Exploring the Potential of Machine and Deep Learning Models for OpenStreetMap Data Quality Assessment and Improvement

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Abstract

The OpenStreetMap (OSM) project is a widely-used crowdsourced geographic data platform that allows users to contribute, edit, and access geographic information. However, the quality of the data in OSM is often uncertain, and assessing the quality of OSM data is crucial for ensuring its reliability and usability. Recently, the use of machine and deep learning models has shown to be promising in assessing and improving the quality of OSM data. In this paper, we explore the current state-of-the-art machine learning models for OSM data quality assessment and improvement as an attempt to discuss and classify the underlying methods into different categories depending on (1) the associated learning paradigm (supervised or unsupervised learning-based methods), (2) the usage of extrinsic or intrinsic-based metrics (i.e., assessing OSM data by comparing it against authoritative external datasets or via computing some internal quality indicators), and (3) the use of traditional or deep learning-based models for predicting and evaluating OSM features. We then identify the main trends and challenges in this field and provide recommendations for future research aiming at improving the quality of OSM data in terms of completeness, accuracy, and consistency.

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1 Introduction

The OpenStreetMap (OSM) project\textsuperscript{2} is a collaborative effort to create a free, editable map of the world. The OSM database is built and maintained by a community of volunteers who contribute data on various geographical features such as roads, buildings, and points of interest. For this purpose, there are various editors that can be used to edit OSM data, including web-based editors such as iD and Potlatch\textsuperscript{3}, and desktop editors such as JOSM\textsuperscript{4} and Merkaartor\textsuperscript{5}. Each editor has its own set of features and tools, making them suitable for different types of mapping tasks. For example, JOSM is a powerful editor that has a wide

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\textsuperscript{2} https://www.openstreetmap.org
\textsuperscript{3} https://www.systemed.net/potlatch/
\textsuperscript{4} https://josm.openstreetmap.de/
\textsuperscript{5} http://merkaartor.be/

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range of advanced features and is suitable for experienced mappers, while iD is a web-based editor that is easy to use and is suitable for beginners. Additionally, some editors like JOSM have plugins that can automate certain tasks, such as checking for errors in the data.

The importance of OSM data lies in its wide range of applications. It is essentially used in many fields such as navigation, emergency response, transportation and urban planning. It is also used to create custom maps for specific needs, such as hiking and biking maps, and is used as a base map for many other applications. Besides, OSM data can be used to create map tiles and other map products that can be used on websites and mobile applications. Despite its usefulness and its reliability, the quality of OSM data is strongly dependent on the accuracy and completeness of the contributions (edits or changes) made by volunteers. In fact, as the OSM database continues to grow, the need for automated methods to assess and improve its data quality becomes increasingly important.

On the other hand, numerous machine and deep learning models have been applied to various different tasks in the area of GIS (geographic information systems) and web-mapping, including map digitization using features generated by artificial intelligence (AI) predictions. For instance, one could extract building footprint binary masks from drone imagery via different deep learning segmentation models, transform those masks into georeferenced polygons, and then overlay those geometries on OSM base-map for quality assessment. This will allow us to build AI tools capable to assist the mappers detect incomplete regions and vandalism cases when there is a mismatching between the predicted features and the existing annotations created by the contributors within a certain area of interest (AOI) in OSM.

In this paper, we review some of the state-of-the-art machine learning models for OSM data quality assessment while describing the proposed approach and the important findings for each work.

2 Machine Learning Models for OSM Data Quality Assessment

Mapping systems are crucial for navigation, transportation and other applications, but they can be costly to maintain due to the need for regular updates. Traditional maps, also known as authoritative maps, may not be updated as frequently due to budget constraints and may result in inaccuracies in terms of temporal, spatial and completeness. An alternative solution is Volunteered Geographic Information (VGI) [9], which relies on the contributions of individuals to create and update maps. One of the most popular VGI projects is OpenStreetMap (OSM), which was launched in 2004 and currently has over 10 million users from around the world. OpenStreetMap (OSM) is a VGI project which serves as an alternative to traditional map sources and is open to the public for retrieving, adding and editing spatial features. While OSM data is constantly being improved, the completeness and quality of the data may vary depending on the number of contributors and their mapping skills [19]. For instance, OSM coverage is more or less complete in urban areas compared to rural areas [10]. Additionally, it is not uncommon to encounter missing roads and inaccuracies in terms of positional accuracy [28] and semantic tags [6, 14].

Despite these limitations (i.e., issues related to data completeness and its quality), OSM has been widely used in a variety of applications, including land cover mapping and classification [5, 25, 3, 26], navigation (e.g., traffic estimation) [16], 3D city modeling and location-based services [22], building footprint detection using aerial imagery [27, 18], location-based map services [30] and indoor mapping [8].
To evaluate and improve the quality of OSM data, researchers have proposed various methods to tackle issues related to completeness [15], positional accuracy [4], semantic tag accuracy [7] and topological consistency [21]. Other works approached OSM data quality assessment [24, 13] by performing OSM meta-analysis, such as examining the activities of the contributors [20, 2].

