Classifying Apartment Rent Prices Based on Property Features

line 1: 1st Given Name Surname
line 2: *dept. name of organization (of Affiliation)*
line 3: *name of organization (of Affiliation)*
line 4: City, Country
line 5: email address or ORCID

line 1: 2nd Given Name Surname
line 2: *dept. name of organization (of Affiliation)*
line 3: *name of organization (of Affiliation)*
line 4: City, Country
line 5: email address or ORCID

line 1: 3rd Given Name Surname
line 2: *dept. name of organization (of Affiliation)*
line 3: *name of organization (of Affiliation)*
line 4: City, Country
line 5: email address or ORCID

line 1: 4th Given Name Surname
line 2: *dept. name of organization (of Affiliation)*
line 3: *name of organization (of Affiliation)*
line 4: City, Country
line 5: email address or ORCID

line 1: 5th Given Name Surname
line 2: *dept. name of organization (of Affiliation)*
line 3: *name of organization (of Affiliation)*
line 4: City, Country
line 5: email address or ORCID

line 1: 6th Given Name Surname
line 2: *dept. name of organization (of Affiliation)*
line 3: *name of organization (of Affiliation)*
line 4: City, Country
line 5: email address or ORCID

ABSTRACT

This paper introduces a machine learning solution to predict apartment rent prices by property attributes. An end-to-end data mining pipeline was implemented, involving thorough data preprocessing, feature construction, and the utilization of three different classification algorithms: Gaussian Naïve Bayes, Decision Trees, and a Multilayer Perceptron. Experimental results indicate that the highest accuracy of 91.8% is achieved using the Decision Tree classifier, largely outperforming the Naïve Bayes (40.9%) and the MLP (81.3%) models. These results exhibit that data mining methods are useful in uncovering intricate, nonlinear relationships between rentals and effectively constructing a reliable decision support system tool for market participants in the fiercely competitive real-estate business

Keywords—*Apartment rent prices; Property features; Machine learning; Data mining; Classification; Decision Trees; Gaussian Naïve Bayes; Multilayer Perceptron; Feature engineering; Data preprocessing.*

I. INTRODUCTION

In the competitive rental market of today, pinpointing apartment rent prices according to property attributes is essential for both tenants and property owners. Tenants require sound estimates to plan their budgets, while landlords are looking for fact-based information to establish competitive prices and achieve maximum occupancy. Established appraisal techniques—typically built on local knowledge and straightforward heuristics—are ineffective in capturing intricate, nonlinear patterns between attributes like unit space, location, amenities, and time trends. Here, we present a complete machine-learning pipeline that takes historical rental postings and learns these trends automatically. Having undergone significant feature engineering and data preprocessing, we train three different classifiers—Gaussian Naïve Bayes, Decision Trees, and an elementary Multilayer Perceptron (MLP)—on binning rents into four classes. Our highest accuracy model is a fine-tuned Decision Tree, scoring 91.8 % on held-out data and proving the potency of data mining in real-estate decision support.

II. LITERATURE REVIEW

Machine-learning Machine-learning methods have grown in popularity for forecasting rental prices, as they can model intricate, nonlinear interactions between property characteristics and market influences. In research on Munich's rental market, Müller et al. used a set of algorithms—such as ensemble methods, neural networks, linear regression, and tree-based models—and showed that tree ensembles and deep networks outperformed conventional regressions by a wide margin in terms of predictive power [1]. Rahman and Aziz systematically reviewed office-building rental forecasts and concluded that Random Forest, Decision Trees, Support Vector Machines, and Neural Networks are most widely used methods whose superiority on big, heterogeneous real-estate data is emphasized [2]. Senthil Kumar R. et al. contrasted Convolutional Neural Networks with Naïve Bayes for metro-city rent prediction and found that CNNs performed above 95 % compared to 89 % for NB, highlighting the importance of deep feature extraction [3]. Last but not least, Lindström et al. utilized historical property data and Stockholm local amenity features to train and test several ML models and concluded that well-tuned Decision Trees can compete with more sophisticated networks when interpretability is paramount [4].

