# SONET: A Semantic Ontological Network Graph for Managing Points of Interest Data Heterogeneity

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## ABSTRACT

Scalability, standardization, and management are important issues when working with very large Volunteered Geographic Information (VGI). VGI is a rich and valuable source of Points of Interest (POI) information, but its inherent heterogeneity in content, structure, and scale across sources present major challenges for interlinking data sources for analysis. To be useful at scale, the raw information needs to be transformed into a standardized schema that can be easily and reliably used by data analysts. In this work, we tackle the problem of unifying POI categories (e.g. restaurants, temple, and hotel) across multiple data sources to aid in improving land use maps and population distribution estimation as well as support data analysts wishing to fuse multiple data sources with the OpenStreetMap (OSM) mapping platform or working with projects that are already configured in the OSM schema and wish to add additional sources of information. Graph theory and its implementation through the SONET graph database, provides a programmatic way to organize, store, and retrieve standardized POI categories at multiple levels of abstraction. Additionally, it addresses category heterogeneity across data sources by standardizing and managing categories in a way that makes cross-domain analysis possible.

## CCS CONCEPTS

• **Information systems → Network data models**.

## KEYWORDS

big data, openstreetmap, ontology, points of interest, graph database

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## 1 INTRODUCTION

Volunteered Geographic Information (VGI) offers researchers a wealth of accessible, geographic data; with that, it is especially valuable in regions of the world traditionally considered data poor. VGI is dominated by user-generated information such as Points of Interest (POIs), that provide insight into the type of facility or land use present and its social function at a specific location. Increasingly, in this era of widely available open source data, the linchpin of analysis is often a disconnect between the schema of disparate data sources. Although the conflation of POIs from multiple platforms would dramatically improve both spatial and categorical coverage, source heterogeneity makes it difficult to examine POI data from more than one or two platforms simultaneously. Maximizing the utility and efficiency of using this data requires addressing the data heterogeneity at the category level by curating, wrangling, and deploying this data in a standardized schema. Each VGI platform classifies POIs into a number of categories such as Zoo, Water Park, Restaurant, or Temple, using a specific, semantic schema, which informs the type or use of the facility or area. With this facility and area level information, land use of cities, regions, and countries can be estimated for areas of the world that traditionally lack land use maps. Because different platforms approach category generation from the top-down (i.e., Facebook and Google) or the bottom-up (i.e., OpenStreetMap (OSM) and Wikimapia), platforms contain between 21 to over 10,000 categories at varying levels of abstraction and consistency. Currently, there exists surprisingly little research exploring the conflation of POIs across different open-source mapping platforms [10]. Our work aims to fill this gap by addressing category heterogeneity across VGI sources. We achieve this through the development of a category-level ontological network that uses a graph database of nested categories to assign POIs from different sources, a category based on a consistent schema. This network manages categories in a way that makes cross-platform analysis possible and supports land use mapping and population modeling. Using the long-standing and popular OSM tag structure, each set of source categories are matched to one or more corresponding OSM category tags and stored in a scalable, extensible graph database. In the database, these category tags are clustered by land use and facility type, creating a hierarchy of land use types. We also connect source categories of original data sources and their OSM-matched tags with each other for querying purposes. Thus, land use types are mapped at the individual scale or at a larger, more generalized scales (e.g., Residential or Non-Residential). The resulting ontological network advances VGI-based research in two ways. First, it enables cross-platform analysis of POI data, thus maximizing both spatial, categorical, and social coverage. Second, the hierarchical network structure allows for the application of POI data in land use and population dynamics research.


