-cleaned for the purposes of this exercise.