III. DATASET DESCRIPTION

A. Data Source and Extraction

Our main goal dataset, houses_for_rent_classified_10K.csv, is a 10,000-listing sampling from an underlying 100K-record repository of U.S. rent postings. It was scraped from a dozen web sites (e.g., RentLingo, RentDigs.com) between late 2019 and early 2020. We chose the 10K example for initial prototyping to allow quick iteration while guaranteeing both representative geography and feature variation. houses_for_rent_classified_10K.csv.

B. Feature List and Data Types

The raw data set consists of 22 features across identifiers, text descriptions, numeric measurements, and category labels. Highlighted features are bathrooms (float), bedrooms (float), square_feet (int), price (int, USD), latitude/longitude (float), and time (UNIX timestamp). Categorical fields like has_photo, pets_allowed, price_type, cityname, and source preserve listing metadata and source. We also keep amenities (comma-separated strings) for encoding downstream. In preprocessing, we remove high-cardinality text columns (title, body, address) and constant columns (fee, currency), engineer price_per_sqft, and extract temporal features (month, weekday, hour) from the timestamp.

C. *Missing Values and Initial Statistics*

Early EDA shows that 35.5 % of listings do not have an amenities entry and 41.6 % do not have pets_allowed; numeric fields such as bathrooms and bedrooms have fewer than 0.5 % missing, and geocoordinates only miss 0.1 %. We impute numeric medians and replace categorical missing with "Unknown" or mode values. Rent prices vary from $200 to $52,500 (mean $1,486 ± $1,076), and unit sizes vary from 101–40,000 sqft (mean 946 ± 656 sqft). This describe statistics informed our choice of clipping outliers at the 1st–99th percentiles and of log-transforming skewed variables to facilitate stabilized modeling.

IV. Selected Data Mining Technique

A. *Rationale for Data Mining*

The rental housing market produces extensive amounts of disperse data—from quantitative metrics like unit size and number of rooms to categorical descriptors like pet friendly and photo included. These variables interact in nuanced, frequently nonlinear manners that defy easy rule-based valuation. Data mining employs machine learning algorithms to reveal previously unknown patterns and relationships in such high-dimensional datasets, making possible more precise and scalable rent categorization than do conventional statistical approaches [1], [2]. Through data mining methods, we can analyze each feature systematically regarding its relative relevance, address missing or noisy records, and create models that generalize well over diverse geographic markets and listing sources.

B. *Choice of Classification Approach*

Even though rent is a continuous variable, setting the problem up as classification across four discrete ranks ("low", "mid-low", "mid-high", "high") makes subsequent decision-making by tenants and landlords easier. Classification algorithms output explicit probability measures for every rank, which helps risk-based pricing strategies. We chose three complementary algorithms:

1) *Gaussian Naïve Bayes:*

A probabilistic baseline that models feature independence. Its simplicity enables us to measure the value added by our preprocessing and feature engineering stages [3].

2) *Decision Tree:*

An interpretable model that accommodates mixed data types naturally and achieves nonlinear interactions. With tuned depth and split parameters, the Decision Tree recorded the highest accuracy (91.8 %), indicating its capacity to identify dominant decision thresholds in the feature space [4].

3) *Multilayer Perceptron (MLP):*

Feed-forward neural network that is able to learn high-order interactions between features. With L2 regularization and two hidden layers, the MLP generalizes efficiently (81.3 % accuracy) and augments tree-based solutions by picking up on subtle data patterns.

V. Algorithms

A. *Naive Bayes*

Naïve Bayes is a Bayes' theorem-based probabilistic classifier, which estimates the probability of a class based on a given set of features. It makes the "naïve" assumption that all the features are conditionally independent, something that can reduce computation but is usually not the case in real-world applications. Regardless of this "naïve" assumption, Naïve Bayes is capable of performing well in a wide range of applications, including text classification and spam filtering.

B. *Decision Tree*

Decision Trees are supervised learning algorithms applied in classification and regression problems. They operate by repeatedly partitioning the data into subsets based on feature values, developing a tree structure of decisions. Every internal node is a decision rule, and every leaf node is an outcome. Decision Trees are appreciated due to their interpretability and simplicity.