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**Table 1: Total number of POIs and unique categories for each social media platform maintained in PlanetSense.**

| Platform | Unique Categories |
|---|---|
| Google | 124 |
| Facebook | 1,634 |
| OSM | 520 |
| Wikimapia | 7,204 |
| Vkontakte | 69 |
| Here | 458 |
| TomTom | 382 |
| Foursquare | 938 |

## 2 RELATED WORK

The past several years has been host to a rise in the use of VGI in a variety of research applications, including work evaluating data quality on a variety of VGI platforms. To date, much research exploring POIs has been limited to using data from one or two datasets, or has focused on collecting data for a small area (i.e., a case study) [5–7]. Because different VGI platforms have been used more in some locations than others or to document certain types of information, there may be applications for which one dataset may perform better than another [7]. Though logistically and computationally expensive, the ability to conflate multiple POI datasets can undoubtedly offer a more comprehensive understanding of geographic context than any source can offer alone. Some attempts to conflate POIs have been made recently, including a few approaches for matching individual POIs from two different platforms [8, 10]. A few tools exist to create a semantic network of tags in OSM [2, 4]. These tools identify relationships and provide structure to key:value pairs in OSM, contributing to our understanding of the semantic web and VGI. The value of this Linked Open Data (LOD) to work in the geospatial humanities is significant and serves as a future goal for this project. Our work differs in that we are creating a wide-spanning ontology inclusive of many VGI data sources, not just OSM, that can be used to to inform land use and population dynamics research. Additional ontological work with POIs includes recommender system applications specifically geared towards tourism [1] however the scope of this work is limited to the tourism domain. With this work we hope to expand the applications of such an ontology to meet the needs of a broad range of geospatial research topics.

## 3 DATA

We compiled a list of categories from 8 different data source platforms platforms for this work: Google, Facebook, OSM, Wikimapia, Vkontakte (VK), Here, TomTom, and Foursquare. All information was obtained through APIs and stored in the PlanetSense service[12]. The fields available vary by data source, but there are consistently name, category, and coordinates fields. The information populating these fields is added by a variety of volunteer users ranging from researchers, humanitarian volunteers, and business owners, to independent enthusiasts. This character of VGI makes the data valuable and unique as well as prone to errors and inconsistencies. Here we acknowledge the difficulties of this type of data but see its immense benefit in areas of the world that are lacking in curated, authoritative data of this type. Depending on the data source, some categories are static and curated by the owners of the platform. In others, such as OSM and Wikimapia, users are free to add category tags, creating an ever expanding list of categories assigned to POIs. In PlanetSense, four category fields: osmCategory, categoryLevel0, categoryLevel1, and categoryLevel2 fields are directly added to POI data from the SONET graph database, which will be discussed below.

## 4 POI CATEGORY MATCHING

Once the categories have been collected from each platform and ingested into PlanetSense, unique categories from each data source are extracted and matched to a set of appropriate OSM tags. OSM is one of the most widely-used and information rich sources of VGI [9]. Each POI within OSM has a set of tags composed of key-value pairs that provide categorical information about the land use or facility present. A maintained wiki provides recommendations for best-practice tagging and a list of commonly used tags, but users may assign and create tags freely. As a result of this open structure, OSM currently has 71,016 keys and 97,420,453 unique tags (key-value pairs) according to TagInfo, a database of OSM tags maintained by the OpenStreetMap Foundation. Each POI in OSM is assigned multiple tags identifying various characteristics of the POI, such as the building type and services or activities that are expected to occur there. We choose to map the source categories from Google, Facebook, Here etc. to this OSM format because of its broad use across geospatial disciplines, particularly in the humanities, and its rich source of category types. In keeping with the OSM tag structure, POI category matching may be a one-to-many match (*Hospital* matched to *amenity=hospital* and *building=hospital*), or a one-to-one (*City* is matched to only *place=city*). We chose to maintain this standard of consistency to maximize integration of the work with platforms that utilize and render in the OSM schema. There are three desired overall outcomes from this matching:

(1) Standardize category syntax across multiple data sources
(2) Consolidate similar categories within data sources
(3) Consolidate similar categories across data sources

The process of matching source categories to OSM tags is achieved through human encoding. There are three primary criteria for assigning OSM tags to the source category.

