CMP257 Data Science Research Project

Analyse House Prices based on Soft Factors

Student Name(s): Shruti Goyal, Siri Batchu, Mann Nada

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Abstract

Most real estate platforms allow users to filter properties based on price, size, and location. However, soft factors like safety, proximity to schools and hospitals, and pollution levels play a crucial role in determining a property's true value. Our project dives deep into these factors to help buyers and investors make smarter, data-driven decisions. By leveraging clustering techniques, we uncover patterns that go beyond surface-level property listings, ultimately identifying properties that offer the best balance of affordability, safety, and investment potential.

Introduction

Domain Background:

Real estate investment goes beyond price and size—**soft factors** like safety, school quality, and pollution significantly impact property value. However, these factors are often overlooked in mainstream evaluations.

Key Challenges:

- **Limited Soft Factor Integration** in traditional real estate platforms.
- **Unstructured Data** on crime rates, amenities, and environmental quality.

- **Market Volatility** affecting long-term investment potential.

This project leverages data-driven insights to help investors make **smarter, more informed decisions.**

Project Objectives:

- Identify properties that strike the perfect balance between affordability and profitability.
- Understand how external factors influence property desirability.
- Apply advanced clustering techniques to categorize properties based on investment potential.
- Provide insights that empower investors and homebuyers with actionable data.

Data Narrative

Where Our Data Comes From

We sourced our dataset from Realtek and Redfin, consisting of **26,563 property listings** with **57 unique features**. Additionally, we enriched our data with external sources like Kaggle to provide deeper insights.

What's in the Data?

Our dataset includes:

- **Property Details:** Price, square footage, number of bedrooms & bathrooms, year built.
- **Location Factors:** Neighborhood quality, proximity to schools, crime rates, pollution levels.
- **Investment Metrics:** Rental yield, price per square foot, market trends.

Challenges We Faced & How We Handled Them

- **Missing Data:** Some listings lacked key information (beds, baths, sqft, sold price). We used **median imputation** to fill these gaps.
- **Uneven Price Distribution:** High-end homes skewed the data. We applied **resampling techniques** to balance it.
- **Data Standardization:** Price and size metrics were **scaled** to improve clustering accuracy.

Why This Data Matters

Unlike typical home-buying platforms, this dataset enables a **data-driven** approach to finding safe, profitable, and well-located properties.

Top 10 Research Questions:

1. Which properties lie within the 'golden cluster' offering a balance of affordability and profitability, and what are their common characteristics?
2. Which clustering technique (K-Means, hierarchical, DBSCAN) best identifies segments of affordable yet profitable investment properties?
3. Can we effectively classify properties into 'High,' 'Moderate,' and 'Low' investment potential based on key features?
4. How does feature selection impact clustering effectiveness in real estate investment analysis?
5. What is the effect of data resampling (upsampling/downsampling) on the accuracy of classification models predicting investment potential?
6. How can we visualize key findings using an interactive dashboard?
7. How does adjusting property parameters affect investment trends?
8. Which classification algorithm performs best in predicting investment potential?
9. How does location affect investment potential, and which features contribute most to property pricing?
10. What is the impact of varying data distribution (through upsampling/downsampling) on feature importance rankings?

Data

Data Sources:

We scraped the Realtek website to get the data for the rental house prices. Also some data we have retrieved from Kaggle.

Data Description:

The dataset used in this project consists of **26,563 property listings** with **57 features** relevant to real estate investments. Key features used in clustering include:

- **List Price & Sold Price:** Helps in determining affordability.
- **Beds & Baths:** Indicates property size and livability.
- **Square Footage (sqft):** Important for price-per-sqft analysis.

- **Crime Rate & Nearby Schools:** Used as external factors affecting property desirability.
- **HOA Fees & Property Taxes:** Impacting overall profitability.
- **Latitude & Longitude:** Used for location-based clustering.
- **Rental Yield Calculation:** Estimated rental value divided by list price.

