# **OpenStreetMap Data Project**

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date: December 15, 2016

# Map Area

I chose Austin, Texas as the area for this project. I am new to this city and thought this project would assist me in exploring Austin.

# **Identifying Problems in the Map**

After taking a sample of the 1.16 GB dataset using sample\_region.py, I used three techniques to identify problems in the sample:

Utilized Sublime to view portions of the data in it's original form.

Analyzed the audit.py script output to view unusual street names and postal codes.

Analyzed the CSV files created by the process\_osm. script to view the data (in schema.md format) before and after cleaning code was applied.

# **Problems Encountered in the Map**

Simplified versions of code for audit and cleaning the following problems is presented below.

#### Overabbreviated street names

Spell out over abbreviated street tyoes:

import xml.etree.cElementTree as ET from collections import defaultdict import re import pprint

```
OSMFILE = "sample.osm" street type re = re.compile(r'\b\S+.?\$', re.IGNORECASE)
expected = ["Street", "Avenue", "Boulevard", "Drive", "Court", "Place", "Square", "Lane", "Road", "Trail",
"Parkway", "Commons"]
UPDATE THIS VARIABLE mapping = { "St": "Street", "St.": "Street", "Ave.": "Avenue", "Rd.": "Road" }
def audit street type(street types, street name): m = street type re.search(street name) if m: street type =
m.group() if street type not in expected: street types[street type].add(street name)
def is street name(elem): return (elem.attrib['k'] == "addr:street")
def audit(osmfile): osm file = open(osmfile, "r") street types = defaultdict(set) for event, elem in
ET.iterparse(osm file, events=("start",)):
        if elem.tag == "node" or elem.tag == "way":
             for tag in elem.iter("tag"):
                  if is street name(tag):
                      audit_street_type(street_types, tag.attrib['v'])
    osm file.close()
    pprint.pprint (dict(street types))
    return street types
def update name(name, mapping):
    # YOUR CODE HERE
    m = street_type_re.search(name)
    if m:
        street_type = m.group()
        if street_type in mapping.keys():
             print 'Before: ', name
             name = re.sub(m.group(), mapping[m.group()], name)
             print 'After: ', name
```

#### **Erroneous City names in dataset**

import xml.etree.cElementTree as ET import pprint

# audit way tags for unexpected city names in Austin map

audit of sample file shows names which appear to be outside of what would be considered Austin (eg Buda > 60mi away)

this would require edit specific entries; these can be ignore for analysis purposes in most cases with no material effect

Manchaca Cedar Park, TX Buda Sunset Valley Buda Lakeway Sunset Valley Cedar Park

#### **Postal Codes**

```
sqlite> SELECT tags.value, COUNT() as count
...> FROM (SELECT FROM nodes_tags
...> UNION ALL
...> SELECT * FROM ways_tags) tags
...> WHERE tags.key='postcode'
...> GROUP BY tags.value
...> ORDER BY count DESC;
```

#### abbreviated results of unusual values:

Texas|2

78724-1199|10

78728-1275|2

78754-5701|2

78759-3504|2

78704-5639|1

78704-7205|1

78753-4150|1

78758-7008|1

10130-1000|1

78758-7013|1

TX 78613|1

TX 78724|1

TX 78728|1

TX 78735|1

TX 78745|1

TX 78758|1

removal of the items listed as "Texas"; "TX" pre-fix and four digit extensions can be ignored in analysis

#### **Data Overview**

#### File sizes

austin\_map.osm ....... 1.16 GB
austin\_map.db ....... 773 MB
nodes.csv ....... 499 MB
nodes\_tags.csv ...... 9 MB
ways.csv ....... 40 MB
ways\_tags.csv ...... 144 MB
ways\_nodes.cv ...... 59 MB
for validation and data familiarity:
austin\_map\_sample.osm .... 59 MB
test\_sample.osm ..... 9 MB

#### **Number of nodes**

sqlite> SELECT COUNT(\*) FROM nodes; 5,358,645 sqlite> SELECT COUNT(\*) FROM nodes\_tags; 2,011,149

## Number of ways, ways\_nodes and ways\_tags

sqlite> SELECT COUNT(\*) FROM ways; 564388 sqlite> SELECT COUNT(\*) FROM ways\_nodes; 58,992,639 SELECT COUNT(\*) FROM ways\_nodes; 5,892,639

## Number of unique users

sqlite> SELECT COUNT(DISTINCT(e.uid))
FROM (SELECT uid FROM nodes UNION ALL SELECT uid FROM ways) e;
1644

## Top 10 contributing users

sqlite> SELECT e.user, COUNT(\*) as num
...> FROM (SELECT user FROM nodes UNION ALL SELECT user FROM ways) e
...> GROUP BY e.user
...> ORDER BY num DESC
...> LIMIT 10;

patisilva\_atxbuildings|2492624 ccjjmartin\_atxbuildings|1062000 ccjjmartin\_\_atxbuildings|834577 jseppi\_atxbuildings|273706 wilsaj\_atxbuildings|249835 kkt\_atxbuildings|157845 lyzidiamond\_atxbuildings|135318 woodpeck\_fixbot|77816 johnclary\_axtbuildings|48232 richlv|46822

238

# Number of users with only 1 posting

sqlite> SELECT COUNT()
...> FROM
...> (SELECT e.user, COUNT() as num
...> FROM (SELECT user FROM nodes UNION ALL SELECT user FROM ways) e
...> GROUP BY e.user
...> HAVING num=1) u;

# **Additional Data Exploration**

## Top 10 appearing amenities

```
sqlite> SELECT value, COUNT(*) as num
...> FROM nodes_tags
...> WHERE key='amenity'
... > GROUP BY value
... > ORDER BY num DESC
...> LIMIT 10;
parking|1885
restaurant|700
waste basket|601
fast food|501
school|437
place of worship|413
bench|359
fuel|347
shelter|230
bank|150
```

## Most popular cuisines

```
sqlite> SELECT nodes_tags.value, COUNT(*) as num
...> FROM nodes tags
...> JOIN (SELECT DISTINCT(id) FROM nodes tags WHERE value='restaurant') i
... > ON nodes tags.id=i.id
...> WHERE nodes_tags.key='cuisine'
... > GROUP BY nodes tags.value
... > ORDER BY num DESC
...> LIMIT 10;
mexican|60
american|27
pizza|23
chinese|22
indian|14
sandwich|14
italian|13
regional|13
sushi|13
thai|13
```

# **Biggest religion**

```
sqlite> SELECT nodes_tags.value, COUNT(*) as num
...> FROM nodes_tags
...> JOIN (SELECT DISTINCT(id) FROM nodes_tags WHERE value='place_of_worship') i
...> ON nodes_tags.id=i.id
...> WHERE nodes_tags.key='religion'
...> GROUP BY nodes_tags.value
...> ORDER BY num DESC
...> LIMIT 1;
christian|367
```

# **Dataset Improvement**

Classification issues from original source input is one of the most significant issues with this dataset and one of the most challenging to address. This is most often the cases with new contributors to the dataset. A periodic scrubb of input from contributors with less than 5 entries may effectively address this concern.

#### Conclusion

The Austin OpenStreetMap dataset is a quite large and a bit messy. However, I believe the dataset is not materially deficint for the analysis purposes of this project. By quwrying the dataset, I learned a number of new things about Austin which will benefit me as I continue to explore this town. The dataset is very useful, though areas for improvement exist.