(1) Assign at least one tag from the Map Features Wiki
(2) Assign one more specific tag from either Map Features of Tag Info Wiki
(3) Assign one *building* = * tag where appropriate

In some cases, there may not be tags of all three types that are appropriate for a POI, so the priority is to select at least one that is presented on the Map Features Wiki. Given the vast number of tags and the potential to assign multiple different tags to the same POI, we ask at least two questions when choosing an appropriate tag: 1) How is the space used; 2) When is the space used. The temporal aspect of this work is inspired by research indicating temporal differences in open/close times for POIs of certain categories [11]. Sparks et.al [11] identified temporal signatures of open/close times for POIs such as Retail and Restaurant types. Distinct patterns emerged across cities from different countries, solidifying the notion that how a space is used and what kinds of activities occur there is to some degree reflected in its operating times. These two factors help classify functionally similar POIs into the same group. In addition to human encoding, the Levenshtein Distance Algorithm is used to generate best guesses for new categories based on the accumulated corpus of source categories already matched to OSM tags currently in SONET. These algorithm generated guesses are then reviewed by a human before final ingestion into the SONET database.

**Table 2: Sample output for a query extracting POI source, source category, and matched OSM Tags from categoryLevel0 Non-Residential, categoryLevel1 Retail, and categoryLevel2 Food Categories.**

| Source | Source Category | OSM Tags |
|---|---|---|
| OSM | bar | amenity=bar;building=retail |
| Facebook | Whisky Bar | amenity=bar;building=retail |
| TomTom | bar | amenity=bar;building=retail |
| Google | bar | amenity=bar;building=retail |
| Wikimapia | beach bar | amenity=bar;building=retail |
| Facebook | Restaurant | amenity=restaurant;building=retail |
| Google | food | amenity=restaurant;building=retail |
| Wikimapia | eatery | amenity=restaurant;building=retail |
| HERE | Bistro | amenity=restaurant;building=retail |