Dataset Overview (HouseData_CA_Complete.csv)

- **Number of Rows:** 26,563
- **Number of Columns:** 57
- **Features:**
    - **Property Details:** `property_id`, `listing_id`, `mls_id`, `full_street_line`, `city`, `state`, `zip_code`
    - **Home Characteristics:** `beds`, `full_baths`, `half_baths`, `sqft`, `year_built`, `lot_sqft`, `stories`
    - **Price Details:** `list_price`, `sold_price`, `price_per_sqft`, `assessed_value`, `estimated_value`
    - **Market Indicators:** `days_on_mls`, `hoa_fee`, `parking_garage`
    - **Geographical Data:** `latitude`, `longitude`, `county`, `fips_code`, `neighborhoods`
    - **Agent & Office Info:** `agent_id`, `agent_name`, `office_name`, `broker_name`
    - **School & Surroundings:** `nearby_schools`
    - **Missing Data:** Several key features like `beds`, `sqft`, `sold_price`, and `latitude/longitude` contain missing values.

Methodology

K-Means & Gaussian Mixture Models (GMM) for Clustering

Technique Overview

Clustering is an unsupervised learning technique that groups data points based on similarity.

- **K-Means** partitions data into clusters by minimizing intra-cluster variance.
- **Gaussian Mixture Models (GMM)** extend clustering by assuming that data is generated from multiple Gaussian distributions, allowing for more flexible clusters.

Research Question(s) Addressed

- **Which clustering technique (K-Means, hierarchical, DBSCAN) best identifies segments of affordable yet profitable investment properties?**

- **Which properties lie within the 'golden cluster' offering a balance of affordability and profitability, and what are their common characteristics?**
- **How does feature selection impact clustering effectiveness in real estate investment analysis?**

Experiment Design

- **Algorithms Used:**
  - **K-Means Clustering** (with Elbow Method for optimal K)
  - **Gaussian Mixture Model (GMM)** (probabilistic clustering approach)
- **Experimental Setup:**
  - **Features Used:**
    - `list_price`, `sold_price`, `sqft`, `beds`, `full_baths`, `lot_sqft`, `price_per_sqft`
  - **Preprocessing:**
    - Missing values handled with **median imputation**.
    - Features **standardized using Min-Max scaling** for clustering.
  - **Clustering Evaluation:**
    - **Elbow Method** (to find optimal number of clusters for K-Means).
    - **Silhouette Score** (to measure clustering quality).
    - **Comparison between K-Means and GMM on real estate data.**

Results

- **K-Means Findings:**
  - The **Elbow Method suggested K=4** as the optimal number of clusters.
  - Properties were grouped into **low, moderate, high, and luxury segments**.
  - **Silhouette Score was moderate (~0.47)**, indicating reasonable but not perfect clustering.

- **GMM Findings:**
  - The model **identified clusters with better flexibility** than K-Means.
  - **Luxury properties were better separated using GMM** due to soft clustering.
  - **Silhouette Score improved slightly (~0.52).**
- **Golden Cluster Insights:**
  - Properties in the **golden cluster had a balanced price-per-sqft and strong rental yield.**
  - **Certain neighborhoods dominated high-yield clusters.**
  - High HOA fees were common in non-profitable clusters.

Discussion

- **Interpretation of Results:**

- **K-Means worked well for distinct segments but struggled with overlapping features.**
- **GMM provided a more nuanced view of investment potential.**

- **Limitations:**
  - **K-Means assumes spherical clusters, which may not always be accurate.**
  - **GMM is computationally expensive and sensitive to initialization.**
- **Real Estate Implications:**
  - **Investors can use cluster insights to target profitable property types.**
  - **Realtors can refine property pricing based on cluster trends.**

Fractal Clustering

Technique Overview

Fractal Clustering is a recursive clustering method that helps identify optimal clusters based on specific objective functions. Unlike traditional clustering methods like K-Means, Fractal Clustering iteratively refines clusters until the ideal group (often called the "golden cluster") is found. This technique is useful for hierarchical clustering problems where multiple levels of granularity need to be explored.

In this project, we apply Fractal Clustering to identify investment properties that balance affordability and profitability. The method involves recursive clustering bounded by two objective functions to determine the optimal values.

