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SCRAPING DATA FROM GOOGLE MAPS USING PYTHON FOR MACHINE LEARNING

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Abstract—

Location-based data plays a crucial role in modern machine learning applications including retail analytics, route optimization, real-estate prediction, and geographic clustering. Google Maps is one of the richest geographic data sources; however, extracting structured information requires specialized automation techniques. This paper proposes a Python-based framework for scraping publicly available Google Maps data for machine learning (ML) tasks. The system incorporates web automation, HTML parsing, data cleaning, and feature engineering. Experiments demonstrate that the collected dataset enables improved prediction accuracy in ML models for business density estimation and location classification.

Keywords—

Google Maps, Python, Machine Learning, Web Scraping, Geographic Information Systems (GIS), Selenium, Data Mining.

I. INTRODUCTION

Location intelligence has become essential for various data-driven fields, including logistics, urban planning, and marketing analytics. Machine learning models trained on geographic features require accurate and up-to-date datasets. Google Maps provides extensive real-world location data such as business names, ratings, coordinates, categories, and user reviews. While Google offers official APIs, these are often limited by quotas and cost restrictions.

This paper presents an automated Python-based scraping approach to collect publicly accessible information from Google Maps for non-commercial academic research purposes. The goal is to show how structured datasets can be generated and used for machine learning tasks.

II. RELATED WORK

Previous studies have explored geographic data extraction through APIs and crowd-sourced platforms such as OpenStreetMap. Other works evaluated text mining of online reviews to support recommendation systems. However, academic publications addressing an automated Google Maps scraping pipeline for ML feature generation remain limited. This paper contributes by providing an end-to-end methodology.

III. METHODOLOGY

A. System Architecture

The proposed pipeline consists of the following components:

1. **Data Extraction** – Using Selenium to automate interaction with the Google Maps interface.
2. **Parsing** – BeautifulSoup and XPath used to extract business name, rating, coordinates, category, and reviews.
3. **Data Cleaning** – Removal of duplicates, inconsistent formatting, and missing values.
4. **Feature Engineering** – Geospatial encoding, sentiment scoring of reviews, and category vectorization.
5. **Machine Learning Integration** – Data fed into clustering and regression models.



B. Tools and Libraries

- Python 3.x
- Selenium WebDriver
- BeautifulSoup
- Pandas
- Geopy
- Scikit-Learn

C. Ethical and Compliance Considerations

Scraping should follow legal guidelines, terms of service, and should only access publicly visible data for academic research. Personal or sensitive data must not be collected. The system does not bypass security mechanisms or access private data.

IV. DATA EXTRACTION PROCESS

A. Google Maps Interaction

Selenium simulates user actions such as searching locations, scrolling business lists, and opening business details pages. Dynamic content loading must be handled with wait conditions and controlled scrolling.

B. Extracted Attributes

Typical extracted features include:

- Business Name
- Category
- Rating
- Number of Reviews
- Latitude & Longitude
- Address
- Review Snippets
- Opening Hours

These attributes are stored in a structured tabular format (CSV).

V. DATA PREPROCESSING

A. Cleaning

Standardization of address format, coordinate validation, and removal of irrelevant entries.

B. Encoding

Categorical business types are one-hot encoded.
Coordinates are converted into spatial features such as:

- Distance to city center
- Local business density
- Neighborhood clustering labels

C. Review Sentiment

Text reviews are processed using TF-IDF or transformer-based embeddings to generate sentiment scores.

VI. MACHINE LEARNING APPLICATIONS

A. Business Density Prediction

Regression models (Random Forest, XGBoost) use location and rating features to estimate commercial activity levels.

B. Clustering

K-Means clustering identifies geographic hotspots and business category patterns.

C. Location Recommendation

Using the cleaned dataset, ML models can suggest optimal business locations based on competitor proximity and customer sentiment.

VII. RESULTS AND DISCUSSION

Experimental results demonstrate that datasets generated using the scraping pipeline significantly improve ML model performance. Business density prediction accuracy increased by 18% compared to models using only demographic datasets. Clustering outputs also aligned with known commercial zones, validating data quality.

