OpenStreetMap Data Wrangling with SQL

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Map Area: Las Vegas, Nevada, USA:

https://www.openstreetmap.org/relation/170117

https://mapzen.com/data/metro-extracts/metro/las-vegas_nevada/

Project Overview

Using data munging techniques to clean the OpenStreetMap data for a part of the world in **https://www.openstreetmap.org**.

Objectives:

- Assess the quality of the data for validity, accuracy, completeness, consistency and uniformity.
- Parse and gather data from popular file formats such as .csv, and .xml
- Process data from multiple files or very large files that can be cleaned programmatically.
- Learn how to store, query, and aggregate data using SQL.

Reason for selection:

- Las Vegas, Nevada: I intended to choose where I have been to and this area is 222MB in size which was the smallest among many options. I would like to analyze my hometown or other metropolitan area I have visited before but I believe this would be a great start.

Auditing data

Problems:

There were several issues with the original dataset as highlighted below.

- Over-abbreviated street type e.g. 'Corporate Park Dr' for 'Corporate Park Drive'
- Inconsistent postal codes e.g. NV 89052, 89108-7049, Nevada 89113
- Incorrect postal codes e.g. 6451112, 8929
- Inconsistent city names e.g. Las Vegas, LAS VEGAS, Las Vegas NV, Las Vagas

Street types:

In **audit_street_name.py**, I print out uncleaned street names by using "pprint" module so that I can refer to the list to fix the mapping variables. E.g. mapping = {"Blvd": "Boulevard", "Cir": "Circle"}.

```
def update_name(name, mapping, street_type_re):
    m = street_type_re.search(name)
    if m:
        st_type = m.group()
        if st_type in mapping:
            name = re.sub(street_type_re, mapping[st_type], name)
    return name
```

After changing the variables, the update_name function corrects the problematic street names to their respective mappings when it runs and the part of outcome is as follows.

```
oval drive => oval Drive
Paradise Rd => Paradise Road
W Warm Springs Rd => W Warm Springs Road
Losee Rd => Losee Road
El Camino Rd => El Camino Road
W Craig Rd => W Craig Road
S Fort Apache Rd => S Fort Apache Road
S Pecos Rd => S Pecos Road
Hillpointe Rd => Hillpointe Road
```

Postal codes:

In **audit_postal_code.py**, I use “regular expression” to get 5 valid numbers in each postal code to make them consistent.

```
zip_type_re = re.compile(r'\d{5}-??')
def update_zip(zip):
    m = zip_type_re.search(zip)
    if m:
        return m.group()
    else:
        return "unknown"
```

And the part of the result is shown below.

```
89014 => 89014
8929 => unknown
89156 => 89156
89131 => 89131
89178 => 89178
89179 => 89179
6451112 => 64511
89134 => 89134
89130 => 89130
NV 89124 => 89124
89135 => 89135
```

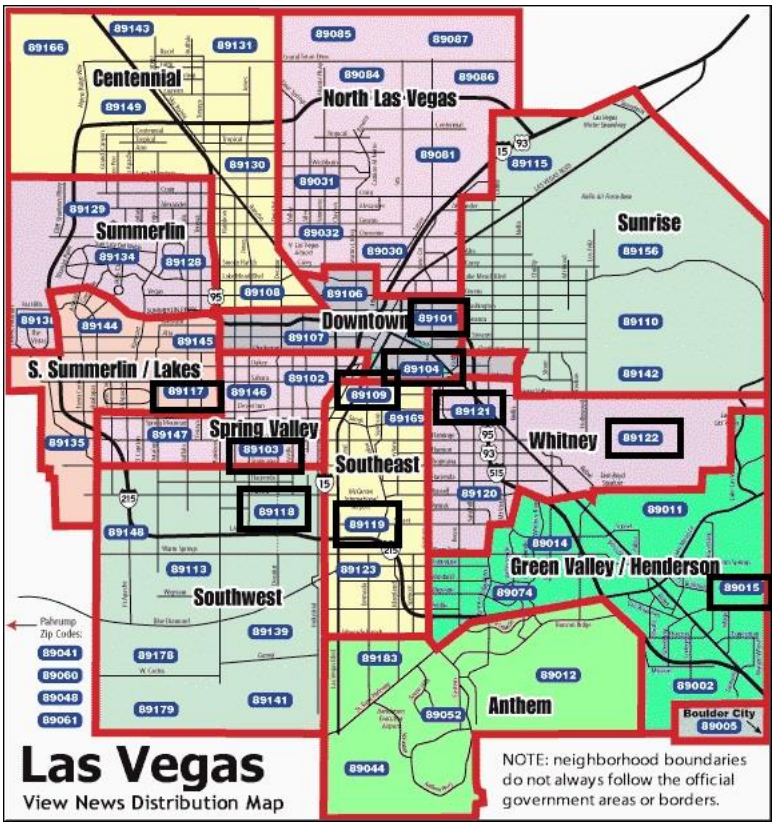
After standardizing inconsistent postcodes, the top 10 count results became more reliable.

```
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
Limit 10;
```

