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**Machine learning models and generative AI
for automated real estate valuation in Hungary**

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Abstract

Accurately estimating real estate prices is an important yet challenging task for both sellers and buyers. This study presents an innovative approach that integrates large language models, economic indicators, and advanced data science techniques within a regression model framework to enhance the accuracy and interpretability of real estate price predictions, specifically in the Hungarian market.

We trained gradient boosting and other machine learning models on a dataset of approximately 50,000 real estate listings from the Hungarian market and tested it on an additional dataset of 10,000 listings. We place special emphasis on interpreting the results using SHAP values and the integrated gradients method to understand the importance of the features. Our findings indicate that economic and location variables significantly improve the accuracy of the estimate and these variables can often be condensed into a single feature. Additionally, features extracted from property descriptions using large language models have a notable impact on the results, particularly in outlier cases, highlighting their utility to improve prediction accuracy.

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1 Introduction

Estimating property prices accurately and efficiently is crucial for various stakeholders in the real estate industry, from individual buyers and sellers to investors and policymakers. Traditional appraisal methods can be time-consuming, costly, and subjective, highlighting the need for automated and user-friendly solutions. Given the inherent complexities and regional variations in property valuation, machine learning offers a promising avenue for enhancing both accuracy and accessibility in this domain.

Regression models have a long history of application in property price estimation, dating back to early hedonic models like Rosen’s influential work [1]. These models sought to quantify the impact of various property characteristics on price. The advent of advanced machine learning algorithms, coupled with increased computing power and the availability of rich real estate datasets, has revolutionized the field. Examples of this transformation include [2, 3, 4]. Researchers have explored both time-series forecasting of market dynamics and cross-sectional price prediction based on static market snapshots. In Table 1, we summarized numerous articles about property valuation, with various different dataset sizes, origin locations and model choices, giving an overview of the current scientific state of the topic. We found that most researchers experiment with multiple machine learning models. In studies done after the emergence of gradient boosting libraries such as XGBoost for example, the gradient boosting model family provides with the best prediction accuracy. In less recent articles, neural networks and support vector machines were the optimal choice of regression model. Some of these studies also analyze their results with different methods aiding interpretability. Notably, most of them use one single algorithm, SHapley Additive exPlanations [5]. Interestingly, apart from living area, there is not much correlation between the most important features for price prediction, but one can see that location plays a significant role in the predictions, because a feature related to the location is almost always mentioned among the most important aspects.

Table 1: Summary of related works

Ref. No	Dataset size (row x column)	Features	Type of properties	Location	Time range	Models	Important features	Time dynamics	Findings
[6]	5359x76	Mostly intrinsic	sold town-houses	Fairfax County, Virginia	2004-2007	DT, Ripper, NB, Ada	-	-	Ripper outperformed the other, Ada was the second
[7]	40000x27	intrinsic, local, settlement related	flat, houses	Alicante, Spain	2019-2021	GB, LGB, XGB, RF, ETR	-	-	GB methods better, less prone to overfitting
[8]	21613x20	Mostly intrinsic	actual house-sales	King County, USA	2014-2015	SVR w. linear, poly and RBF kernel	-	-	RBF kernel is was the best, PCA is important.
[9]	2500x130	intrinsic, geographical	house listings on the web	Montréal, Canada	2014	SVR, kNN, RF	-	-	kNN + RF ensemble is the best
[10]	7407x36	intrinsic, local	transaction prices	Ljubljana, Slovenia	2008-2013	Hedonic, OLS, RF	Year of construction, liviling area, data land, age	yes	RF was the best
[11]	200x12	intrinsic	house listings on the web	Christchurch, New Zealand	2003	Hedonic, NN	-	-	NN outperformed Hedonic
[12]	5741x46	Mostly intrinsic	transaction prices	Turkey	2004	Hedonic, NN	water system, pool	-	NN outperformed Hedonic
[13]	3906x6	intrinsic	transaction prices of single family homes	Rutherford County, Tennesse	1993-1994	MRA, NN,	-	-	NN performs better
[14]	20000x14	intrinsic, 1 location	actual transaction prices	California	1990	RF, ET, GBDT, XGB	-	-	XGB is the best single model, ensemble performs much better
[15]	1480x9	intrinsic	actual transaction prices	Bengaluru, India	2017	Ridge, Lasso, SVR, XGB	-	-	XGB was the best
[16]	32215x23	Mostly intrinsic	actual transaction prices	Taichung, Taiwan	2016-2019	SVR, GRNN, CART, BPNN	-	-	SVR was performing the best
[17]	11937x13	Mostly intrinsic	internet listings	China	2017-2018	SVR, ARIMA	-	yes	ARIMA outperformed SVR
[18]	84x a lot	intrinsic, from text-mining	actual transaction prices	Shanghai, China	2011-2016	LR, ElasticNet, RF, Lasso, Ridge	-	-	RF performed best
[19]	1460x79	intrinsic	actual transaction prices	Ames (Iowa)	2006-2010	Lasso, Ridge, SVM, RF	Living area, neighborhood	-	SVR with gaussian kernel was the best
[20]	790631, proprietary data	proprietary data	actual transaction prices	Spain	proprietary data	Decision Trees, RF, boosting, bagging	-	-	Ensemble was the best
[21]	2848x10	intrinsic	internet listings	Saint-Petersburg, Russia	2010	RF, kNN, CART, RBF, Boosted trees, CHAID, MLP	District, house type, time to center	-	RF was the best
[22]	36586x	intrinsic, econimic, location	transaction data	California, Florida, Texas	2011-2016	OLS, RF, GB, XGB	NOI, green space within 30 mins, construcion year	-	Gradient Boosting and XGB were the best
[23]	12 mil x less than 20	Mostly intrinsic	housing ads	all over Brazil	2015-2018	RF, NNs	-	-	both are good, but combining them is better
[24]	40000x12	1 location, others intrinsic		Hong Kong	1996-2014	RF, GBM, SGD, SVM	1. floor area 2. distance from center, but by a lot	-	RF, GMB are accurate