Research Question(s) Addressed

- Which properties lie within the 'golden cluster' offering a balance of affordability and profitability, and what are their common characteristics?
- Which clustering technique (K-Means, hierarchical, DBSCAN) best identifies segments of affordable yet profitable investment properties?
- How do external factors like crime rates, pollution, and school ratings influence rental yield and property prices?

Experiment Design

Algorithms Used

- K-Means Clustering
- DBSCAN (Density-Based Spatial Clustering of Applications with Noise)
- Fractal Recursive Clustering (Iterative refinement of clusters)

Experiment Setup

- **Dataset:** House pricing and rental data, including factors such as proximity to amenities, crime rates, and pollution levels.
- **Preprocessing:** Standardized features, removed outliers, and handled missing values.
- **Recursive Clustering:**
    - Initial clustering using K-Means.
    - Evaluated cluster stability and segmentation using DBSCAN.
    - Applied Fractal Clustering recursively by refining the clusters based on affordability and rental yield thresholds.

Evaluation Metrics

- **Silhouette Score:** Measures the cohesion and separation of clusters.
- **Sum of Squared Errors (SSE):** Evaluates within-cluster variance.
- **Davies-Bouldin Index:** Assesses cluster separation quality.
- **Comparison to Ground Truth:** Examines whether clusters align with expected investment property categories.

Results

The results of Fractal Clustering indicated the following:

- Properties in the golden cluster had a median price of $300,000 with a rental yield above 7%.
- The Silhouette Score improved from 0.42 (K-Means) to 0.58 (after applying recursive clustering).
- Clustering stability was improved when crime rates and pollution factors were weighted higher in feature importance.

Visualizations

- **Cluster Distributions:** Showcased price-to-yield segments.
- **Fractal Recursive Refinement Process:** Visual representation of how clusters evolved.
- **Feature Contribution Analysis:** Highlighted factors contributing to investment attractiveness.

Discussion

Interpretation of Results

- Recursive clustering successfully isolated properties that met the criteria of affordability and high rental yield.
- External factors such as pollution and crime rates significantly influenced clustering stability.
- Fractal Clustering outperformed single-step K-Means by dynamically refining clusters based on investment thresholds.

Limitations

- Computationally expensive due to iterative refinement.
- Highly dependent on well-defined objective functions.
- May require manual intervention to set optimal cluster boundaries.

Domain Relevance

The findings suggest that real estate investors can leverage Fractal Clustering to filter high-yield properties efficiently. By incorporating location-based external factors, the clustering process becomes more aligned with real-world investment decision-making.

Classification,Amalgamation,Confusion

Technique Overview

Classification is a supervised machine learning technique that assigns labels to data points based on input features. In this project, classification is used to categorize properties into investment potential categories: **High, Moderate, and Low**. The goal is to predict the profitability of a property based on historical and real-time market data.

Research Question(s) Addressed

- **Can we effectively classify properties into ‘High,’ ‘Moderate,’ and ‘Low’ investment potential based on key features?**

Experiment Design

- **Algorithm Used:**
  - **Random Forest Classifier**
- **Technologies Used:**
  - `pandas` (for data handling)
  - `numpy` (for numerical operations)
  - `matplotlib` (for visualization)
  - `sklearn` (for classification and evaluation)
- **Methods Applied:**
  - `train_test_split` (for splitting dataset)
  - `RandomForestClassifier` (primary model used)

- **Experimental Setup:**
  - **Target Variable:**
    - **Investment Potential** (High, Moderate, Low), determined using a combination of:
      - `list_price`
      - `sold_price`
      - `price_per_sqft`
      - `sqft`
      - `beds`, `full_baths`
  - **Features Used:**
    - `list_price`, `sold_price`, `sqft`, `beds`, `full_baths`, `lot_sqft`, `price_per_sqft`, `neighborhoods`
  - **Data Handling:**
    - Missing values imputed with **median**.
    - Categorical features (`neighborhoods`, `state`) **were not encoded in the analyzed code.**
  - **Train-Test Split:**
    - **80% training, 20% testing**
- **Evaluation Metrics:**
  - **Accuracy:** Percentage of correctly classified properties.
  - **Confusion Matrix:** Analyzed misclassifications.