## 5 MATERIALS AND METHODS

### 5.1 Building a Graph Database

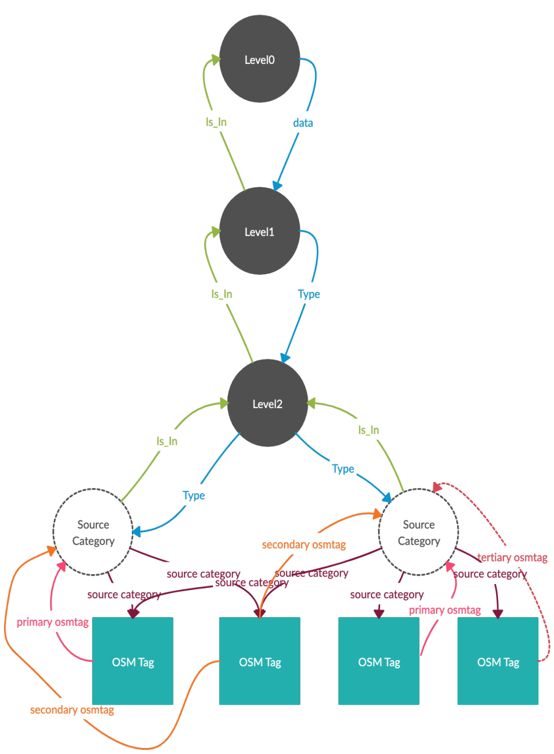


**Figure 1: SONET database schema.**

To address the major challenge of organizing and accessing this large amount of data in a scalable way, several approaches were considered. First, we considered a dictionary, accessible through Python or R programming languages. The size and complexity of the data makes this a cumbersome option. A second approach considered was a hierarchical tree data structure. The major drawback for this approach is structure limitations in order to maintain a balanced tree and limitations of only having one root node. Due to the nature of this data, there may be too many nodes or too few at each level for each node to have the appropriate number of children. A crucial aspect of this data is the relationships between the data points; categories that are semantically similar will be more closely aligned than others due to shared OSM tags but, they may also have relationships to other, less similar categories at various levels of abstraction. Because of this, we chose the graph database structure to organize the POI categories and their matched OSM tags. The database includes nodes at 4 different levels: 3 categoryLevel0 categories, 13 categoryLevel1, and 44 categoryLevel2, and currently 11,329 source categories matched to 2,545 OSM Tags. As new data is collected, processed, and added to the database, the number of source categories and OSM tags may increase, but it is not expected to be substantial. In creating an ontology of POI categories for land use mapping and population modeling, land use and facility types were adapted from the LandScan project [3] to create the categoryLevel0, categoryLevel1, and categoryLevel2 nodes. At the top of the database structure (see Figure 1), three categoryLevel0 nodes, Residential, Non-Residential, and Administrative facility types provide an important base for land use mapping and population modeling. Under Residential, 3 categoryLevel2 categories, Single Family, Multi-Family, and Refugee/IDP Settlements, create an additional level of abstraction. The Administrative level contains 2 categoryLevel2 categories, National and Sub-National. This accommodates source categories that do not fit precisely into Residential or Non-Residential types, such as City, Country, and Country. Non-Residential takes the bulk of the data, being divided into 13 categoryLevel1 categories and 34 categoryLevel2 categories. Table 2 illustrates a few examples of the types of categoryLevel1 and categoryLevel2 categories in this division. Traversing the graph down from the categoryLevel2 , is the sourcecategory level. This includes source categories from each of the VGI data sources we collect POIs from. Connected to each of these source categories is a set of OSM Tags that describe the type of facility or place it is. There may be some OSM Tags, such as *building=retail*, that are associated with a very large number of source categories; in this case, there are 2,916 source categories associated with that tag. In other cases, only a few source categories may be associated with any given OSM tag. The graph may be traversed from the bottom up to reveal clusters of similar source categories based on shared OSM tags or, from the top down based on categoryLevel2 associations.

## 6 DISCUSSION

The primary motivation for this research is the construction of a graph database to organize, store, and retrieve standardized POI categories in support of land use and population dynamics research at multiple scales. Researchers have several options for accessing the

**Table 3: Non-Residential categoryLevel1 and categoryLevel2 Categories**

| Retail | Institutions/Public Services | Commercial | Military | Agriculture | Entertainment | Transportation |
|---|---|---|---|---|---|---|
| Food | Religious | Office Building | Facility | Outdoor Agriculture | Night Club | Rail |
| Store | Education | Manufacturing | Base | Indoor Agriculture | Theater | Road |
| Kiosk | Healthcare | Power Plant | Explosives | | Sports | Air |
| Market | Public Service | Chemical Refining | Barracks | | Park | Sea |
| Hospitality | Learning Facilities/Tourism | | | | Indoor Recreation | Warehouse |
| Filling Stations | | | | | Outdoor Recreation | Transportation Repair |

data including a browser interface or connection through Python, R, or Java drivers. The database can be queried to produce both a visualization and a table of the desired output. Tables may be exported as csvs for use in other programs. Connections between a source category of interest such as *Soccer Stadium*, OSM tags that it has been matched to, and other source categories such as *Football Stadium* that share the OSM tag *building=stadium*, can be collected for analysis across multiple data sources. It also has the potential to be used as an aid for adding appropriate tags to new POIs in OSM or OSM dependent platforms. Currently, the database is not publicly available but it will be made accessible to researchers in the near future. The categories compiled from the 8 data sources used to build SONET contain data at a global scale; the places and their use, their significance, and their name, vary significantly from place to place, whether at the country, regional, or city scale. These platforms however, have preexisting category schemas, regardless of whether the they classification system is bottom-up (e.g., OSM, Wikimapia) or top-down (e.g., Facebook, Google) that data contributors must use to classify the data they are inputting. This puts a heavy burden on VGI data contributors to appropriately approximate a categorization of their information that best reflects their language and culture. In SONET, the source categories used, are largely in English with some exceptions in from Wikimapia. The standardization of global POI categories to an English based schema could present problematic issues in loss or misinterpretation of such information and it is an issue we keep in mind during this process of building this database. Because the categories we start with, that is the native Google, Facebook, Here etc. categories, are in English and are used as such globally, we keep with this standard in SONET. The additional categories *categoryLevel0*, *categoryLevel1*, and *categoryLevel2*,are intended to be general enough to accommodate cultural differences but we are sensitive to the fact that any classification scheme makes assumptions, creates abstractions, and results in the loss of some subtlety based on the specific parameters of the schema. However, we do our best to make sure that as much information is preserved as possible, making sure to maintain all source categories we find in association with POIs collected through any of the data sources. Many examples exist in *Religious* type POIs where there is a large variety of denominations and types of religious buildings represented. On example, the source category *eidgah* from Wikimapia, is assigned the *osmCategory* of *amenity=place_of_worship;religion=muslim;building=mosque* in an effort to preserve information about any points that might have been assigned this category by a data contributor. This is largely an effort to create an ontology built from the bottom up rather than the top down.