Our research adopts a cross-sectional view of the market, and aims to show the substantial potential for improvement in accuracy by leveraging expanded datasets and cutting-edge techniques. These include location features considering every point of interest in the area, economic indicators related to the settlement, and large language models (LLMs), which offer novel ways to process unstructured textual data.

While powerful, advanced machine learning models often operate as "black boxes," providing limited insights into the factors driving predictions. Interpretability techniques like SHapley Additive exPlanations (SHAP), [5] have emerged to address this challenge, offering a robust and trusted method for understanding model behavior. As mentioned before, SHAP values are already being applied to interpret property price predictions, enhancing transparency and trust [25, 26, 27].

Beyond traditional tabular data, images and free-text property descriptions represent a rich, yet often underutilized, source of information. Advances in computer vision and natural language processing have enabled the effective integration of these data modalities into price estimation models. For instance, Nouriani *et al.* demonstrated improved accuracy over Zillow’s Zestimate by using image processing to classify room luxury levels [28]. Similarly, Baur *et al.* found that BERT (Bidirectional Encoder Representations from Transformers, [29]) significantly reduced prediction error when applied to property descriptions [30].

The Hungarian real estate market is an especially diverse case to observe and study. Over the past decade, the market has been shaped by a confluence of economic growth, urbanization, and strategic foreign investments, particularly in Budapest and other major cities. Budapest, as the largest and most developed city in the country, exhibits numerous distinctive characteristics in the real estate market compared to other regions. Similarly, the Balaton region stands out, where foreign buyers exert significant upward pressure on prices. (Figure 3 created from our dataset, also illustrates this peculiarity.) This economic diversity together with special policies aiding families to buy houses with government funds [31] make the Hungarian market an interesting subject for a comprehensive study.

To the best of our knowledge, this is the first paper investigating real estate price prediction for the Hungarian market. The size of our dataset also differentiates this study from the rest: our analysis is based on a dataset scraped from the largest Hungarian real estate website, containing over 500,000 listings, with an exceptionally diverse set of features (e.g. 62 based on location and 37 on economic attributes of the settlement). An important contribution of this paper is that we present a unique description processing method, based on LLMs, can be utilized in property price prediction. In addition, we focus on optimizing and interpreting every step of the prediction process. We test the performance of different regressors such as Linear Regression, Random Forests and XGBoost. Furthermore, we use interpretable machine learning methods, such as SHAP values and the integrated gradients method, to enhance model transparency. We demonstrate that the prediction RMSE of the listed price of properties can be improved by 20% compared to using only the data scraped from the website.