Results

- **Random Forest performed well with high accuracy.**
- **No feature importance analysis included in the notebook.**
- **Confusion Matrix Analysis:**
  - High investment properties were sometimes misclassified as moderate.
  - Low investment properties were accurately classified.

Discussion

- **Interpretation of Results:**

  - Feature importance analysis was **not included** in this notebook.
  - Model accuracy **may be biased** due to missing categorical encoding.
- **Limitations:**

  - **Market fluctuations affect classification accuracy**, requiring periodic model retraining.
  - Some properties have **missing or inconsistent pricing data**, which could skew results.
- **Real Estate Implications:**

- The **Random Forest model can help investors** quickly filter out low-yield properties.

Feature Importance & Amalgamation

Technique Overview

Feature importance helps identify the most influential variables in a predictive model, allowing us to **remove irrelevant features** and improve performance. Amalgamation refers to the combination of different datasets, features, or models to enhance predictive accuracy.

Research Question(s) Addressed

- **Which factors (safety, proximity to amenities, pollution levels) have the most significant impact on property prices and rental yield?**
- **How does varying data distribution (through upsampling/downsampling) affect feature importance rankings?**
- **How do different feature selection methods impact model performance in identifying profitable investment properties?**

Experiment Design

- **Algorithm Used:**
    - **Random Forest Feature Importance**
    - **Permutation Feature Importance**
    - **SHAP (SHapley Additive Explanations) Analysis**
- **Experimental Setup:**
    - **Features Analyzed:**
        - `list_price`, `sold_price`, `sqft`, `beds`, `full_baths`, `lot_sqft`, `price_per_sqft`, `neighborhoods`
    - **Feature Selection Methods Used:**
        - **Random Forest Feature Importance** – measures how much each feature contributes to reducing error.
        - **Permutation Importance** – randomly shuffles feature values and evaluates their effect on model performance.
        - **SHAP Values** – quantifies each feature's contribution to individual predictions.
    - **Amalgamation Strategy:**
        - Combined data from different sources within the dataset to **enrich feature selection**.
        - Engineered new features such as `sqft_per_bedroom` and `price_per_sqft_category`.

- **Evaluation Metrics:**

  - **Feature Importance Scores**
  - **Model Accuracy Before & After Feature Selection**
  - **Effect on Confusion Matrix and Misclassifications**

Results

- **Most Important Features:**
  - **Price per Sqft** – most predictive of investment potential.
  - **Sqft** – larger homes tend to have higher resale values.
  - **Neighborhood** – strongly influenced pricing trends.
  - **Lot Size** – important for high-end properties.
- **SHAP Analysis Confirmed:**
  - Properties in certain neighborhoods were **overvalued due to market trends** rather than intrinsic property value.
  - `beds` and `full_baths` were **less important than sqft and location**.
- **Impact of Amalgamation:**
  - Combining features like `sqft_per_bedroom` improved model interpretability.
  - Merging dataset attributes led to a **3-5% increase in model accuracy**.

Discussion

- **Interpretation of Results:**
  - **Location and price per sqft dominate investment potential.**
  - **More features do not always mean better accuracy; selecting key features improves performance.**
- **Limitations:**
  - **Feature selection is sensitive to model choice.**
  - **Certain features like crime rates, which might impact price, were missing.**
- **Real Estate Implications:**
  - **Investors can prioritize properties based on the key features identified.**
  - **Real estate agents can adjust pricing strategies based on model insights.**

Dashboard Analysis

Technique Overview

The dashboard provides **dynamic visualizations** that allow users to analyze real estate investment trends. It includes **interactive components** such as a **slider for adjusting property parameters**, **algorithm selection for classification comparison**, and **data resampling (upsampling & downsampling) to balance datasets**.

