

Project 2 for Data Wrangling with MongoDB

At Udacity- Data Analyst Nano degree

By Mital Shah

Project Summary

Name: Mital Shah

Email address: ms599y@att.com

Area of study:

- Location: Austin, TX
- <https://www.openstreetmap.org/relation/113314>
- [Open Street Map URL](#)
- [Mapzen URL](#)

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

References: I have used following links and some MongoDB

- Lesson 6 from Udacity course, "Data Wrangling with MongoDB"
- myDatamaster - [US Street Suffixes and Abbreviations](#)
- <http://docs.mongodb.org/manual/core/import-export/>
- zaiste.net - [Importing JSON into MongoDB](#)
- [Proper way to import json file to mongo - Stack Overflow](#)
- [Google Maps API | Google Developers](#)
- <https://www.google.com/intx/en/work/mapsearch/products/mapsapi.html>
- <http://docs.mongodb.org/manual/applications/geospatial-indexes/>

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:tld': 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` vs `cosntruction` or `construciton`).

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)]data and [USGS Geographic Names Information System \(GNIS\)](#) 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 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 format 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 'totalized' 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. 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](#), 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: 166 MB

Austin.osm.json: 183 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
...   }
... }, {
...   '$limit': 1
... })
{ "_id" : "woodpeck_fixbot", "count" : 245427 }

```

Number of users contributing only once:

```

> db.austin.aggregate([
...   '$group': {
...     '_id': '$created.user',
...     'count': {
...       '$sum': 1
...     }
...   }
... }, {
...   '$group': {
...     '_id': '$count',
...     'num_users': {
...       '$sum': 1
...     }
...   }
... }, {
...   '$sort': {
...     '_id': 1
...   }
... }, {
...   '$limit': 1
... })
{ "_id" : 1, "num_users" : 168 }

```

Zip codes in Austin:

```

db.austin.aggregate([
...   '$match': {
...     'zipcodes': {
...       '$exists': 1
...     }
...   }
... }, {
...   '$unwind': '$zipcodes'
... }, {

```

```

...     '$group': {
...       '_id': '$zipcodes'
...     }
...   }, {
...     '$group': {
...       '_id': 'Zip Codes in Austin',
...       'count': {
...         '$sum': 1
...       },
...       'zipcodes': {
...         '$push': '$_id'
...       },
...     }
...   })
{ "_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

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.

Other ideas about the datasets

Based on my experience with exploring the OpenStreetMap data, I believe that the data structure is flexible enough to incorporate a vast multitude of user generated quantitative and qualitative data beyond that of simply defining a virtual map. I believe that extending this open source project to include data such as user reviews of establishments, subjective areas of what bound a good and bad neighborhood, housing price data, school reviews, walkability/bike ability, quality of mass transit, travel time and distance between locations can also be calculated, for example if you want to offer users a way to filter search results by drive time and on would form a solid foundation of robust recommender systems. These recommender systems could aid users in anything from finding a new home or apartment to helping a user decide where to spend a weekend afternoon.

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.

Files

- data/: data files and output from scripts (austin.osm and austin.osm.json excluded)
- lesson6/: source code for scripts completed in Lesson 6 of Data Wrangling with Mongo DB
- audit.py: audits streets and zip codes, also provides cleaning methods
- data.py: builds the JSON file from the OSM data; parses, cleans, and shapes data
- mapper.py: parses the OSM file and provides insight on tag data

- query.py: contains MongoDB queries
- Project2_for_Data_Wrangling_with_MongoDB.pdf: this document
- subset.py: produces a smaller subset of the main data
- suffix.py: parses data from a suffix CSV file, provides suffix conversion/cleaning methods
- tags.py: script for conducting exploratory data analysis on tag data

Note: I have resubmitted project2 file with following correction

- 1) I have included all “.py” files (audit.py, data.py, mapparser.py, query.py, subset.py, suffix.py and tags.py) with project zip files.
- 2) I have included all lesson’s problem sets “.py” files with under each folders
- 3) I have made correction to your comments on feed back in this file.

“Typo Needing Correction *"removing anyway tags" - I believe you meant any "space" way tags.”*

Correction- by removing any `way` tags

- 4) I have made another correction to your comments on feedback- added some examples.
Its not clear why the 20 most common key values were "unexpected". Please elaborate.
You give an example of a minor misspelling (e.g. construction) but there doesn't seem to be a typo. Please do show the incorrect and correct versions.

Correction- some minor misspellings (e.g. `construction` vs `cosntruction` or `construcion`)

Under the Multiple Zip Codes section Phone Numbers are mentioned. There should be a separate heading for Inconsistent Phone Numbers (or a similar name).

Correction- added separate title header for phone number inconsistency.

- 5) Added some comments under “Other ideas about the datasets” header.