The remainder of this paper is structured as follows: Section 2 outlines the methods employed and provides a detailed description of the experiments conducted. Section 3 presents our findings, accompanied by a discussion of their underlying causes and implications. Finally, Section 5 summarizes the results and discusses potential improvements and limitations.

2 Data and methods

This section details the methodology employed in this study, encompassing the data collection and preprocessing steps, the construction of predictive features, the selection and training of machine learning models, and the techniques used for model evaluation and interpretation. We begin by describing the various data sources, including web scraping, API calls, and official statistics. Subsequently, we outline the data cleaning and preprocessing procedures undertaken to ensure data quality and consistency. An overview of the methodology used in this paper is presented in Figure 1. The feature engineering process, incorporating intrinsic property attributes, location-based features, economic indicators, and novel LLM-derived features from property descriptions, is then explained. Finally, we describe the chosen machine learning models, the experimental setup for model comparison, and the methods used to interpret model predictions and understand the influence of different feature groups.

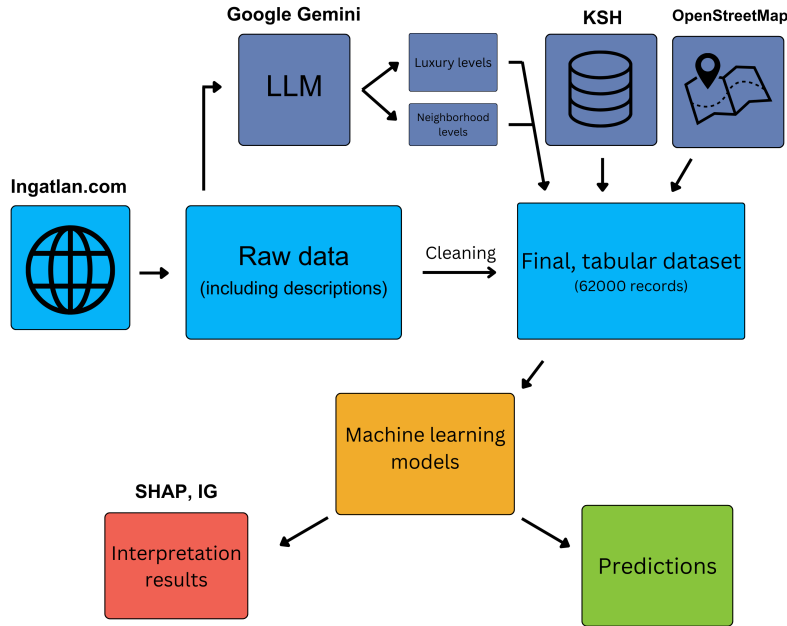


Figure 1: Overview of the pipeline

2.1 Data sources

The core of our analysis is built upon a dataset of over 517,000 real estate advertisements scraped from Ingatlan.com (ingatlan.com), Hungary’s largest online real estate platform. Data collection took place weekly from January 2022 to July 2022, capturing a snapshot of market dynamics during this period. All data used in this study were publicly available at the time of collection.

To enrich the scraped data with geographical context, we utilized the Nominatim API to obtain GPS coordinates for each property based on the provided addresses. The API also provides an uncertainty measure, representing the radius within which the true location likely falls. This uncertainty metric was incorporated into our analysis to account for potential geocoding errors.

Further enhancing the spatial dimension of the data, we leveraged OpenStreetMap to identify and quantify points of interest (POIs) near each property. These POIs provide valuable contextual information about the surrounding neighborhood and amenities.

Finally, we integrated socio-economic indicators for each settlement from the Hungarian Central Statistical Office (KSH). These indicators provide a broader macroeconomic and demographic context for each property, capturing factors that can significantly influence property values.

2.2 Data Cleansing

The dataset used in this study was obtained through web scraping from a publicly accessible real estate platform. As the platform allows users to upload property listings without verification of their content, data inconsistencies and errors are prevalent. Therefore, rigorous data cleansing was a necessary step in our preprocessing pipeline to ensure the reliability of the analysis.

- **Selection of Property Type:** The raw dataset included various property types—such as flats, houses, and office buildings—and different listing categories (e.g., properties for rent and for sale). To achieve a high level of homogeneity in the dataset, we restricted our analysis to the largest, most consistent subset: flats listed for sale. This filtering process yielded a dataset of 160,285 records, allowing for

a focused analysis on comparable property types and reducing confounding variability introduced by other types of real estate.