C. *Neural Network (MLP)*

A Multilayer Perceptron (MLP) is a type of feedforward artificial neural network made up of a minimum of three layers: an input layer, multiple hidden layers, and an output layer. All neurons within a layer connect to all the neurons in the next layer, and every connection carries an associated weight. MLPs can learn complex nonlinear mappings and are popular in applications ranging from image and speech recognition to natural language processing and expert systems.

VI. Results

The research sought to categorize apartment rent prices into four classes according to different property attributes with three machine learning models: Naïve Bayes, Decision Trees, and Multi-Layer Perceptron (MLP). The data was divided into training and test sets with almost equal class distributions:

- Training set: [2049, 1962, 1992, 1997]
- Testing set: [501, 499, 501, 499]

A. *Naïve Bayes Results*

Naïve Bayes classifier had a total accuracy of 40.9%, which was much lower than the other models.

- Class 0: High precision of 0.73 but extremely low recall (0.13), indicating that while the model had high confidence in predicting this class, it did not capture most true class 0 instances.
- Class 1: Moderate performance with recall of 0.70 and F1-score of 0.47.
- Class 2: The model completely broke down for this class with 0 recall and F1-score, which means zero correct predictions.
- Class 3: Improved results with recall of 0.81 but only moderate precision (0.44).

Generally, the model had a bias towards preferring some of the classes (particularly class 3) while neglecting others (class 2), producing unbalanced predictions. This may be because Naïve Bayes has a strong feature independence assumption, which isn't applicable to this complex multi-feature dataset [1].

B. *Decision Tree Results*

The Decision Tree classifier, with max_depth=20 and min_samples_split=2, worked extremely well with an accuracy rate of 91.8%.

- All classes had excellent performance with F1-scores between 0.88 and 0.95.
- Class 0 and 3 were predicted with extremely high accuracy (F1: 0.95).
- Class 1 was slightly worse in precision and recall but still well-performing (F1: 0.89).
- The model had picked up subtle interactions in the data and handled feature interactions well, which is the reason behind its good generalization ability.

This level of high performance proves that Decision Tree model works well in uncovering non-linear relationships between house attributes and rental prices [2].

C. *MLP Classifier Results*

The MLP (Neural Network) model was optimized with two layers of 50 neurons and alpha=0.001.

- Reached an accuracy of 81.3%, which is evidence of good though not excellent, generalization.
- Class 0 performed best (F1: 0.89, Recall: 0.93), while class 2 had values slightly lower than these (F1: 0.74).
- Class 3 had great accuracy (0.97) but slightly less recall (0.81).

This indicates that the MLP model well picked up underlying trends but possibly overfit or underfit some class boundaries because of architectural or hyperparameter limitations [3].

1) *Summary of Comparison*

Model	Accuracy	Best Class	Weakest Class	Notes
Naïve Bayes	40.9%	Class 3	Class 2	Struggles due to feature independence assumption
Decision Tree	91.8%	All	Slightly Class 1	Excellent all-around; best performer
MLP	81.3%	Class 0	Class 2	Strong performance; some class imbalance effects

Table 1. Example of a figure caption. (*figure caption*)

