GeoShapley: A Game-theory Approach to Measuring the Importance of Location in Machine Learning

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Background and Objective

- Geographers have long been interested in understanding and measuring **the importance of location (where things are)** in determining behaviors and phenomena.
- **Machine learning and AI** have been increasingly used to model geospatial data with location components.
- This project develops **GeoShapley**, a method to quantify the importance of location in machine learning models applied to geospatial data.
- GeoShapley is a **model-agnostic** method that can be applied to any pre-trained supervised model (e.g., tree-based, neural nets).

GeoShapley Principles

GeoShapley extends from Shapley values which originate from the field of coalitional game theory, were named in honor of Nobel Prize Laureate Lloyd Shapley, who introduced the concept in his seminal work Shapley (1953). Shapley value considers how to fairly distribute contribution among players participating in a coalition game. GeoShapley consider location features as a single player in a model prediction game. Here, location features refer to model inputs that describe the location of a geo-referenced observation, which are often used to account for spatial effects such as spatial autocorrelation and spatial heterogeneity. The estimation of GeoShapley values follows the works of Shapley (1953), SHAP (Lundberg and Lee, 2017), and joint Shapley value (Harris et a., 2017).

GeoShapley additively decomposes individual model prediction into four components:

$$\hat{y} = \phi_0 + \phi_{GEO} + \sum_{j=1}^{p} \phi_j + \sum_{j=1}^{p} \phi_{(GEO,j)}$$

where 1) ϕ_0 is a constant base value. This is the average prediction value given the background data and serves as the global intercept; 2) $\boldsymbol{\phi_{GEO}}$ is a vector with size *n* measuring the intrinsic location effect in the model; 3) $\boldsymbol{\phi_j}$ is a vector with size *n* for each non-location feature *j* giving location-invariant effect to the model; and 4) $\boldsymbol{\phi_{(GEO,j)}}$ is a vector with size *n* for each non-location feature *j* giving the spatially varying interaction effect to the model. If no location effects are in the model, then the term $\boldsymbol{\phi_{GEO}}$ and $\boldsymbol{\phi_{(GEO,j)}}$ will be zero, and this equation will reduce to the SHAP values proposed by Lundberg and Lee (2017). The detailed algorithm can be found in Li (2024).

GeoShapley Python Package

GeoShapley is accessible as an open-source python package and is distributed in PyPI (The Python Package Index) that can be installed using command ***pip install geoshapley***. The package is hosted at https://github.com/Ziqi-Li/geoshapley. The main function of the package is to compute GeoShapley values for a pre-trained predictive model. The package can be seamlessly integrated with popular machine learning libraries such as *scikit-learn, xgboost, lightgbm*. It also offers a several visualization tools for visualizing both spatial and non-spatial effects.

GeoShapley

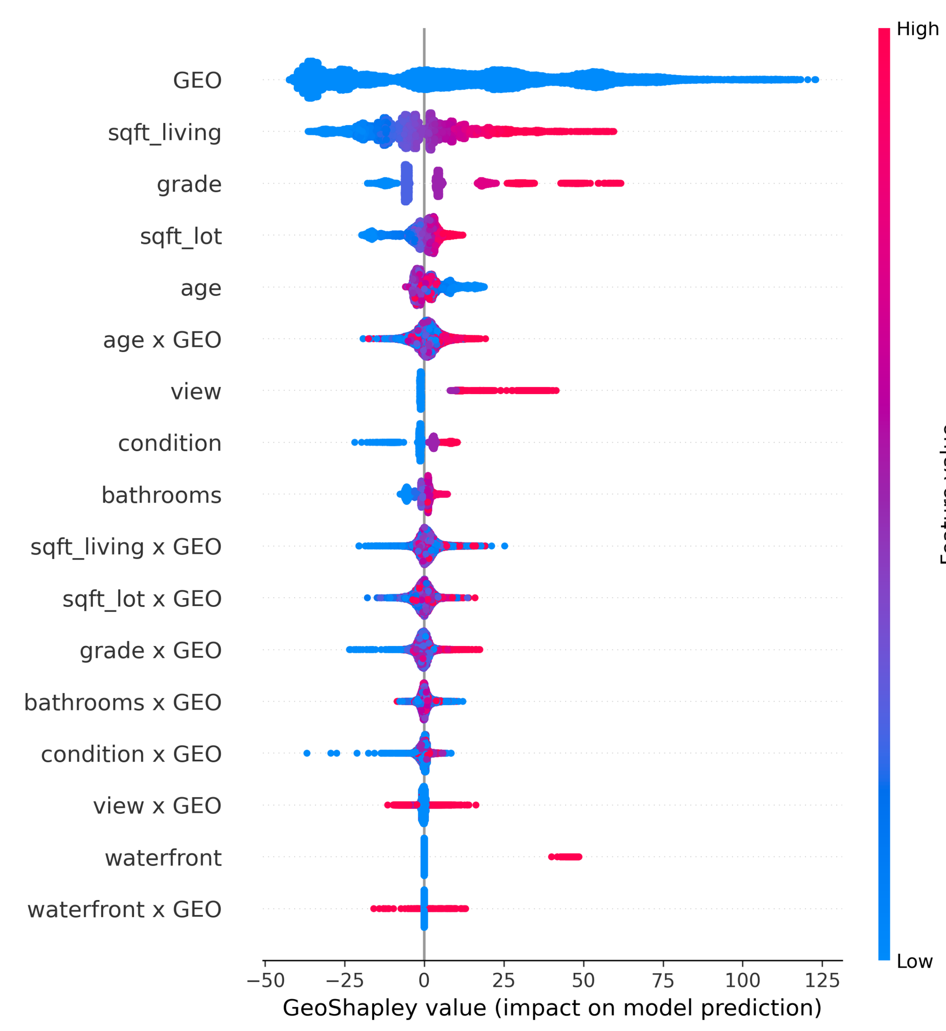
Installation:

GeoShapley can be installed from PyPI:

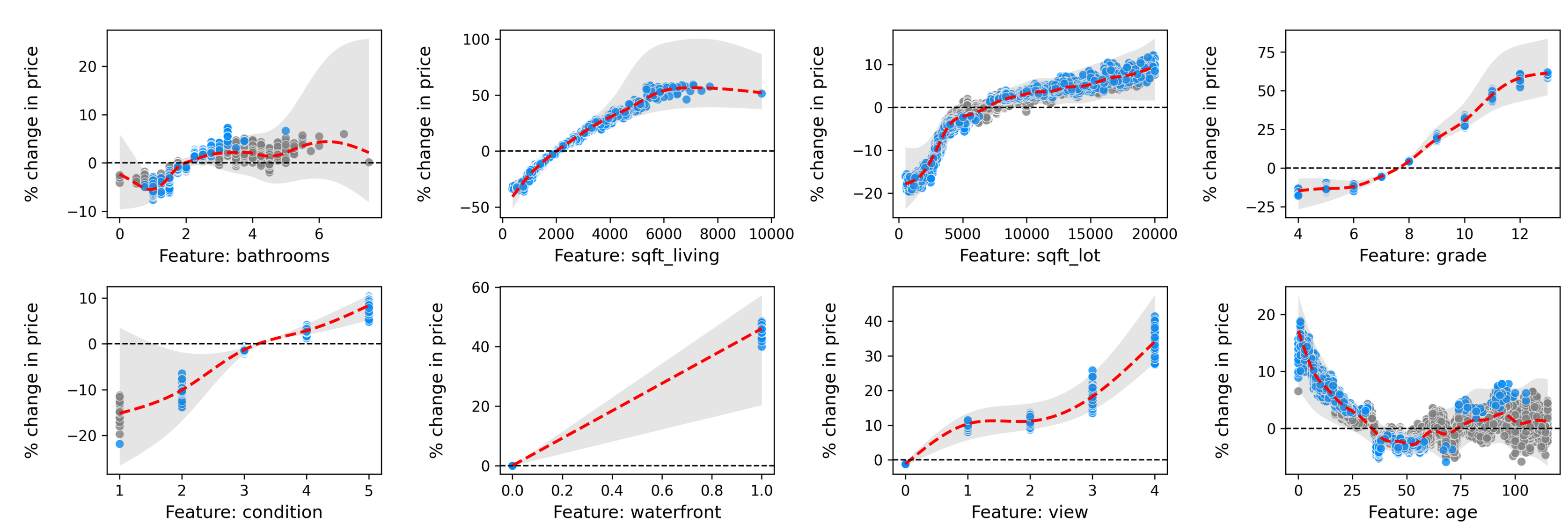
```
$ pip install geoshapley
```

An Example of House Price Modeling

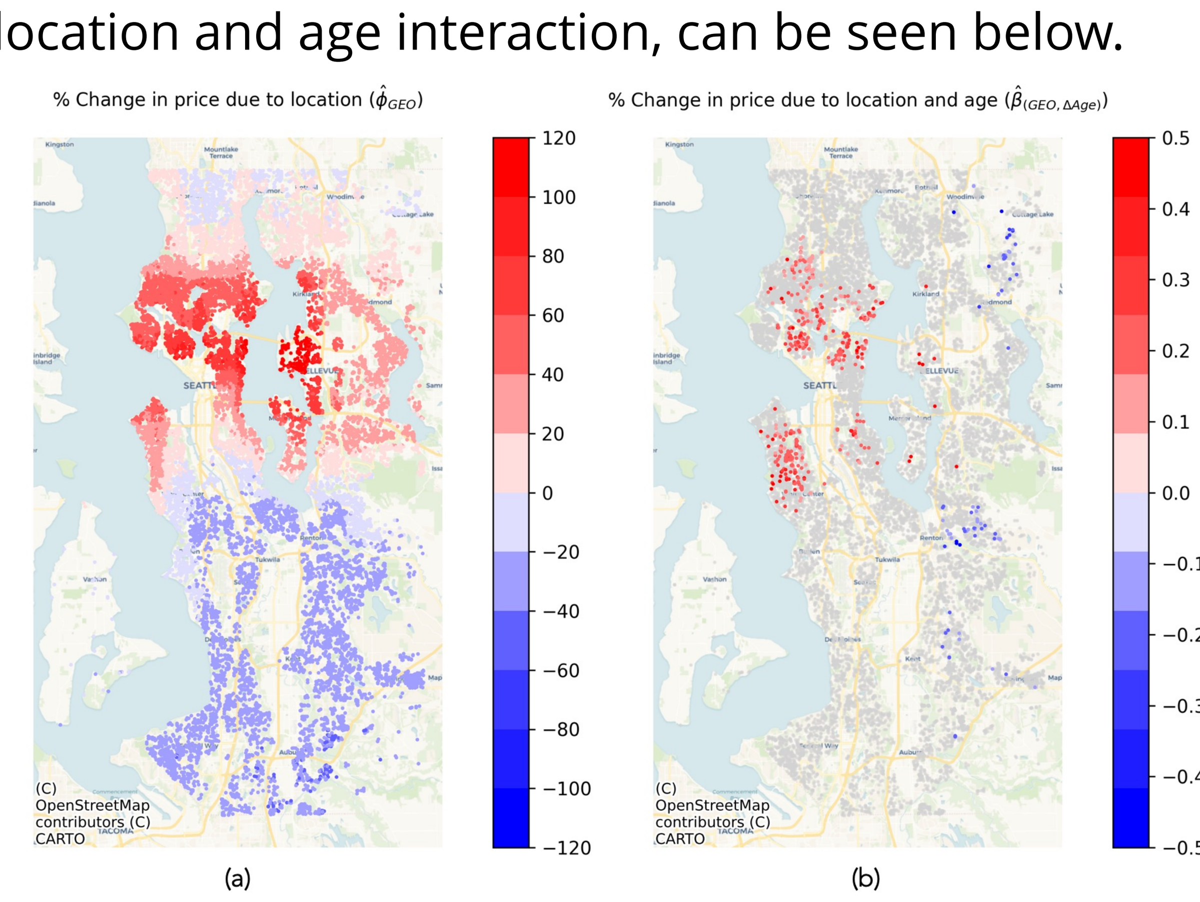
The method is demonstrated using both a synthetic dataset based on known data-generating processes (which can be found in Li, 2024) and an empirical example of house price modeling. Here, I used a Seattle house price dataset containing 16,581 property sale records. The log of property price is regressed against 8 housing attributes plus the location (coordinates) of the property. Multiple machine learning models are tested, and the best performing model is XGBoost, with an out-of-sample R^2 value of 0.91. GeoShapley value is then used to explain the trained XGBoost model. The figure below shows a summary plot of feature importance ranking from top to bottom. GeoShapley values here measure the percentage change to the property price. The contribution from the location (GEO) emerges as the most important feature influencing a house's price, decreasing it by up to 43% or increasing its value by as much as 123%, depending on the location. Housing characteristics, including the square footage of the living area and grade, follow in importance.



Non-linear effects of housing features on house prices can be seen in the plots below.



Location effect, including how house price is influenced by location and by location and age interaction, can be seen below.



Reference

Li, Z. (2024). GeoShapley: A Game Theory Approach to Measuring Spatial Effects in Machine Learning Models. *Annals of the American Association of Geographers*. Open-access via QR Code.