



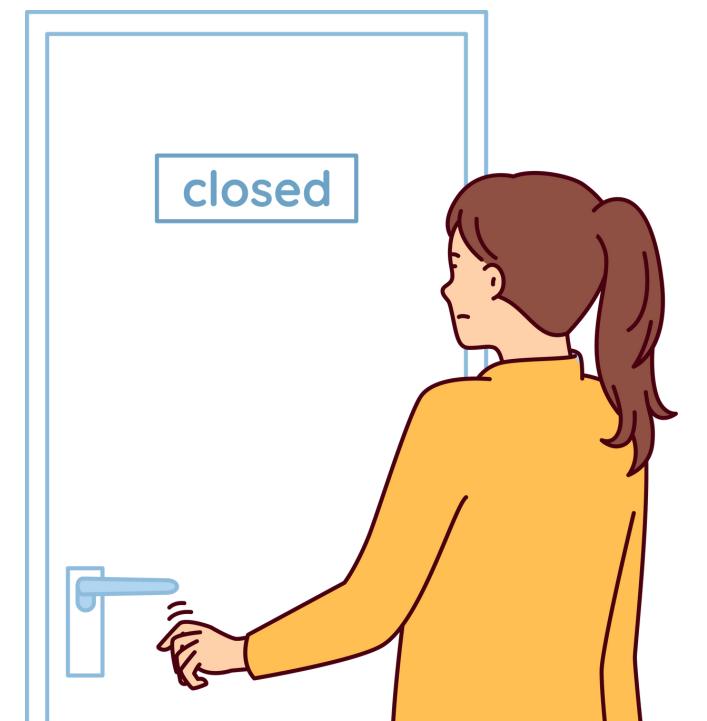
How much does property cost?



The trouble with pricing property



Overpricing

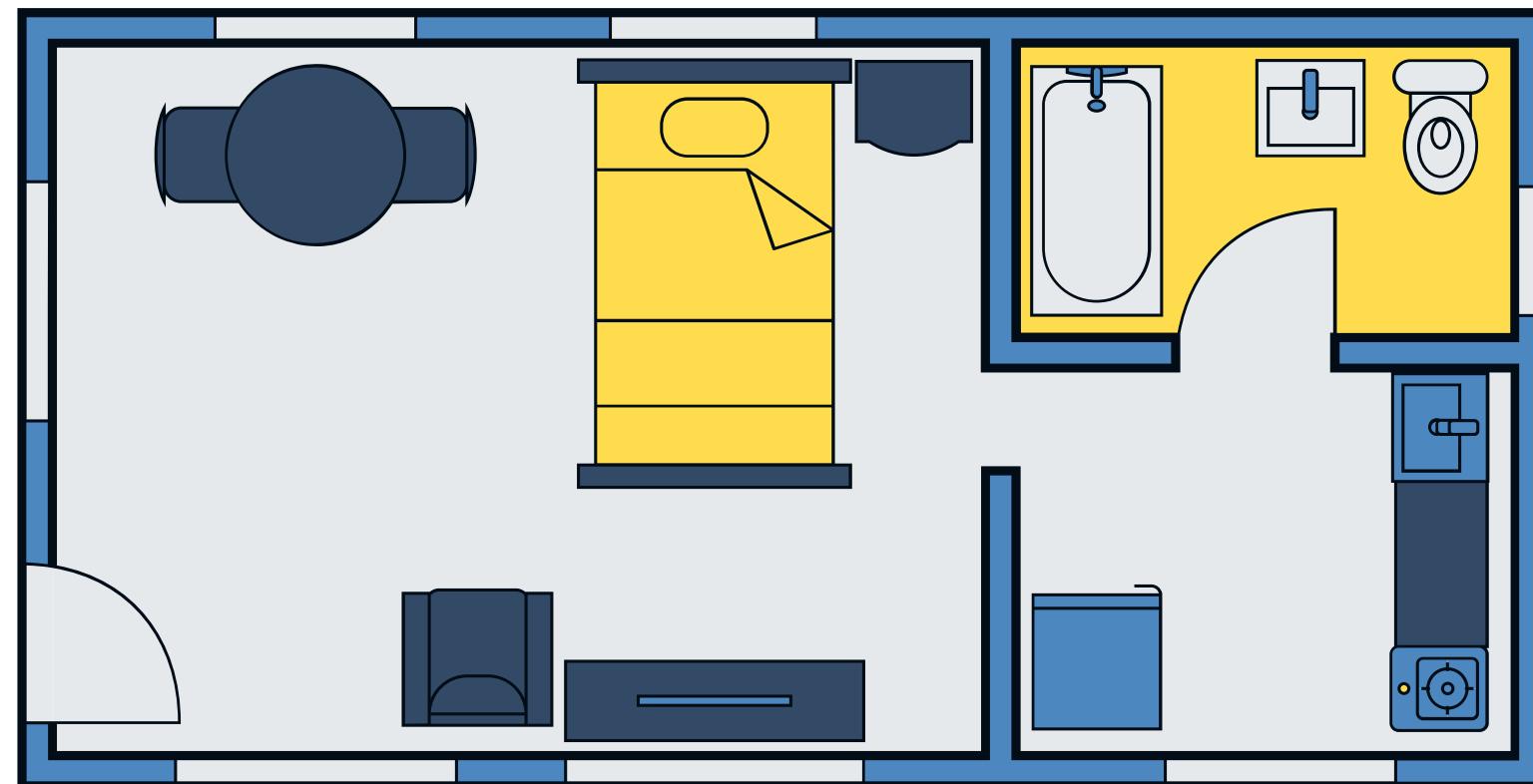


Inaccessible information



Subjective appraisals

The trouble with pricing property



Naive way of pricing property

= Floor Area x (Price / m²)

Property valuation needs to be **data-driven**.