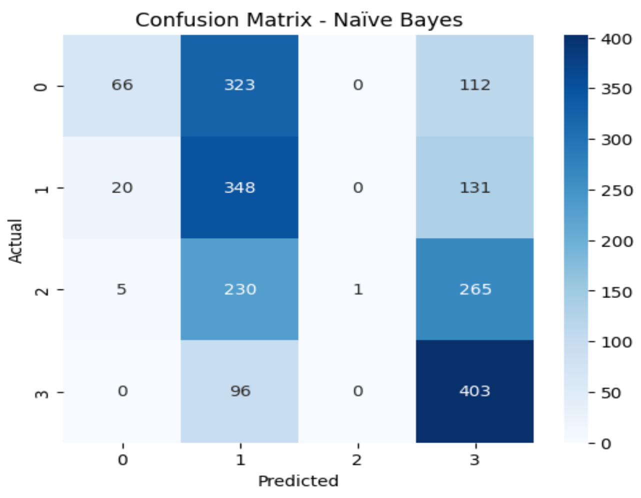


Fig. 1. Confusion Matrix-Naive Bayes

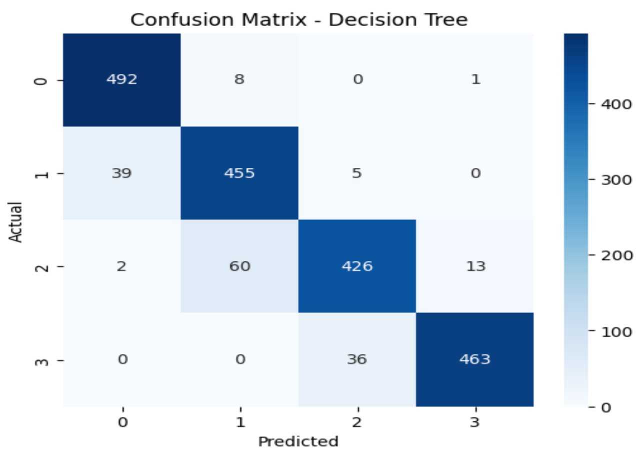


Fig. 2. Confusion Matrix-Decision Tree

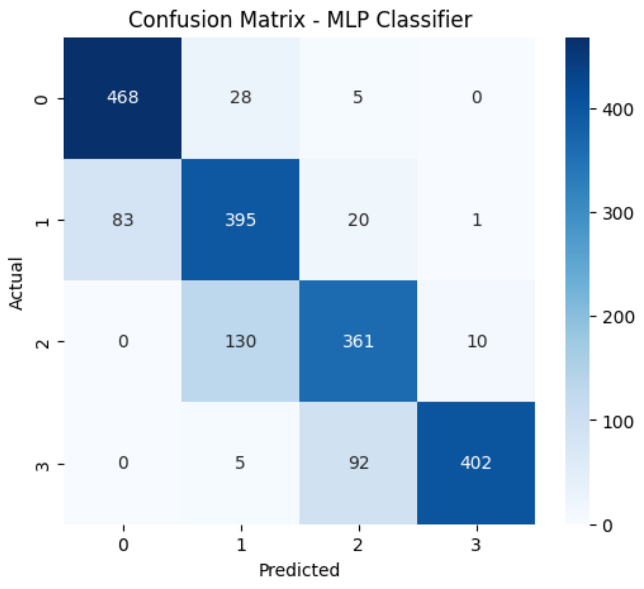


Fig. 3. Confusion Matrix-Meural Network (MLp)

VII. Work Stages

A. *Highest Positive & Negative Correlation Analysis*

Correlation analysis is looking at the interaction between two variables to see how they vary together. A positive correlation shows that as one variable goes up, the other also goes up, whereas a negative correlation shows that as one variable goes up, the other will go down. Finding the highest positive and negative correlations between features can assist in choosing appropriate variables to model.

B. *Data Preprocessing*

Data preprocessing is an important process of getting raw data ready for modeling. It encompasses several methods to clean and convert data into a proper format.

C. *Feature Engineering*

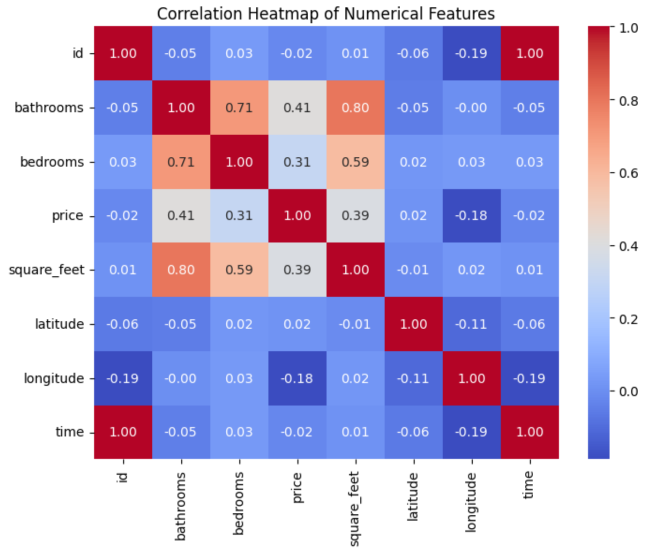
Feature engineering refers to the method of generating new input features from existing features in order to enhance the performance of machine learning models. This can include methods like polynomial features, interaction terms, or domain-specific transformations.