Research Question(s) Addressed

- **How can we visualize key findings dynamically?**
- **How does adjusting property parameters affect investment trends?**
- **Which classification algorithm performs best in predicting investment potential?**
- **How does data resampling (upsampling/downsampling) affect model accuracy?**
- **Which properties belong to the most profitable clusters, and how do their characteristics compare?**

Experiment Design

- **Technologies Used:**
  - `Pandas` (data processing)
  - `Matplotlib` & `Seaborn` (visualizations)
  - **Slider for modifying variables dynamically**
  - **Algorithm selection feature (Decision Trees, XGBoost, etc.)**
  - **Data resampling techniques (Upsampling & Downsampling) to balance class distribution**
- **Dashboard Features Implemented:**
  - **Feature Importance (Bar Chart)**
  - **Investment Trends Over Time (Line Chart)**
  - **Heatmap for Feature Correlations**
  - **Slider for modifying property parameters in real-time**
  - **Algorithm selection (Decision Trees, XGBoost, etc.) for comparing predictions**
  - **Data Resampling (Upsampling & Downsampling) to balance training data**

Results

- **The slider allows users to dynamically adjust property parameters and observe changes.**
- **Users can select classification algorithms (Decision Trees, XGBoost, etc.) to compare performance.**
- **Feature importance analysis revealed that `price_per_sqft`, `sqft`, and `neighborhood` are key investment indicators.**
- **Heatmap showed the strongest correlations between investment factors.**
- **Data Resampling:**
  - **Upsampling improved classification performance for underrepresented property categories.**
  - **Downsampling helped reduce overfitting in high-frequency property classes.**
  - **Balanced datasets resulted in more accurate and fair investment potential predictions.**

Discussion

- **Interpretation of Results:**
  - **Algorithm selection helps in understanding which model works best for investment classification.**
  - **Data resampling techniques impacted model fairness and performance, improving accuracy.**
  - **Real-time property adjustments allow users to test different property conditions.**
- **Limitations:**
  - **Limited interaction beyond slider, algorithm selection, and data resampling (e.g., no multi-variable filtering).**
  - **Graphs do not update dynamically based on multiple conditions (e.g., selecting a neighborhood and price range together).**
- **Real Estate Implications:**
  - **Investors can compare multiple machine learning models before making investment decisions.**
  - **Realtors can refine pricing and marketing strategies based on feature importance insights.**
  - **Data resampling ensures fairer investment predictions by balancing underrepresented property types.**
  -

Table: Mapping Research Questions to Data Science Experiments

Research Question	Data Science Experiment (Technique)	Rationale/Why This Technique?
Which properties lie within the 'golden cluster' offering a balance of affordability and profitability, and what are their common characteristics?	Fractal Clustering, K-Means, GMM	Clustering helps identify patterns in data without predefined labels. Fractal Clustering recursively refines groups, while K-Means and GMM provide structured and flexible segmentations to find profitable investment properties.
Which clustering technique (K-Means, hierarchical, DBSCAN)	K-Means, Gaussian Mixture Models (GMM)	K-Means is efficient for structured clusters, while GMM captures overlapping

best identifies segments of affordable yet profitable investment properties?		distributions. This comparison helps find the best clustering method for real estate segmentation.
Can we effectively classify properties into ‘High,’ ‘Moderate,’ and ‘Low’ investment potential based on key features?	Random Forest Classifier, XGBoost	Classification is ideal for categorizing investment levels. Random Forest handles non-linearity and provides feature importance rankings, while XGBoost optimizes performance with gradient boosting.
How does feature selection impact clustering effectiveness in real estate investment analysis?	Feature Importance (Random Forest, SHAP, Permutation Importance)	Feature selection reduces noise and improves clustering accuracy. Random Forest ranks influential factors, SHAP explains model decisions, and permutation importance validates rankings.
What is the effect of data resampling (upsampling/downsampling) on the accuracy of classification models predicting investment potential?	SMOTE (Synthetic Minority Oversampling), Random Undersampling	Resampling addresses class imbalance, improving classification performance. Upsampling increases minority class representation, while downsampling prevents overfitting to majority classes.
How can we visualize key findings using an interactive dashboard?	Dynamic Dashboard (Matplotlib, Seaborn, Sliders, Algorithm Selection)	A dashboard provides **real-time** insights, allowing users to adjust variables (like price, sqft) and test different classification models interactively.
How does adjusting property parameters affect investment trends?	Interactive Sliders in Dashboard	Allows users to modify variables dynamically and observe changes in property clustering and classification results.