Business Value

Seller



Buyer



Informed Pricing

Market Trends

Problem Statement:

Can we produce an accurate housing price prediction model and determine **the factors that drive property prices?**



Machine Learning 2

The House of Us: Metro Manila Housing Price Prediction using Machine Learning

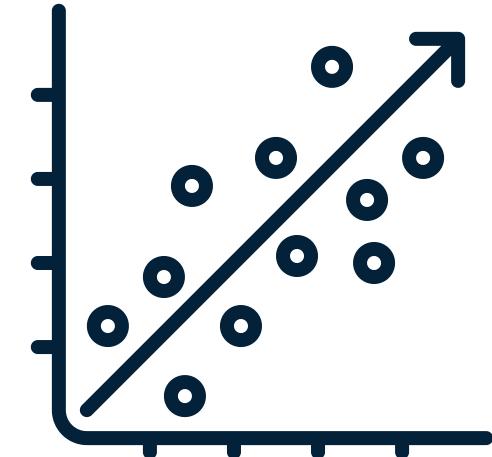
Bulatao, de la Paz, Satiada, Soliman

Previous work on housing price prediction models (PH)



**Tree-based
models are better**

(Jagan Chowhaan et al., 2023)



**Linear regression
models for Metro Manila**

(Abellana et al., 2021)



**No instance-based
valuation models
for Metro Manila**

Objectives



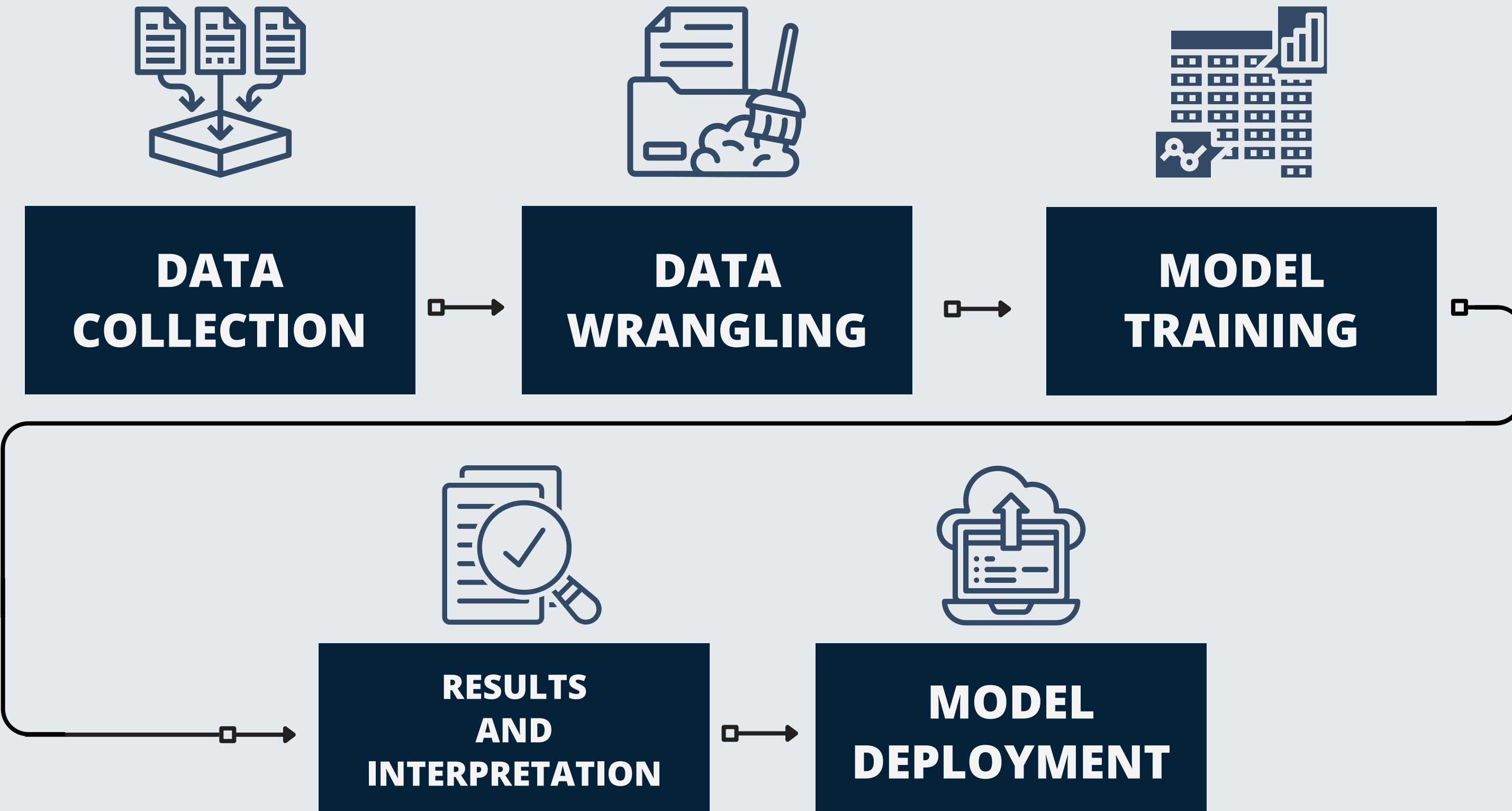
01

Create an **instance-based machine learning model** that can approximate property prices in Metro Manila using property features and amenity data.

02

Investigate **factors that drive property prices** aside from floor area.

Methodology



Data Description



Metro Manila Lamudi
Listings Dataset (2022)



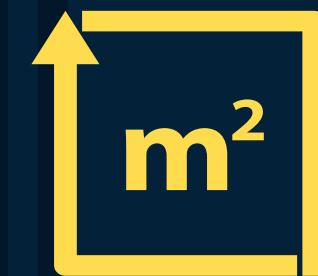
Bedrooms



Bath



Geographic
Coordinates



Floor Area



Price

Data Description

Amenity Types



Healthcare



Food



Transportation



Finance



Public Service



Education



OpenStreetMap
Dataset

Data Description



Metro Manila Lamudi
Listings Dataset (2022)



OpenStreetMap
Dataset

List of Models Trained

GradientBoosting

Random Forest

XGBoost

AdaBoost

Linear Regression

Linear Regression (L1)

Linear Regression (L2)

KNearestNeighbor

R² Score

	Base (Random Forest)	with Amenities (Gradient Boosting)
Mean Train-Validation Score	99.16	99.86
Mean Test Score	98.91	99.08

NOTE: One sample T-Test statistic provides **95% confidence** that the change is significant!

Mean Absolute Error (MAE)

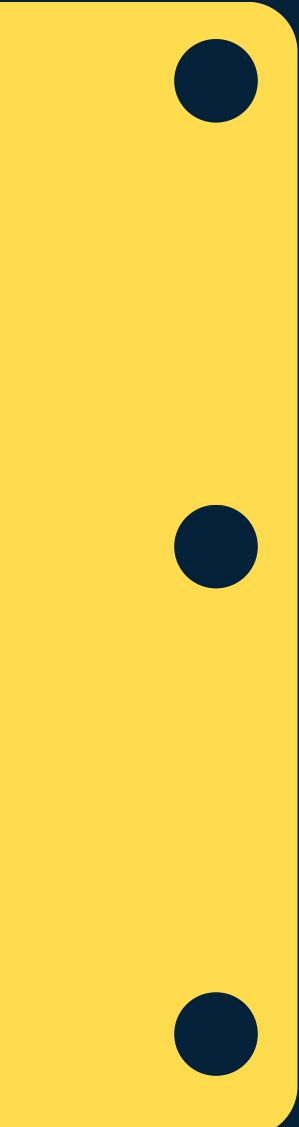
	Base (Random Forest)	with Amenities (Gradient Boosting)
High (27,431,000)	PHP 710,000	PHP 575,000
Medium (15,492,000)	PHP 279,000	PHP 279,000
Low (7,667,973)	PHP 510,000	PHP 262,000

NOTE: One sample T-Test statistic provides **95% confidence** that the change is significant for high and low-priced properties.