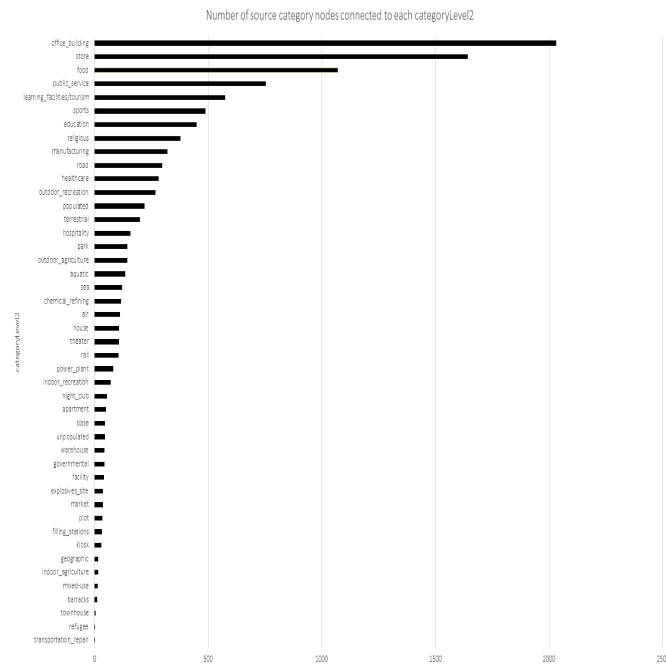


**Figure 2: The number of distinct *sourcecategory* nodes across all data sources that are associated with each categoryLevel2 node is shown here. By far, *office building* is the largest group followed by *store* and *food* types.**

## 6.1 Land Use Mapping

Depending on project needs, land use mapping may be done at various scales, from general use classifications such as Residential and Non-Residential, to more specific land use types such as Retail, Commercial, and Military. The ability to approach land use at various scales using VGI data can be optimized with the category standardization, organization, and retrieval abilities afforded by this graph database. In many cases, there are multiple categories within one data source that have a sufficient level of similarity to unite under the same category. Facebook for example, has 96 specific restaurant type such as *Italian Restaurant*, *Pakistani Restaurant*, *Soul Food Restaurant*, and *Belgian Restaurant*. In the absence of a graph database, quickly creating a land use layer identifying types of retail stores would require the manual identification and aggregation of all the various Restaurant categories. Searching for POIs tagged with many different categories is time-consuming and prone to errors of omission. However, the graph database stores