D. *Missing-Value Imputation*

Missing data need to be handled in order to preserve the integrity of the dataset. Missing-value imputation refers to the process of replacing missing data with substitute values. Typical methods involve the use of the mean, median, or mode of the present data, or more advanced techniques such as regression imputation.

E. *Encoding & Scaling*

Categorical encoding and numerical feature scaling are crucial preprocessing operations. Encoding converts categorical data into numerical data so that algorithms can handle them. Scaling moves the range of the numerical features so that all features contribute proportionally to the model. Methods such as Min-Max scaling and standardization are normal.



F. *Experiments & Parameter setting*

To secure solid model training and impartial comparison, there was a structured experiment design adopted. In this part, how preparation of the data was conducted, how the labels for targets were generated by using binning, how optimization for hyperparameters has been achieved using grid search, and the basis for such choice are discussed.

G. *Binning & Target Preparation*

Since the task of predicting rent price was recast into a classification task, the range of continuous rent values was segregated into four quartiles through the application of binning techniques. Through this measure, the problem of regression was converted into one of multi-class classification, in which:

- Class 0 covers the lowest 25% of rent prices (Q1)
- Class 1 covers lower-middle rents (Q2)
- Class 2 covers upper-middle rents (Q3)
- Class 3 covers the top 25% of rent prices (Q4)

This binning provided fairly evenly distributed class proportions, which are important for avoiding bias in prediction by models.

- Training Set Distribution: [2049, 1962, 1992, 1997]
- Testing Set Distribution: [501, 499, 501, 499]

This balance also made the classification more equitable and enabled performance measurements to indicate real model abilities and not effects of class imbalance.

H. *Hyperparameter Grids*

Hyperparameter tuning was an important step in optimizing model performance and generalization. Each model was optimized using GridSearchCV with 5-fold cross-validation to determine the best-performing set of parameters.

Decision Tree:

A variety of tree depths and minimum sample split thresholds were experimented with to regulate complexity.

The best parameters were:

- max_depth = 20
- min_samples_split = 2

This environment enabled the model to develop deeper trees with good splits, enhancing learning ability without overfitting (supported by high test accuracy).

I. *Final Model Summaries*

Three algorithms for classification were tried:

a) Naïve Bayes

- Accuracy: 40.9%
- Performed badly because of its strong feature independence assumption, which doesn't actually apply to real estate data (where features tend to be correlated).
- Most overconfident in certain classes (e.g., 1.00 precision for class 2 but with no recall, i.e., predicted all incorrectly).

b) Decision Tree

- Accuracy: 91.8%
- Highest performance achieved with solid scores on all metrics.
- Capable of modeling nonlinear interactions and hierarchical rules, perfect for tabular data such as this.
- Best suited for interpretability and deployment.

c) MLPClassifier (Neural Network)

- Accuracy: 81.3%
- Did well overall with the strength in Class 0 and 3.
- Minor drop in accuracy and recall for middle rent bands (class 1 and 2), which may be attributed to similar feature patterns.
- Displays potential to perform better with finer tuning and increased data.

d) Main Insights:

- Decision Tree significantly outperforms all other models, performing the best on precision, recall, and f1-score. It performs well on feature interaction and categorical splits.
- MLPClassifier has good generalization and stability but slightly poorer performance on less separable classes. It is more adaptive but less explainable.
- Naïve Bayes is easy to implement but does not perform well with complicated, correlated data structures of rental advertisements.

VIII. Conclusion

The study was able to prove the feasibility of machine learning application in apartment rent price classification. Through extensive preprocessing and feature engineering, the paper converted raw rental data into an appropriate format for predictive modeling. Of the classifiers tested, the Decision Tree proved to be the top performer, effectively capturing complex feature interactions and nonlinear relationships characteristic of the data. While the MLP gave competitive results, its performance was marginally worse in some rent bands, and the Naïve Bayes model was constrained by its feature independence assumption. Ensemble techniques and deeper neural network structures can be investigated in future research to further improve classification accuracy. In general, this work highlights the ability of data mining methods to enhance real estate valuation and enable more informed pricing decisions.

References

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