Mean Absolute Error (MAE)

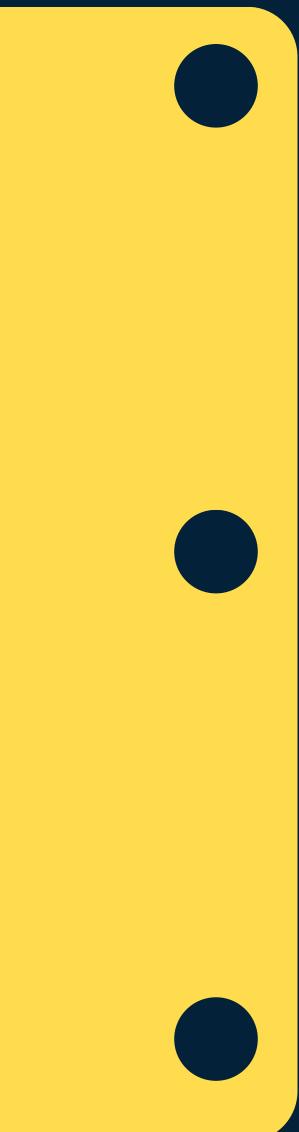
	Base (Random Forest)	with Amenities (Gradient Boosting)
High (27,431,000)	(2.31%)	(2.02%)
Medium (15,492,000)	(1.94%)	(1.94%)
Low (7,667,973)	(7.89%)	(3.39%)

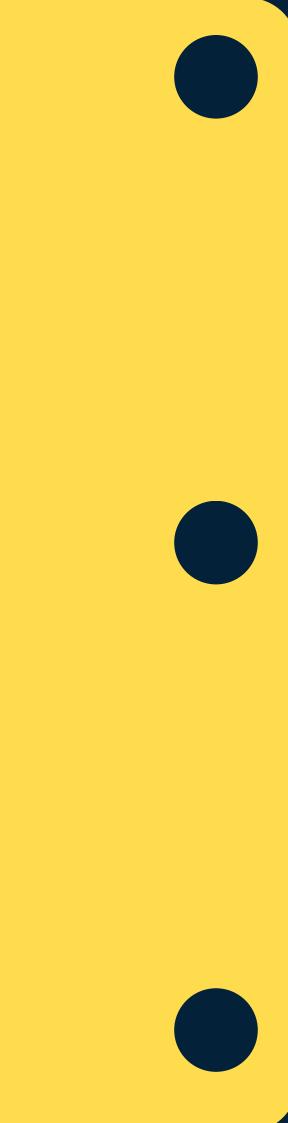
NOTE: One sample T-Test statistic provides **95% confidence** that the change is significant for high- and low-priced property.



What now?