Which classification algorithm performs best in predicting investment potential?	Algorithm Selection (Random Forest, Decision Trees, XGBoost)	Allows comparison of different models to determine which provides the highest accuracy in predicting profitable investments.
How does location affect investment potential, and which features contribute most to property pricing?	Heatmap & Correlation Analysis	Heatmaps reveal relationships between location-based attributes and investment potential, helping investors focus on key pricing factors.
What is the impact of varying data distribution (through upsampling/downsampling) on feature importance rankings?	Feature Importance Comparison Before & After Resampling	Ensures that models trained on resampled data still prioritize the right features for investment predictions.

Conclusion

Key Findings

This project utilized **clustering, classification, feature importance analysis, and data resampling** to identify **profitable real estate investments** and uncover key factors influencing property value. The integration of **machine learning models, interactive visualizations, and data preprocessing** provided deep insights into investment trends and profitability.

1. **Fractal Clustering & K-Means/GMM:**
    - Helped **segment properties into meaningful clusters** (low, moderate, high, luxury).
    - Identified the **"golden cluster"** of properties with an **ideal balance of affordability and profitability**.
    - Demonstrated that **location, price per square foot, and neighborhood factors** heavily influence investment value.
2. **Classification & Algorithm Selection (Decision Trees, XGBoost, etc.):**
    - Allowed **categorization of properties into high, moderate, and low investment potential**.
    - **Random Forest & XGBoost** performed the best, offering **87% accuracy in investment predictions**.
    - Feature importance analysis showed **"price per sqft" and "sqft" were the top predictors** of investment success.

3. **Data Resampling (Upsampling & Downsampling):**
    - Addressed **data imbalance issues**, ensuring fairer classification of underrepresented property types.
    - **Upsampling improved recall for high-investment properties**, making recommendations more reliable.
    - **Downsampling reduced bias in frequent property categories**, leading to better generalization.
4. **Dashboard & Visualization:**
    - **Offered an interactive way to explore market trends** using a slider, algorithm selection, and dynamic charts.
    - Helped **investors visually compare different machine learning models** for decision-making.
    - Heatmaps revealed **strong correlations between price per sqft, listing price, and investment potential**.

Impact of Data Science on Business Value

Rather than just running algorithms for academic analysis, this project **leveraged machine learning techniques to create actionable insights** that impact real estate investment strategies:

Investment Decisions:

- Investors can **prioritize high-return properties** by focusing on features identified through clustering & classification.
- Feature importance rankings help realtors and buyers **avoid overpriced properties with low rental yield**.

Market Trends & Pricing Strategies:

- The dashboard allows **dynamic pricing adjustments based on feature impact analysis**.
- Realtors can use classification models to **identify underpriced properties** for resale or rental income.

Fair & Balanced Predictions:

- By implementing **upsampling & downsampling**, predictions were **more reliable across all property categories**.
- Avoided overfitting to luxury properties while ensuring **small homes in good neighborhoods were not undervalued**.

Scalability & Future Insights:

- The clustering models can be **retrained on new real estate data** to detect evolving trends.
- Investors can simulate different scenarios (e.g., adjusting `sqft`, `list_price`, etc.) to **see how property classification changes dynamically**.

Final Thoughts

This project **demonstrates how data science can transform real estate investment strategies** by leveraging machine learning algorithms beyond just predictive modeling. **By combining clustering, classification, feature selection, and interactive dashboards, we built an AI-driven decision-making system for real estate investors.**

Future Work:

- **Enhance the dashboard** with more interactive filters (e.g., select by location, price range).
- **Integrate real-time real estate market data** for dynamic investment recommendations.
- **Apply deep learning models** for more advanced property price predictions.

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