Geomancer: An Open-Source Framework for Geospatial Feature Engineering

Lester James V. Miranda, Mark Steve Samson, Alfiero K. Orden II
Bianca S. Silmaro, Ram K. De Guzman III, Stephanie S. Sy
Thinking Machines Data Science
Metro Manila, Philippines
{lj,marksteve,ardie,bianca,ram,stef}@thinkingmachines

Abstract

This paper presents Geomancer, an open-source framework for geospatial feature engineering. It simplifies the acquisition of geospatial attributes for downstream, large-scale machine learning tasks. Geomancer leverages any geospatial dataset stored in a data warehouse—users need only to define the features (Spells) they want to create, and cast them on any spatial dataset. In addition, these features can be exported into a JSON file (SpellBook) for sharing and reproducibility. Geomancer has been useful to some of our production use-cases such as property value estimation, area valuation, and more. It is available on Github[^1] and can be installed from PyPI.

1 Introduction

Geospatial data allows us to gain massive amounts of information based on location. When samples—expressed as points, polygons, or rasters with real-world coordinates—are coupled with large-scale datasets such as OpenStreetMap (OSM) [1], we can gain an information-rich dataset to derive insights from. To illustrate, given your current position, it is possible to obtain, say, the number of malls within 1.5-km, the distance to the nearest supermarket, or the frequency of traffic jams—all of which can be used later on for downstream machine learning tasks.

However, engineering features for geospatial data is a challenging task, requiring significant amount of compute and storage [2][4]. Important considerations include (1) the storage capacity to house geospatial data sources, (2) the compute complexity to query from that source, and the (3) ease of extracting information from these sources [5].

In this paper, we introduce Geomancer, an open-source framework to perform geospatial feature engineering at scale. It leverages a data warehouse, geospatial datasets, and a Python library to pull out information from spatial datasets. In addition, Geomancer provides a solution for versioning and sharing feature transforms for other users. It is open-source and licensed under MIT. Geomancer has been used for production machine learning use-cases such as area valuation, poverty mapping, and real-estate price estimation.

2 Architecture

Concepts The fundamental unit in Geomancer is a logical feature [6] called a Spell. It maps a coordinate into a vector of feature values, \( f^D : \mathbb{V}^2 \rightarrow \mathbb{R}^q \), where \( \mathbb{V} \) is the set of feasible coordinates (latitude and longitude in EPSG:4326 [7]) and \( q_j \) is the dimensionality of the \( j \)th

[^1]: https://github.com/thinkingmachines/geomancer

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Figure 1: *Information flow in the Geomancer framework.* In order to obtain the features needed for modelling, a set of raw coordinates and reference datasets (e.g. OpenStreetMap, Waze, etc.) are supplied to the logical feature functions.

A feature vector. A collection of spells, i.e., a *SpellBook*, is then defined as a set of feature functions $\mathcal{F}^D = \{f_j | j = 1 \ldots m\}$.

Figure 1 shows the information flow in the Geomancer framework. Given a reference data source $\phi$, Geomancer allows users to define feature transforms $\mathcal{F}^D$, and apply these functions to a dataset containing spatial coordinates $D'$. The result is a feature matrix $X^{D'}$ that can be used for downstream machine learning tasks:

$$X^{D'} = \mathcal{F}^D(D', \phi) = (f^D_1(D', \phi), \ldots, f^D_m(D', \phi))$$  \hspace{1cm} (1)

### System Design

There are three main components in the Geomancer framework: a Python library client, a data warehouse server, and a reference data source (Figure 2).

- **Python library client** The [geomancer library](https://pypi.org/projects/geomancer) serves as the framework’s user-interface. Users can define feature functions (Spells or SpellBooks), export/read SpellBooks, and apply transforms to any given spatial dataset. Creating new features is done via the factory design pattern whereas the SpellBook mechanism is accomplished using the builder pattern.

- **Data warehouse server** The data warehouse provides the storage and compute capacity in the framework. The library client can connect to multiple databases at the same time, and can handle both online transactional (OLTP) or analytical (OLAP) processing workloads. The extracted features can be stored inside the warehouse or exported as a dataframe for immediate consumption.

- **Reference data source** A reference data source is loaded inside the warehouse as basis for feature engineering. For example, if we want to obtain the number of malls within a 1.5-km radius, we should have some knowledge of all mall locations within the area in question. Fortunately, open datasets such as OpenStreetMap (OSM) exists to give such information. Usually, we create Extract-Transform-Load (ETL) pipelines to deliver timely, rich, and accurate data from external sources.

### 3 Usage

In practice, Geomancer enables researchers to (1) define geospatial features for extraction, (2) connect to various data warehouses, and (3) replicate and version features. The following sections will demonstrate how this can be done in the framework.

**Feature functions for geospatial feature engineering** A Spell provides a declarative interface to define logical features. They can be cast to a set of coordinates after instantiation. For example, if we wish to get the distance to the nearest embassy given a sample of coordinates, we write the following:
Figure 2: Architecture of the Geomancer framework. The user defines feature functions $F$ (Spells or SpellBook) via a Python library, which are then executed by the DBCore as query dialects at runtime. These function-calls then interact with a data warehouse to fetch and store the extracted features. As of now, Geomancer supports BigQuery, PostgreSQL, and SQLite for storage with OpenStreetMap (OSM) and Waze as a reference data source.

```python
from geomancer.spells import DistanceToNearest
from tests.conftest import sample_points

# Load a sample of points as a DataFrame
df = sample_points()

# Define a spell
spell = DistanceToNearest("embassy",
                          source_table="ph_osm.gis_osm_pois_free_1",
                          dburl="bigquery://geospatial",
                          feature_name="dist_embassy")

# Cast the spell
df_with_features = spell.cast(df)

from geomancer.spells import DistanceToNearest, NumberOf
from geomancer.spellbook import SpellBook
```

Connect to various data warehouses Geomancer can establish a connection to any warehouse by providing a valid database URL. In practice, this feature has been helpful when engineering features across tables from different locations (e.g., OSM dataset is stored in BigQuery, traffic dataset in PostGIS, etc.). So far, Geomancer supports the following database backends:

- BigQuery, an analytics data warehouse from the Google Cloud Platform [9][10].
- PostGIS, a geospatial extension for PostgreSQL [11][12].
- SpatiaLite, a geospatial extension for SQLite [13][14].