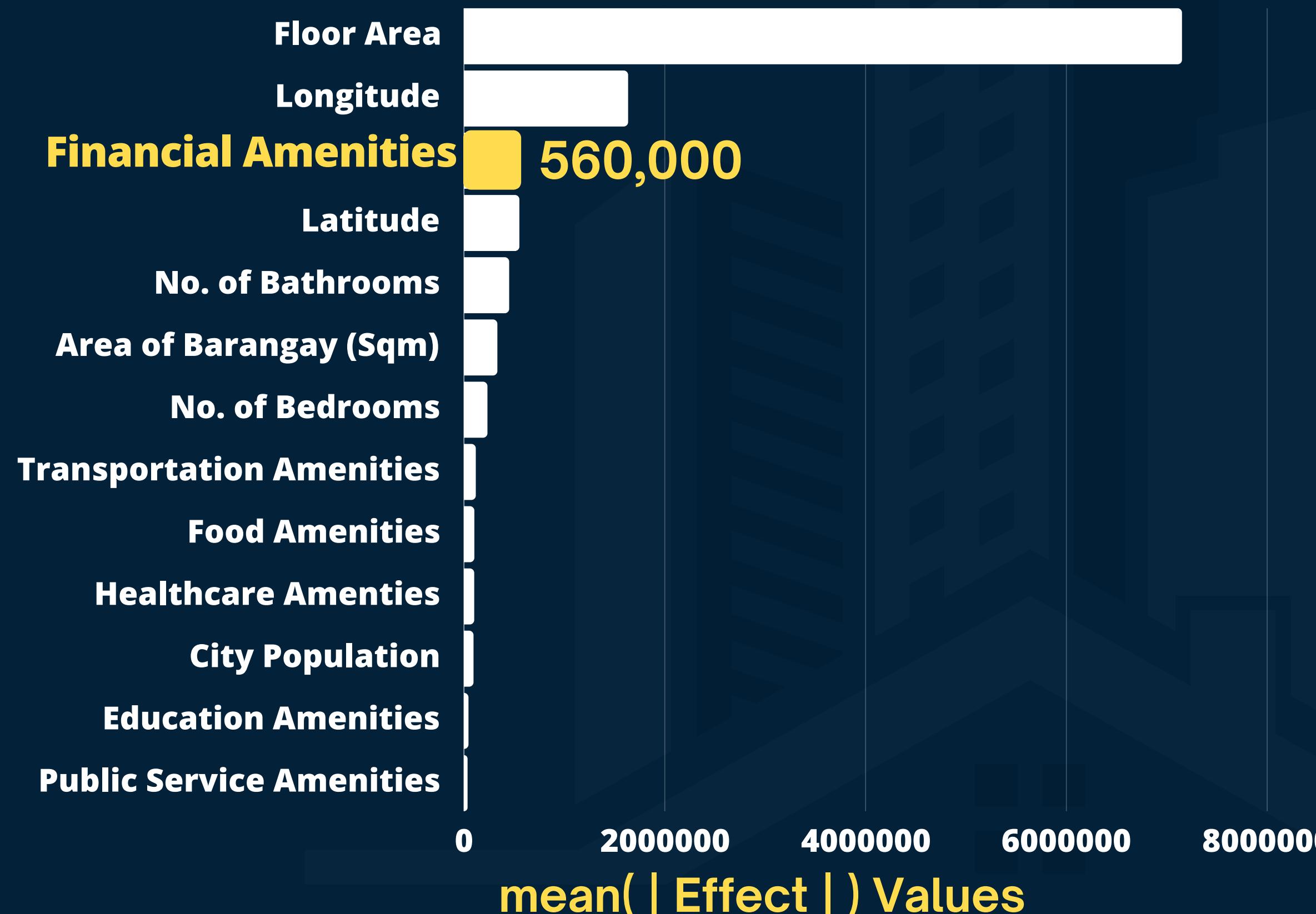


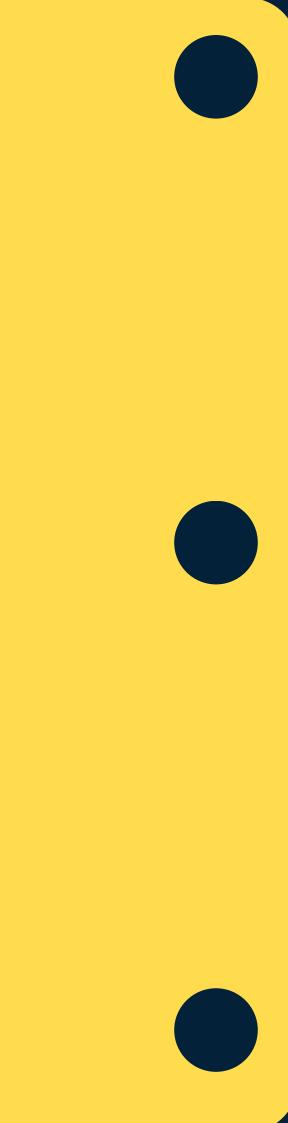


**“Where is a good
place to invest in?”**



Shap Global Explainability



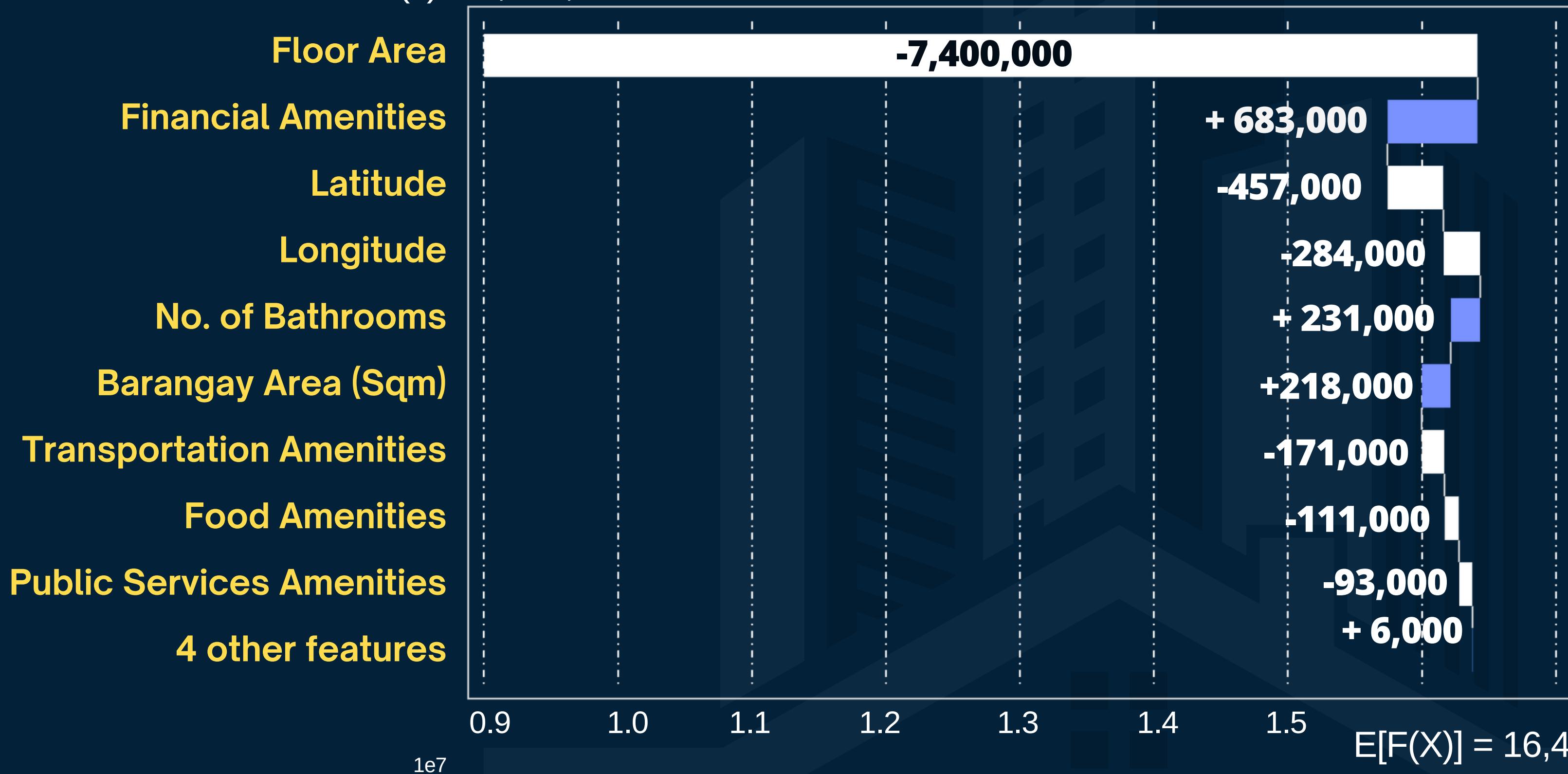


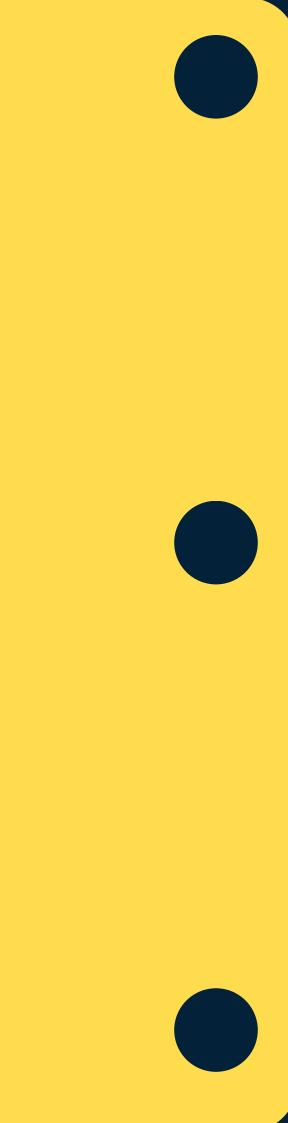
**“How much will financial
amenities in the area affect
my property’s value?”**



The Sapphire Bloc Ortigas I 1 Bedroom for sale

$$f(x) = 9,021,000$$





“I want to sell my property at 10 million pesos but it’s currently being valued at 9 million.