In recent years, there has been an increasing interest in automating tasks related to OSM data. In fact, numerous works have used machine learning and remote sensing techniques to improve OSM data, while deep learning [29] has been used to extract information from OSM data to train image recognition models. Overall, the combination of machine learning, earth observation and OSM data has the potential to address global challenges in new ways. Several supervised machine learning based models have been trained on properties of OSM objects to find potential annotation errors. The authors in [1] have proposed three different machine learning based approaches to identify errors (inconsistent tags) in OSM object annotations. The first approach, consistency checking, involves applying a classifier while the user is editing and assigning tags to OSM objects. In this case, the editing tool can inform the volunteer if the assigned tag value is inconsistent with what the classifier predicted. Usually, geometrical, topological, and contextual properties (e.g., the object area) are used to train the supervised learning classifier. The second approach, manual checking, consists of applying a supervised classifier on a selected set of objects from OSM and then having OSM users to manually validate the objects whose tags present inconsistencies with the predictions of the classifier. The third approach, automatic checking, involves using a classifier to automatically correct annotations based on its predictions without human verification.

Conventional methods typically compare Volunteered Geographic Information (VGI) against an authoritative dataset to evaluate the quality of VGI data such as OSM data. While authoritative data is generated by official organizations, VGI is contributed voluntarily by individuals or communities. Also, VGI can be less reliable and accurate due to varying quality and expertise, while authoritative data is more trusted. In addition, VGI is more dynamic but lacks consistent quality control, can have biases, legal concerns, and sustainability challenges. Despite the previous limitations, combining VGI with authoritative or reference data is recommended to tackle the aforementioned shortcomings.

In cases where reference data is unavailable to assess the quality of OSM data, intrinsic methods that evaluate the data itself and its metadata can be employed. The study described in [17] utilizes unsupervised machine learning (k-means clustering algorithm) to analyze OSM history data in Mozambique, aiming to gain insights into the contributors, their timing, and their contributions. The results obtained from the analysis showed that a majority of the data in Mozambique (93%) was contributed by a small group of active contributors (25%). The study also identified a new category of contributors who were newcomers to the area, likely attracted by HOT mapping events during disaster relief operations in Mozambique in 2019. While intrinsic methods cannot serve as a substitute for ground truthing or extrinsic methods, they offer alternative means of gaining insights into data quality and can contribute to efforts aimed at enhancing it.

The study presented in [12] takes a similar approach by examining the OSM database in Ottawa-Gatineau. The focus of the investigation is on historical map features and contributor data to understand how accurately users contribute to the OSM database. To classify the changesets and OSM contributors, two unsupervised machine learning models, namely K-means and Principal Component Analysis (PCA), are utilized. The findings reveal a cluster of skilled contributors identified as OSM experts, based on their strong contribution loadings related to the use of advanced OSM editors, and weaker loadings associated with
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feature creation and frequency of contributions resulting in further correction. Therefore, attributing data quality is done by identifying experienced contributors who are likely to make further corrections and improvements to the OSM database.

On the other hand, the authors in [23] introduced a deep learning approach to address the challenge of detecting buildings in areas with limited data. They achieved this by transferring a pre-trained building detection model on a well-mapped region in OSM to data-scarce areas. The transfer was accomplished through fine-tuning the model using a combination of training samples from the original and target areas. The effectiveness of the method was validated by applying a deep neural networks trained in Tanzania to a site in Cameroon. The fine-tuned model successfully identified numerous OSM buildings that were missing in a specific area of Cameroon. The results demonstrated a significant improvement in the f1-score, even with only 30 training examples from the target area.

Moreover, the paper in [11] presents a novel approach that combines deep learning and crowdsourcing using the MapSwipe\(^6\) platform. The authors devised a strategy for assigning classification tasks to either deep learning or crowdsourcing based on the confidence level of the derived binary classification results. They conducted three case studies in Guatemala, Laos, and Malawi to assess the effectiveness of their proposed workflow. The findings indicated that both crowdsourcing and deep learning surpassed existing earth observation methods and products like the Global Urban Footprint in terms of performance and accuracy.

3 Conclusions and Perspectives

OpenStreetMap (OSM) is a collaborative, open-source project that aims to create a free and editable map of the world. The data in OSM is contributed and maintained by a global community of volunteer mappers, who use various tools to edit and update the map. However, the data in OSM can be inconsistent and contain errors, which can lead to inaccuracies in the map. This paper has discussed the contribution of machine and deep learning models to the assessment of the OSM data quality.

In fact, various traditional machine learning models have been used in several studies to automatically detect errors in OSM data, such as annotation errors, topological errors, and positional errors. Technically, classifiers have been trained to automatically detect errors in new data, and to recommend tag values for new objects being added to the map. Additionally, other works have deployed these models to extract rules from OSM data to help with the disambiguation of geographical objects.

On the other hand, deep learning models have been used largely to segment high-resolution satellite imagery for roads and building footprint detection. The extracted features could be used later on to assess and enrich OSM data quality.

Working on improving the existing machine learning models in terms of providing better training data quality and designing & optimizing larger models will certainly play an important role in making OSM data a more valuable and reliable data source for various real world applications.

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