OpenStreetMap Data Case Study

Map Area

Las Vegas, NV, United States

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

https://www.openstreetmap.org/relation/170117#map=10/36.2670/-115.3510

I chose Las Vegas as an area of data to analyze since it is a city I am familiar with having visited many times.

Data Audit

Since there were different types of tags being used, I audited and counted the unique number of tags:

def test():

I then looked for patterns in the tags (ex. tags containing problem characters, tags that are only lowercase) using the below regular expression.

```
lower = re.compile(r' \land ([a-z]|_) * \$') \\ lower\_colon = re.compile(r' \land ([a-z]|_) * \$') \\ problemchars = re.compile(r'[= +/& <>; \''' \?% # \$ @ \, \. \t \r \n]') \\ Code returned: \\ \{'lower': 300441, 'lower colon': 265414, 'other': 8373, 'problemchars': 0\} \\ \{'lower': 300441, 'lower colon': 265414, 'other': 8373, 'problemchars': 0\} \\ \{'lower': 300441, 'lower colon': 265414, 'other': 8373, 'problemchars': 0\} \\ \{'lower': 300441, 'lower colon': 265414, 'other': 8373, 'problemchars': 0\} \\ \{'lower': 300441, 'lower colon': 265414, 'other': 8373, 'problemchars': 0\} \\ \{'lower': 300441, 'lower colon': 265414, 'other': 8373, 'problemchars': 0\} \\ \{'lower': 300441, 'lower colon': 265414, 'other': 8373, 'problemchars': 0\} \\ \{'lower': 300441, 'lower colon': 265414, 'other': 8373, 'problemchars': 0\} \\ \{'lower': 300441, 'lower colon': 265414, 'other': 8373, 'problemchars': 0\} \\ \{'lower': 300441, 'lower colon': 265414, 'other': 8373, 'problemchars': 0\} \\ \{'lower': 300441, 'lower colon': 265414, 'other': 8373, 'problemchars': 0\} \\ \{'lower': 300441, 'lower colon': 265414, 'other': 8373, 'problemchars': 0\} \\ \{'lower': 300441, 'lower colon': 265414, 'other': 8373, 'problemchars': 0\} \\ \{'lower': 300441, 'lower colon': 265414, 'lower colon': 265414, 'lower colon': 265414, 'lower': 300441, 'lower colon': 265414, 'lower': 300441, 'low
```

Problems Encountered in the Map

As suggested, I initially ran code on a small sample size of the area. One of the main problems encountered in the data were the problematic postcodes and different abbreviations for street names.

Postal Codes

Postcode variations:

- 89105-1900
- 8856
- NV 89014
- Nevada 89113
- 6451112

I ran five different regular expressions to clean the postcodes to what was desired. See code below and a sample of the output for the cleaned postal codes.

```
def update postcode(postcode):
```

```
#searches for postcodes that match desired of 5 digits
  search = re.match(r'^{d{5}}), postcode)
  #searches for postcodes that start w/abbrev. state name
  search2 = re.match(r'^[NV].\{2\}(\d{5})',postcode)
  #searches for postcodes that start with the state name
  search3 = re.match(r'^[a-zA-z].\{6\}(\d\{5\})',postcode)
  #searches for postcodes that have a 4 digit code after
  search4 = re.match(r'^(\d{5})-\d{4}\', postcode)
  if search:
    clean_postcode = search.group()
    # returns `clean_postcode` and exits function
    return clean_postcode
  elif search2:
    clean_postcode = search2.group(1)
    return clean postcode
  elif search3:
    clean_postcode = search3.group(1)
    return clean postcode
  elif search4:
    clean_postcode = search4.group(1)
    return clean postcode
for postcode in postcodes:
  print postcode.encode("utf-8")
  print "updated"
  print update_postcode(postcode)
  print "----"
```

Here's some examples of the uncleaned to clean postal codes. The cleaned ones remain the same, and if they don't match the regex then nothing is returned.

updated 89128 NV 89124	89128-6634	89123
Nevada 89113 89124 updated 89113 NV 89129 updated 8929 updated None 89166 updated 89040 89166 updated 89040 89147-4111	updated	
Nevada 89113 89124 updated 89113 NV 89129 updated 8929 89129 updated None 89166 updated 89040 89166 updated 89040 89147-4111	89128	NV 89124
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89040 89166 updated 89040 89147-4111	None	89166
updated 89040 89147-4111		updated
89040 89147-4111	89040	89166
	updated	
updated	89040	89147-4111
		updated
NV 89123 89147	NV 89123	89147
updated	updated	

Street Name Abbreviations

A second problem found was inconsistence street name abbreviations.

These were some of the variations:

Street abbreviations:

- St. > Street
- Ave > Avenue
- Rd. > Road
- Blvd. > Boulevard
- Pkwy > Parkway
- Cir > Circle
- Dr > Drive

They were corrected using the following mapping:

I used the following code to correct the street names:

```
for street_type, ways in street_types.iteritems():
    for name in ways:
        better_name = update_name(name, mapping)
        print name, "=>", better_name
        if name == "S Rainbow Blvd":
        assert better_name == "S Rainbow Boulevard"
```

Size of OSM File

Las-vegas_nevada.osm 213 MB

Database Exploration using SQL

Below I explore the data of the file providing information such as number of nodes, ways, unique users, and who contributed the most. In addition I also run queries on city demographics such as religion and number of bars/pubs.

Number of Nodes

SELECT COUNT(*) FROM nodes; 994412

Number of Ways

```
SELECT COUNT(*) FROM ways; 102846
```

Number of Unique Users

SELECT COUNT(uid) FROM(SELECT uid FROM nodes UNION SELECT uid FROM ways); 1550

Top 10 Contributors

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|253647 tomthepom|103918 woodpeck_fixbot|73927 alecdhuse|66676 abellao|56785 gMitchellD|46525 robgeb|41212 nmixter|40093 Tom_Holland|34016 MojaveNC|28691

Top 5 Religions

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 5;

christian | 289 jewish | 3 bahai | 2 muslim | 2 buddhist | 1

Number of bars/pubs in Vegas

SELECT COUNT(*)
FROM nodes_tags
WHERE key = 'amenity' and value = 'bar' or value = 'pub';

88

Number of bar and pub separate

SELECT nodes_tags.value, COUNT(*) as num
FROM nodes_tags
JOIN (SELECT DISTINCT(id) FROM nodes_tags WHERE value='bar' or value='pub') i
ON nodes_tags.id=i.id

WHERE nodes_tags.key='amenity' GROUP BY nodes_tags.value;

bar 68 pub 20

Additional Improvement Ideas

One improvement to this dataset could be to have a call to the yelp API to include not only the types of cuisine but have a column for rating and name of restaurant. This would be useful for visitors to know the top restaurants and also be able to narrow down by the type of food. One thing that may be a problem or challenge is that the users entering the cuisine type like Mexican, etc. may make typos or it may not match what yelp considers the cuisine type to be. For example, just looking at the data I see two problematic records one with cuisine called "Beer Cheese" and another called "Fresh_food_from_scratch." If the data is cleaned, having the yelp ratings and names of restaurants would prove to be beneficial for tourists.