The Sapphire Bloc Ortigas | 1 Bedroom

currently being listed at PHP 9 million

Existing Amenity Counts



Food

71



Education

4



Healthcare

5



Public

-



Finance

63



Transpo

8

Counterfactuals



Food

71



Education

4



Healthcare

5



Public

-



Finance

63



Transpo

8

-	9	-	-	86	-
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Conclusion



Accurate



Interpretability

SukatSari

Condo Price Prediction App

Floor Area in (m²)

24.00



Number of Bedrooms (For Studio, input 1)

1



Number of Bathrooms

1



City

Kalookan City



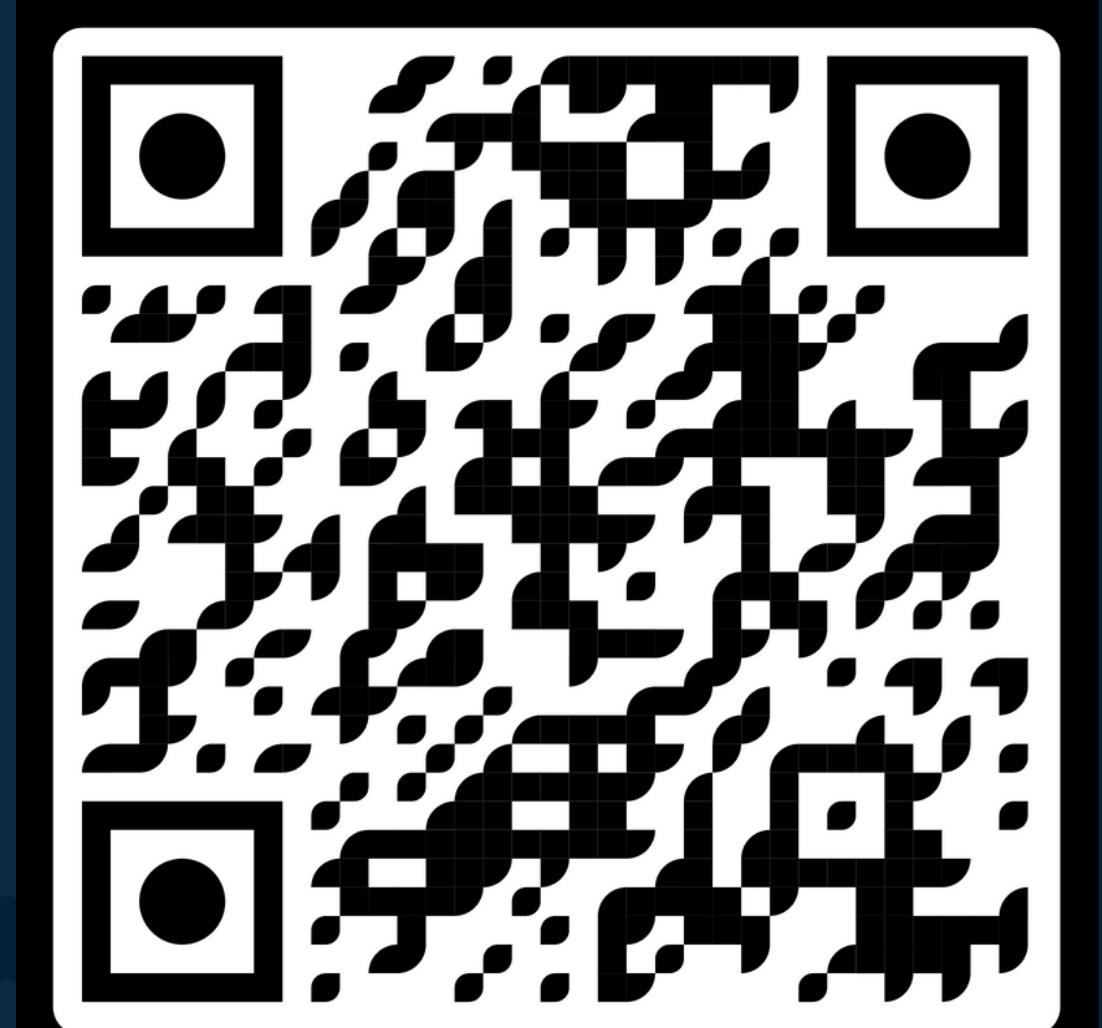
Barangay

Barangay 1



Predict Price

Try our Prototype App!



SukatSari

Try our Prototype App!

Machine Learning 2

Thank you!

References

Abellana, J. A., & Devaraj, M. (2021). Hedonic Modeling for Predicting House Prices during COVID-19 Pandemic in the Philippines. In *Proceedings of the 2021 3rd International Conference on Management Science and Industrial Engineering* (pp. 21–26). Retrieved from <https://doi.org/10.1145/3460824.3460828>

Fontinelle, A. (2023, April 30). *Avoid these mistakes when selling your home*. Investopedia. Retrieved February 24, 2024, from <https://www.investopedia.com/articles/mortgages-real-estate/08/home-seller-mistakes-selling-house.asp>

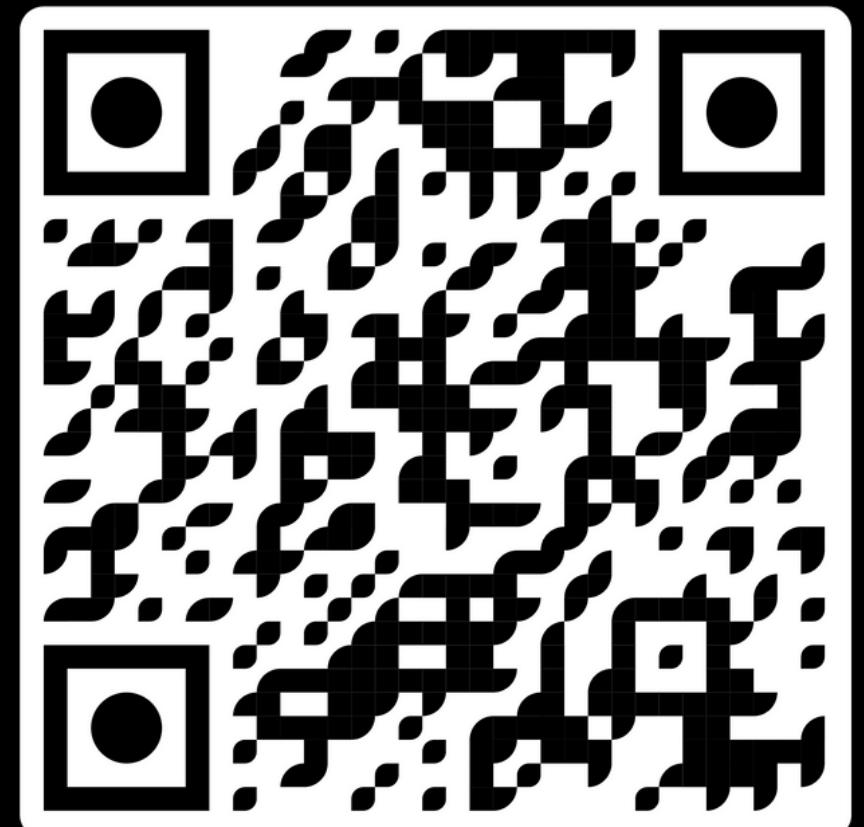
Jagan Chowhaan, M., Nitish, D., Akash, G., Nelli, S., & Shaik, S. (2023). Machine Learning Approach for House Price Prediction. *Asian Journal of Research in Computer Science*, 16, 54-61. Retrieved from <https://doi.org/10.9734/ajrcos/2023/v16i2339>