- To use our introduced location-based features to their fullest potential, location with high accuracy is required. For this reason, we only kept those flats that had approximately the uncertainty of 300m-500m (so anything less accurate than a street name given is excluded), leaving us with 74483 records. This step is needed so that location features can be accurately and reliably assigned to the records.
- Again, by the nature of the platform, there is high probability for typographical mistakes or misclassifications (e.g., an industrial property being listed under the residential category). We have made efforts to filter out such discrepancies. At first, we removed the top 0.5% and the bottom 1.7% with respect to cost per square meter to account for all potential typos in property prices. The cut-off values were selected based on Figure2 where the red lines indicate the cut-offs.
- Another type of misclassification was not listing the full property for sale. This introduces price discrepancies, which we should avoid. To account for this, all records containing the Hungarian equivalents of the following words were omitted: *'leaserights', 'ownership rights', 'lease rights', 'I would trade', '1/6', '1/4', '1/5', '1/3', 'state tender', 'auction', 'test', 'licit', 'I'm searching for', 'test listing'*, because listings containing these do not represent a valid price.
- The fact that different real estate agencies could advertise the same property or one seller could list a property multiple times made it necessary to filter out duplicates. Two properties were considered duplicates if they were built in the same year, were on the same floor, their GPS coordinates matched and their price and floor area were within 10% of each other. After the filtering steps, the dataset ended up containing 61874 records.

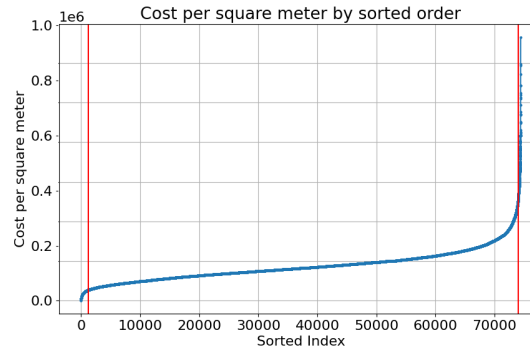


Figure 2: Cost per square meter sorted

A plethora of missing values is also inherent to the nature of the dataset, because users often do not fill all the input boxes the platform provides. Using KNNImputer an imputed version of the dataframe was also created so that regression models that cannot be used on data with missing values could also be experimented with.

The scraped dataset included various metadata attributes, such as internal listing identifiers, that could theoretically enhance the accuracy of listing price predictions. However, these features were deliberately excluded from the analysis to avoid potential data leakage and overfitting. Similarly, the duration a listing remained online was not incorporated into the property valuation model, as this information would typically be unavailable in a real-world context where the goal is to estimate listing prices for newly introduced properties.

Nevertheless, listing duration was analyzed in relation to potential overpricing, as extended time on the market can serve as a reasonable proxy for the property's competitiveness relative to similar listings. It is important to note that the prices within the dataset are listing prices, not actual transaction prices.

Despite this limitation, predicting listing prices is valuable in itself, as sellers often aim to set a competitive yet negotiable price point that accommodates common aspects of the property transaction process, such as negotiation margins and buyer-seller dynamics.

To conduct an initial sanity check and gain an overview of the dataset, we visualized listings across all Hungarian settlements and by district within Budapest. The visualization (see Figure 3) displays average listing prices per unit area, using color gradients to represent price variation, for houses and flats, respectively. This mapping highlights distinct price concentrations, with particularly high values observed in Budapest and around Lake Balaton, and, to a lesser extent, in other major cities.

A comparison of this distribution with data from the Central Statistical Office (2022 data) shows no significant discrepancies, indicating that our dataset does not exhibit any substantial biases. This alignment suggests the data reasonably reflects the true geographic distribution of property values in Hungary.

2.3 Features

Intrinsic features. The attributes directly extracted from the real estate website are categorized as intrinsic features. These encompass a variety of property characteristics, including both numerical and categorical variables. All categorical features, such as the orientation of the flat, underwent one-hot encoding to facilitate their use in machine learning models. A comprehensive overview of these intrinsic features, along with their descriptions and descriptive statistics, is provided in Table 8.