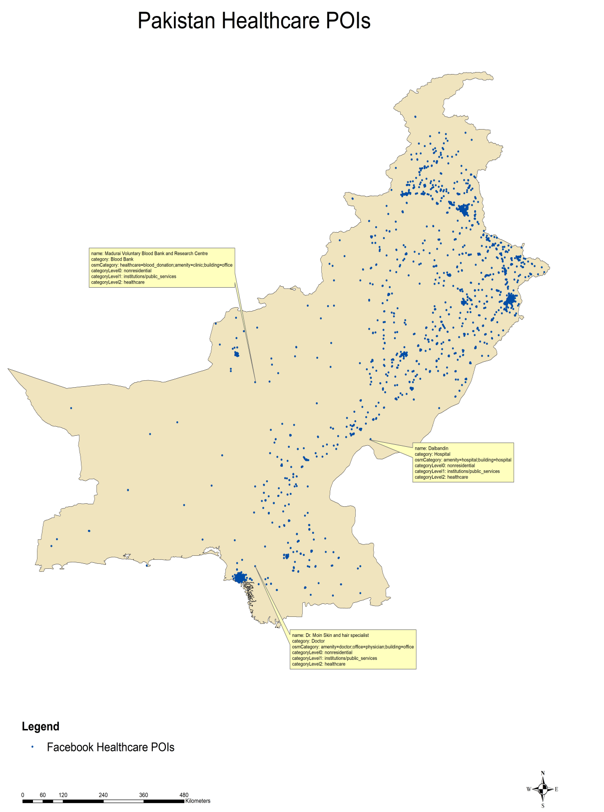


**Figure 3: Example coverage of *Healthcare* POIs from Facebook in Pakistan. This map shows the distribution of all types of healthcare facilities across the country. Several example POIs are indicated to show examples of how the information from SONET is used to group these facilities. The *category* field is the original source category while *osmCategory, categoryLevel0, categoryLevel1*, and *categoryLevel2* are values associated with that given source category in SONET and were added to the data points. Other POIs in the data set that also have the category *Hospital*, for example, will also have *osmCategory* of *amenity=hospital;building=hospital.***

all restaurant types, including other eating establishments such as Cafes or Food Courts, as members of the *Food categoryLevel2* category, which is connected to the larger *Retail/Service categoryLevel1* category. This makes it easy to query the database for all categories (from one or all data sources) in *Food*, retrieve the source categories and their matched OSM tags, and extract all POIs with those source categories or OSM tags from a data storage service such as PlanetSense.

## 6.2 Population Modeling

Population models require very large amounts of spatiotemporal data. VGI sources are valuable sources of such information, especially in areas that are lacking in authoritative data. However, category differences across multiple sources increases the challenges for efficiently using this information to create high resolution models at, for example, the building level. Achieving an appropriate level of precision using VGI generated POIs requires a rectification of the model schema to data source schemas and data source schemas to each other. In most cases, manual matching of categories is required, significantly slowing down project efficiency. In this situation, the graph database can be used to assign standardized categories (i.e., OSM tags) to source categories from diverse sources through an automated process using basic NLP algorithms or in the future, machine learning models trained on the corpus of matched *sourcecategory* to OSM tag values. Additionally, taking advantage of the semantic organization of the database, new categories can be quickly matched to existing, similar categories, providing a potential set of OSM tags in the proper format and adding them to the database. This will significantly increase the efficiency and consistency of preparing data for models that may require a standardized schema for discovering patterns in or making estimations about population density. Preliminary work in this area is still on going.

# 7 CONCLUSION

To the author's knowledge this research is the first attempts to create an ontological network to match categories across multiple heterogeneous sources of POI VGI data. To date, research utilizing POI data has been limited to using one or two sources of POI data, often at small spatial scales. Utilizing graph theoretical approaches will allow for the translation of POI categories from multiple sources into the popular and long-standing OSM tag format. Furthermore, the ontological network is constructed with a hierarchical framework, allowing for the retrieval of categories at varying levels of specificity. The resulting ontological network will advance the study of VGI data in two ways: first, by enabling cross-platform analysis of POI data, spatial and categorical coverage globally will improve. Cross-platform coverage will improve geographic understanding in regions of the world that are traditionally considered data poor. Second, this work supports the use of POI data in land use mapping and population modeling applications. Currently, it is used to enrich millions of new POI data points with *osmCategory,categoryLevel0*, *categoryLevel1*, and *categoryLevel2* fields in an effort to enhance the data quality of the PlanetSense platform. Key applications of this project to the geospatial humanities include disaster relief work with federal agencies, that need to rapidly produce maps of important facilities such as hospitals and schools; understanding the economic landscape of cities using VGI data in locations lacking in authoritative data sources, and identifying patterns of diversity both economic and cultural, in cities using the massive amount of VGI data currently available. Work is in progress to use this data to create a diversity index for cities at multiple scales that can then be used to access change over time as more POI data is collected. In the future, we plan to expand and enrich the ontology graph to include more attributes and make it available to the open source community.

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