Philippines Statistics Authority. (2023, May 10). *Housing Characteristics in the Philippines (2020 Census of Population and Housing)*. Retrieved February 26, 2024 from <https://psa.gov.ph/content/housing-characteristics-philippines-2020-census-population-and-housing>.

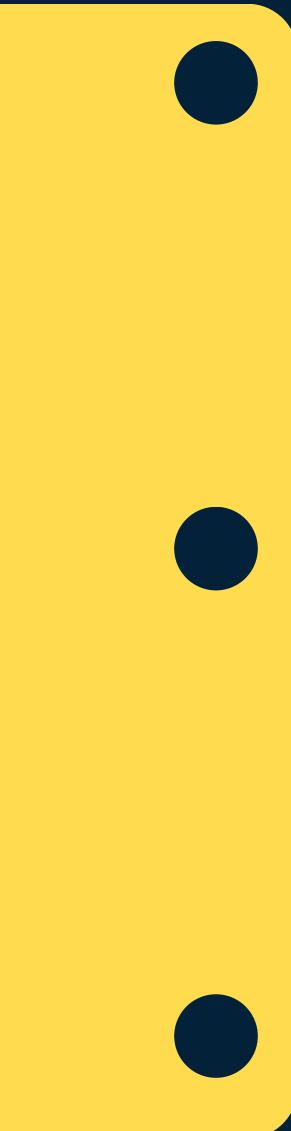
Philippines Statistics Authority & University of the Philippines Population Institute. (2019). *2018 National Migration Survey*. Quezon City, Philippines: PSA and UPPI. Retrieved February 26, 2024 from <https://psa.gov.ph/sites/default/files/2018%20NMS%20Final%20Report.pdf>

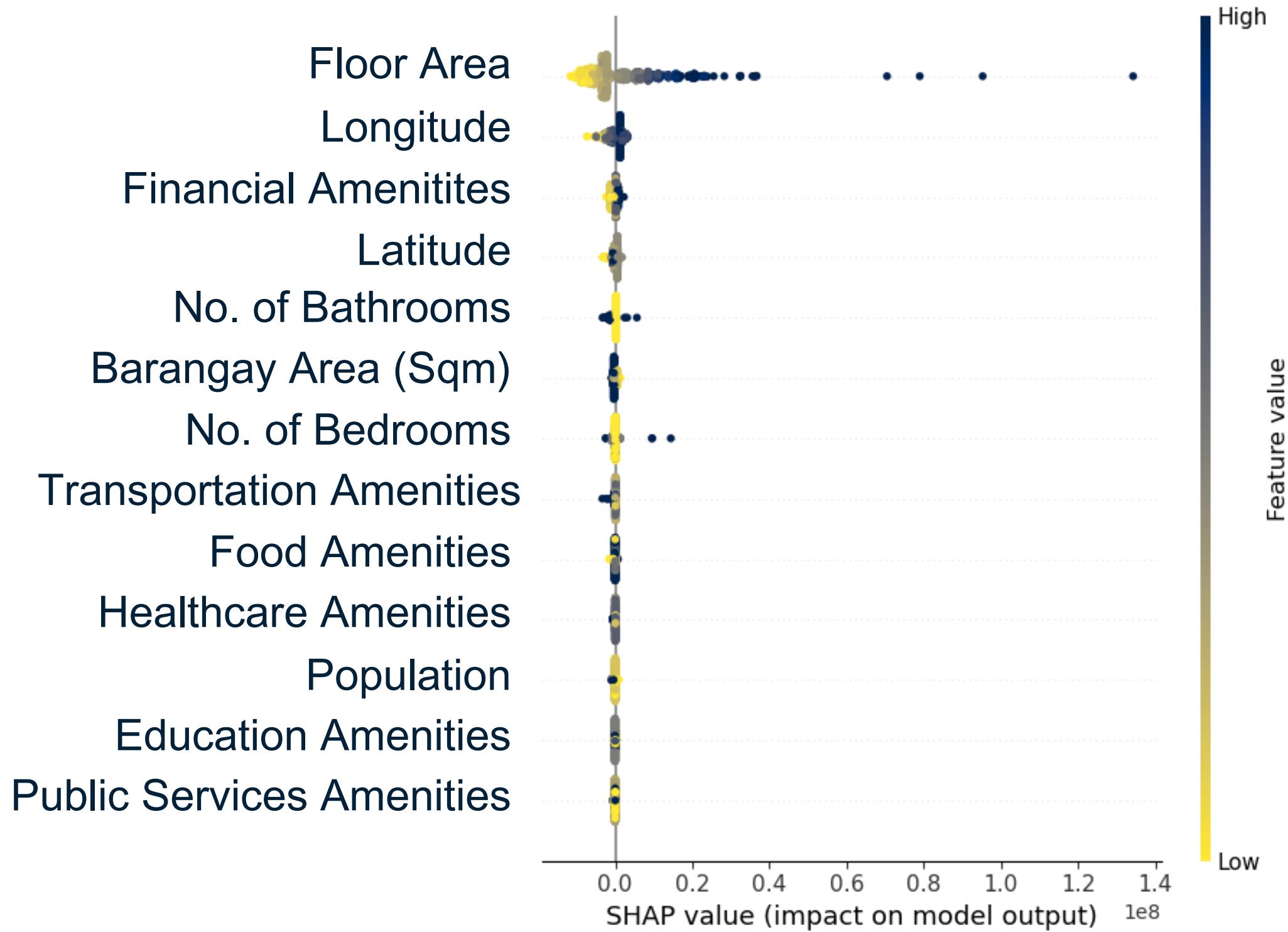
Statista. (2024, January 11). *Philippines: Age structure from 2012 to 2022*. Retrieved February 26, 2024 from <https://www.statista.com/statistics/578779/age-structure-in-philippines/>.