Save and share feature functions Features can be grouped together to form a SpellBook, allowing us to cast multiple Spells at once. In addition, SpellBooks can be exported into a JSON file with various metadata (e.g., author, description, etc.) regarding the feature collection:

```python
from geomancer.spells import DistanceToNearest, NumberOf
from geomancer.spellbook import SpellBook
```
# Create a spellbook
my_spellbook = SpellBook(
    spells=[
        DistanceToNearest("primary",
            dburl="bigquery://geospatial",
            source_table="ph_osm.gis_osm_roads_free_1",
            feature_name="dist_primary"),
        NumberOf("supermarket",
            dburl="bigquery://geospatial",
            source_table="geospatial.ph_osm.gis_osm_pois_free_1",
            feature_name="num_supermarkets"),
    ]
)

# Export SpellBook into a file
my_spellbook.author = "Juan dela Cruz"
my_spellbook.description = "Good Features for Economic Indicators"
my_spellbook.to_json("my_features.json")

Once a SpellBook is exported to a file, it can be version-controlled, shared, and reused to other datasets. In the demonstration below, the Spells in the exported SpellBook, my_features.json, will be casted on a new set of points:

```python
from geomancer.spellbook import SpellBook
from test.conftest import sample_points_new

exported_spellbook = SpellBook.read_json("my_features.json")
df = sample_points_new() # load your own data

# Cast someone's Spells into your own data
df_with_features = exported_spellbook.cast(df)
```

## 4 Case study: property value estimation in Singapore

We used Geomancer to predict residential prices per square foot in Singapore. The raw data was acquired from the Urban Redevelopment Authority’s open listing of apartment and condominium sales in the last four years [15]. We used this information to compile a dataset containing the locations and unit price per square foot for over 50,000 transactions.

Thus, we are given a raw dataset $D = \{V, Y\}$, where $V$ is the property’s spatial coordinate in EPSG:4326, and $Y \in \mathbb{R}$ is the unit price per square foot. We then used Geomancer, coupled with OSM data, to define logical features $F^{D}$ such as the number of restaurants within 3-km, distance to the nearest bus stop, or distance to the nearest nightclub. This resulted to a feature matrix $X^{D}$ that will be used for model training.

For this dataset, we were able to extract 388 geospatial features using points-of-interests in Open-StreetMap (OSM) and logical features from Geomancer. After performing a 70 – 30 holdout split, we fed these features to a random forest regressor model [16, 17] to predict the unit price per square foot. Running the trained model on aggregated areas of Singapore produced a heatmap as shown in Figure 3. It is apparent that the value of an area increases when it’s nearer to common points-of-interests.

By zooming-in to two selected properties in Figure 4, we can see how the features obtained from Geomancer directly influenced a property’s value.

We also compared model predictions to actual selling prices of each property. Using Geomancer-based features, the model was able to perform really well on medium prices, but underestimated properties that are extremely cheap or expensive. Still, we have reliable predictions with error not exceeding SGD 100 per square foot as shown in Figure 5a.

Lastly, we used Geomancer-based features to explain how the model predicts a property’s price. From Figure 5b, we can see that over half of the predictive power comes from the postal district where a unit is located. Within each district, however, it is possible to improve our price estimation by 40
Figure 3: Predictions from a model trained on transaction prices of private residential properties based on proximity to certain points-of-interest. We treat predicted residential price as an attractiveness index to quantify and visualize how attractive different areas in Singapore are.

Figure 4: Even if the apartments are of the same size and postal district, the more luxurious apartment, Boulevard Vue, is closer to a hotel, primary road, ATM and a fast-food restaurant. Accordingly, it is five times more expensive than D’Leedon.

percentage points (pp) by adding Geomancer-based features such as distance to restaurants, hotels, and ATMs. For more information, an interactive map can be accessed through this link.

5 Conclusion

In this paper, we introduced Geomancer, an open-source framework to perform geospatial feature engineering at scale. We described the Spell, a logical feature that serves as the basic building-block of the framework. Then, we showed how it integrates with the overall architecture and demonstrated how it can be used through the Python client library. Lastly, we provided a sample production use-case of Geomancer for predicting residential prices per square foot in Singapore. Using only Geomancer-based features and OpenStreetMap data, we were able to achieve 86% accuracy with an error margin of SGD 100.

For future research, we plan to evaluate user-efficiency and system robustness in more detail. Finally, we also hope to expand the number of database connections (e.g. Amazon Athena, Redshift, etc.) and primitive features to accommodate different cloud providers and other advanced use-cases.

[https://thinkdatasci.carto.com/builder/ed486c74-f19e-4a51-862d-a117705e121c]
Figure 5: (Left) Error margin for the model’s predicted price of various properties in Singapore. On average, predicted prices are within SGD 100 of actual prices, even for units on higher or lower end. (Right) Using different geospatial features allow the model to explain up to 87% of real estate value.

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