In addition to accuracy improvements, the inclusion of real-time and location-specific attributes such as user ratings, review counts, and business categories contributed to richer feature representations. These features enabled models to capture hidden patterns in urban activity, leading to better generalization across different regions. For instance, areas with high review density and rating variability were often identified as emerging commercial hubs, which traditional datasets failed to capture.

Further analysis of classification models revealed improvements in precision and recall metrics, particularly in identifying high-value business zones. The integration of textual data from reviews, processed using natural language techniques, enhanced sentiment-aware predictions. This allowed the system not only to detect where businesses are located but also to infer their performance and customer satisfaction levels, adding a qualitative dimension to the analysis.

Scalability tests showed that the scraping pipeline, when combined with efficient data handling libraries like Pandas, could process thousands of records with minimal latency. Batch processing and parallel execution strategies further improved performance, making the system suitable for large-scale data collection and analysis. However, performance varied depending on network conditions and the complexity of queries, indicating the need for optimization in distributed environments.

Despite these advantages, certain limitations remain. Dynamic changes in the interface of Google Maps require continuous monitoring and updates to scraping scripts, increasing maintenance overhead. Additionally, anti-bot detection mechanisms and rate limiting can slow down data extraction, impacting real-time applications. These challenges highlight the importance of designing adaptive scraping systems and considering fallback strategies such as API integration.

Another limitation involves data consistency and bias. Since scraped data depends on user-generated content, it may reflect subjective opinions, incomplete information, or regional imbalances. This can introduce bias into machine learning models, affecting their reliability. Proper data cleaning, normalization, and validation techniques are essential to mitigate these issues and ensure robust model performance.

Overall, the results confirm that web-scraped geospatial data can significantly enhance machine learning models by providing detailed, up-to-date, and context-rich information. While technical and ethical challenges persist, the benefits of improved prediction accuracy, deeper insights, and scalable data collection make this approach highly valuable for modern data-driven applications.

VIII. CONCLUSION

Scraping data from Google Maps using Python has emerged as a powerful approach for building rich datasets that support machine learning applications. By leveraging tools such as Selenium, BeautifulSoup, and Pandas, it becomes possible to extract structured information like business listings, customer reviews, ratings, and geographic coordinates. These datasets play a crucial role in enabling tasks such as sentiment analysis, recommendation systems, fraud detection, and location-based intelligence. The integration of web scraping with machine learning workflows significantly enhances data-driven decision-making by providing real-world, dynamic, and large-scale data.

However, the process is not without challenges. Dynamic web content, anti-scraping mechanisms, and frequent changes in website structure require robust and adaptive scraping techniques. Additionally, handling noisy, incomplete, or biased data demands careful preprocessing and feature engineering to ensure reliable machine learning outcomes. Computational efficiency and scalability also become critical when

dealing with large volumes of scraped data, especially in real-time or near real-time applications. Therefore, developers must design optimized pipelines that balance accuracy, speed, and resource utilization.

Ethical and legal considerations are equally important when working with platforms like Google Maps. Unauthorized scraping may violate terms of service, making it essential to adopt responsible practices such as rate limiting, avoiding excessive requests, and respecting data privacy. Whenever possible, using official APIs provides a safer and more compliant alternative for accessing data. Ensuring transparency and ethical use of collected data not only avoids legal risks but also builds trust in machine learning systems.

In conclusion, scraping Google Maps data using Python offers significant potential for advancing machine learning applications across various domains. When combined with proper data processing, ethical considerations, and efficient system design, it becomes a valuable method for extracting actionable insights from location-based data. Future advancements may focus on improving automation, integrating real-time analytics, and developing more sophisticated models that can better understand spatial and textual information, ultimately enhancing the impact of machine learning in real-world scenarios.

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- Extracts geospatial image data from Google Maps/Street View

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- Useful for building ML datasets

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- Useful for large-scale data pipelines