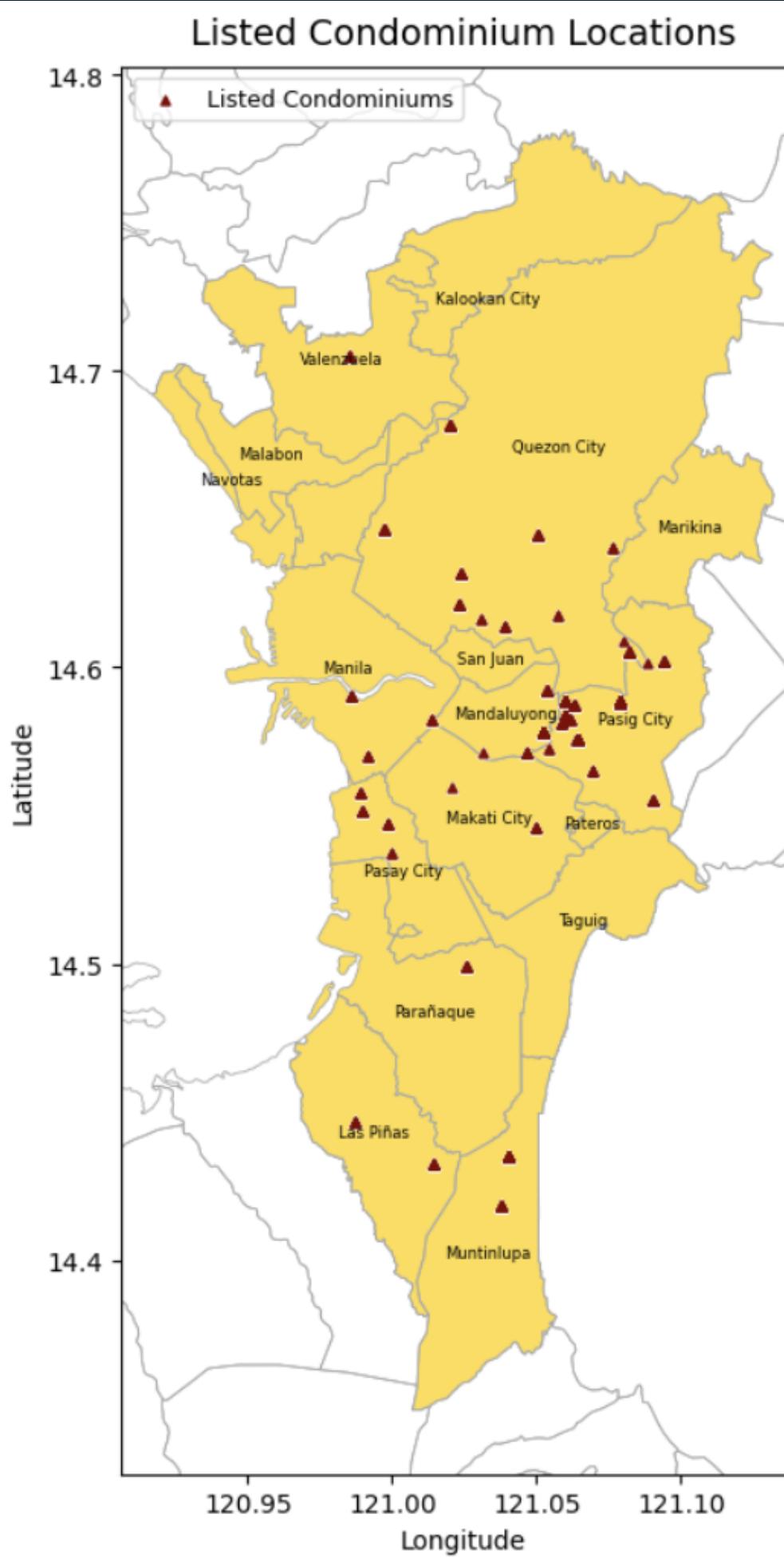
Umbrasas, K. (2022, August 8). *9 mistakes to avoid when selling your home*. Zillow. Retrieved February 24, 2024, from <https://www.zillow.com/learn/mistakes-to-avoid-when-selling-your-home/>



SukatSari







Listed Condominiums and their Locations

Scope and Limitations



Listings are limited to the
2022 Lamudi dataset

- Only condominiums were considered.
- Datapoints pertaining to houses were limited.



OpenStreetMap Dataset
is from 2018

Recommendations



Widen our scope and
acquire updated datasets



Reduce scope of
surrounding amenities
from barangay-level

- Use various radius values (500m, 1km, 2km) around the properties.

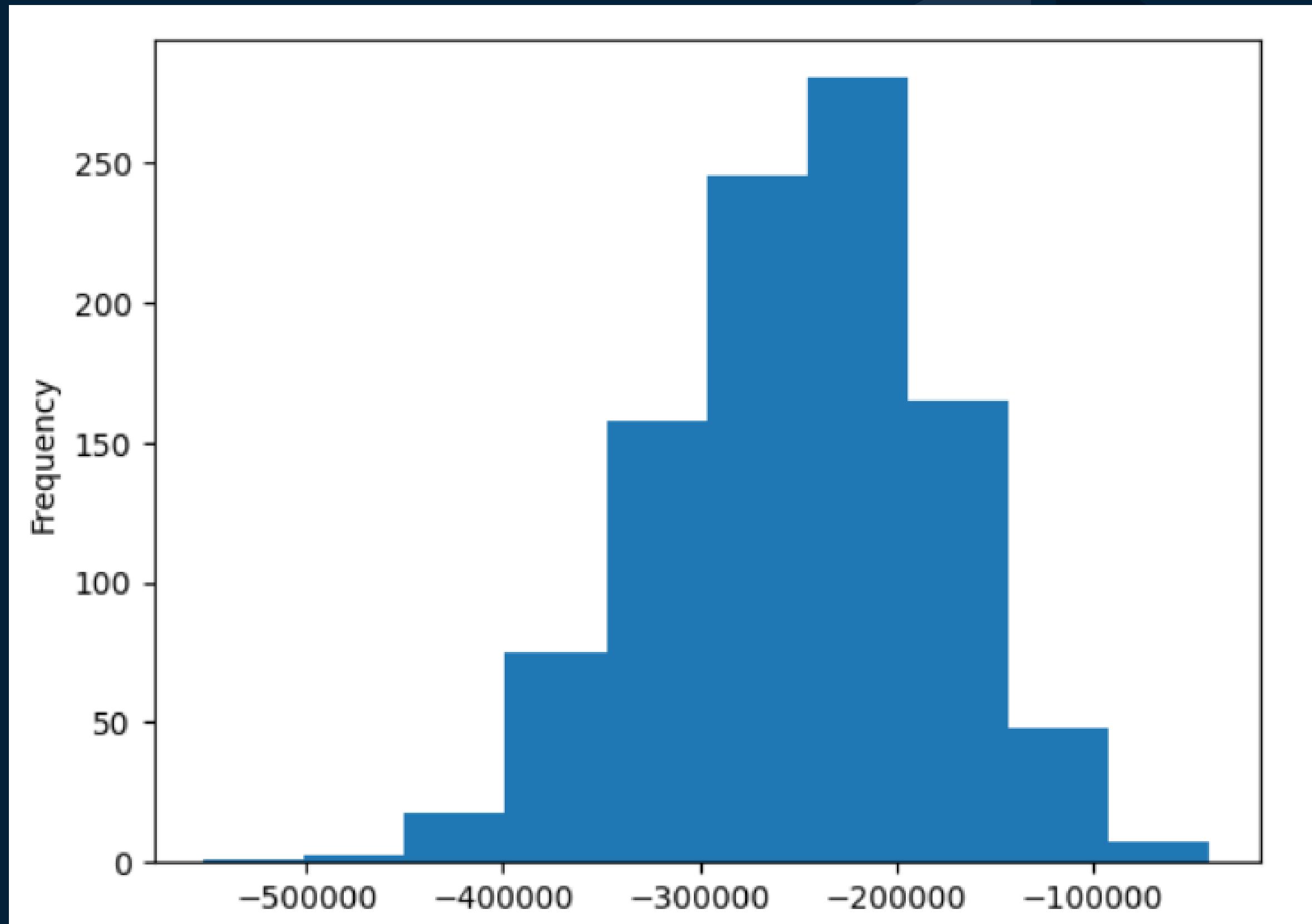
Results - Base (MAE)