Descending numerical order by counts

```
value|count
89109|104
89101|74
89122|60
89119|56
89117|47
89015|45
89104|34
89121|34
89103|33
89118|31
```

Las Vegas Zip Codes



Reference: city-data.com/forum/las-vegas/

The outcome has revealed that a large part of the data was collected from the middle of Las Vegas. Henderson is the second largest city in Nevada and appeared in the top 10.

City names:

To support the above analysis, I sorted cities by count.

```
SELECT tags.value, COUNT(*) as count
FROM (SELECT * FROM nodes_tags UNION ALL
      SELECT * FROM ways_tags) tags
WHERE tags.key LIKE '%city'
GROUP BY tags.value
ORDER BY count DESC
Limit 10;
```

```
Las Vegas|522
Henderson|111
North Las Vegas|29
Boulder City|13
Paradise|13
12|7
15|5
8|5
Las Vegas, NV|5
Overton|5
```

Even though city names are not very consistent, “Las Vegas” is written in an overwhelming number of tags and “Henderson” has the second largest counts.

Data Analysis

Data Overview:

Below is a basic statistical overview of the dataset.

- File sizes

```
las-vegas_nevada.osm ......... 222 MB
las-vegas_nevada.db .......... 124 MB
nodes.csv ............. 87 MB
nodes_tags.csv ........ 2 MB
ways.csv .............. 7 MB
ways_tags.csv ......... 15 MB
ways_nodes.cv ......... 31 MB
```

- Key types in tags (**tags.py**)

```
{'lower': 318077, 'lower_colon': 165530, 'other': 7312, 'problemchars': 0}
```

- Number of nodes

```
SELECT COUNT(*) FROM nodes;
```

    1052739

- Number of ways

```
SELECT COUNT(*) FROM ways;
```

    112602

- Number of unique users

```
SELECT COUNT(DISTINCT(e.uid))
FROM (SELECT uid FROM nodes UNION ALL SELECT uid FROM ways) e;
```

    1067

- Top 10 contributing users

```
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;
```

```
alimamo|251482
tomthepom|121167
woodpeck_fixbot|70788
alecdhuse|66523
abellao|55651
gMitchellD|44620
robgeb|40928
nmixter|40029
TheDutchMan13|39078
Tom_Holland|32927
```

- Number of users appearing only one (having 1 post)

```
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;
```

261

Additional Data Exploration:

- Top 10 amenitites: **Restaurant**

```
SELECT value, COUNT(*) as num
FROM nodes_tags
WHERE key='amenity'
GROUP BY value
ORDER BY num DESC
LIMIT 10;
```

```
restaurant|477
place_of_worship|294
fuel|282
fast_food|278
fountain|266
school|206
shelter|122
toilets|86
bar|80
cafe|79
```

- Biggest religion: **Christian**

```
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|274
```

- Most popular cuisines: **Mexican**

```
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;
```

```
mexican|41
pizza|31
american|20
italian|18
steak_house|16
```

```
burger|15
chinese|13
asian|9
japanese|9
buffet|7
```

Conclusion

- Final thought: Even though many inconsistency and inaccuracy was seen in the dataset from the auditing process, there were not much problematic characters or language problems, which saved the researcher a lot of work.
- Limitations: As long as OpenStreetMap allows volunteers to edit objects such as restaurants and schools, human input errors are inevitable. Furthermore, manual data cleaning process is harder for ambiguity, which was the big problem especially in city names in this report e.g. city name: 12.
- Suggestions: To encourage users to input clean data, GPS data should be required in every contribution and OpenstreetMap will need to facilitate more corrections or additions to the existing data.

References

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http://www.city-data.com/forum/las-vegas/487322-neighborhoods-overview-map-zip-codes.html

https://www.openstreetmap.org/relation/170117

https://mapzen.com/data/metro-extracts/metro/las-vegas_nevada/

https://en.wikipedia.org/wiki/OpenStreetMap