Model	Mean Train Score	Mean Validation Score
Random Forest	498,707	864,257
XGBoost	278,246	919,671
Gradient Boosting	627,730	991,921
KNearestNeighbor	966,041	1,320,325
Linear Regression (L1)	2,523,344	2,561,009
Linear Regression (L1)	2,523,345	2,561,009
Linear Regression	2,523,097	2,561,909
AdaBoost	2,273,031	2,659,213

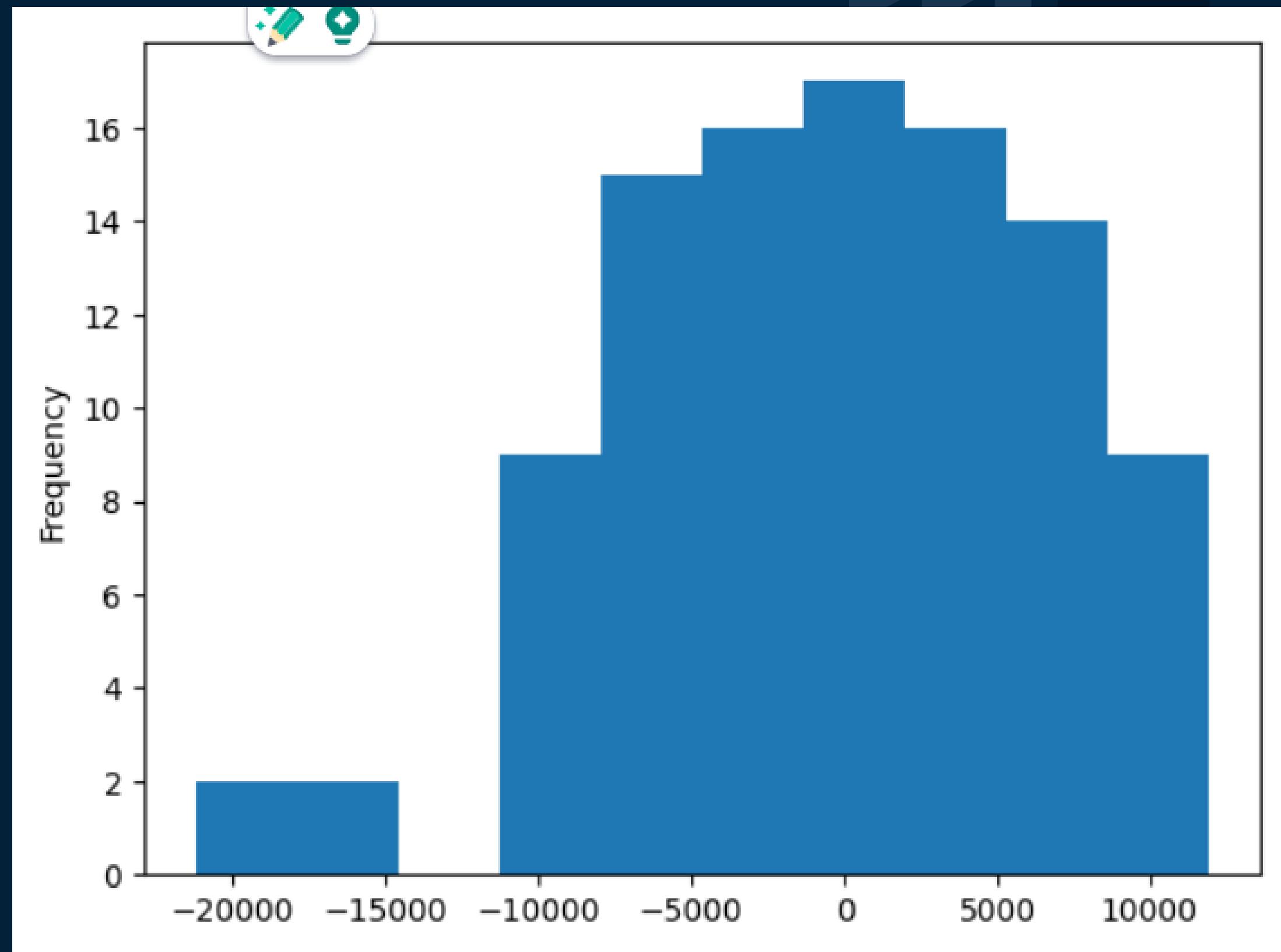
Results - with Amenities (MAE)

Model	Mean Train Score	Mean Validation Score
Gradient Boosting	272,093	743,401
XGBoost	272,093	869,627
Random Forest	509,386	871,004
KNearestNeighbor	321,299	955,220
Linear Regression (L1)	2,351,576	2,445,311
Linear Regression	2,351,576	2,445,311
Linear Regression (L2)	2,351,576	2,445,320
AdaBoostRegressor	2,189,373	2,587,680

Distribution of MAE difference at Low Price



Distribution of MAE difference at Medium Price



Distribution of MAE difference at High Price