Location features. Recognizing the importance of location and surrounding amenities in property valuation, we incorporated a range of location-based features into our analysis. These features were derived from OpenStreetMap data by leveraging the GPS coordinates obtained via the Nominatim API. We engineered 62 distinct location features, encompassing both proximity-based measures (e.g., distance to the nearest school or supermarket) and density-based measures, which aggregate the number or area of specific points of interest within a given radius, applying distance-based exponentially decaying weights. A detailed summary of these location features is presented in Table 9.

Economic features. Macroeconomic and demographic factors play a crucial role in shaping local real estate markets. To capture these influences, we incorporated 37 economic variables at the settlement level (town or district). These variables, detailed in Table 10, provide insights into the economic landscape of each area. Examples include the number of listed companies per capita, reflecting local business activity, and the proportion of residents with university degrees, serving as a proxy for educational attainment and potential earning power. These data were sourced from the Hungarian Central Statistical Office (ksh.hu) and are hypothesized to be valuable predictors of property values, as stronger local economies and higher educational levels are often associated with increased housing demand and price appreciation.

LLM features. Recognizing that free-text property descriptions often contain valuable information not readily captured by structured data, we leveraged the power of large language models (LLMs) to extract additional features. This approach is motivated by the understanding that descriptive text can reveal nuanced aspects of a property, such as its perceived luxury level, neighborhood characteristics, and unique amenities, that are difficult to quantify through traditional means. Using Google’s Gemini 1.0 Pro model and prompt templates detailed in Appendix D, we derived several LLM-generated features. Specifically, we prompted the model to assess both the property’s luxury level and the desirability of the neighborhood on a scale of 1 to 10. Inspired by the work of Nourani et al. [28], which used images to assess luxury, our approach extends this concept to textual descriptions. Furthermore, we tasked the LLM with identifying specific features mentioned in the description that could significantly impact property value, such as a pool, home theater, gym, waterfront location, or historical significance. To prevent data leakage, all numerical values representing prices or other monetary amounts within the descriptions were replaced with "X" prior to processing. For example, a lot of descriptions directly contain a price for the property, the value we are trying to predict, so that would defeat the whole purpose of the study. Any LLM output that did not conform to the specified 0-10 integer scale was treated as a missing value.

Interaction features To account for potential synergistic effects and special connections between features, we incorporated interaction terms into our model. This is based on the premise that the impact of certain features on property price can be dependent on the values of other features. While regression models can implicitly capture some interactions between features, explicitly engineering interaction terms can

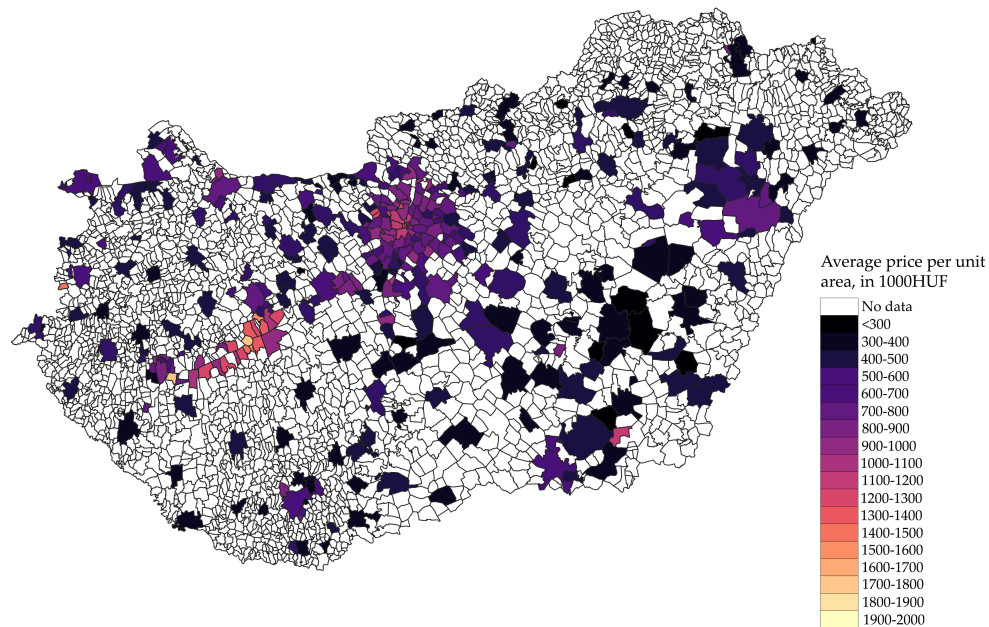
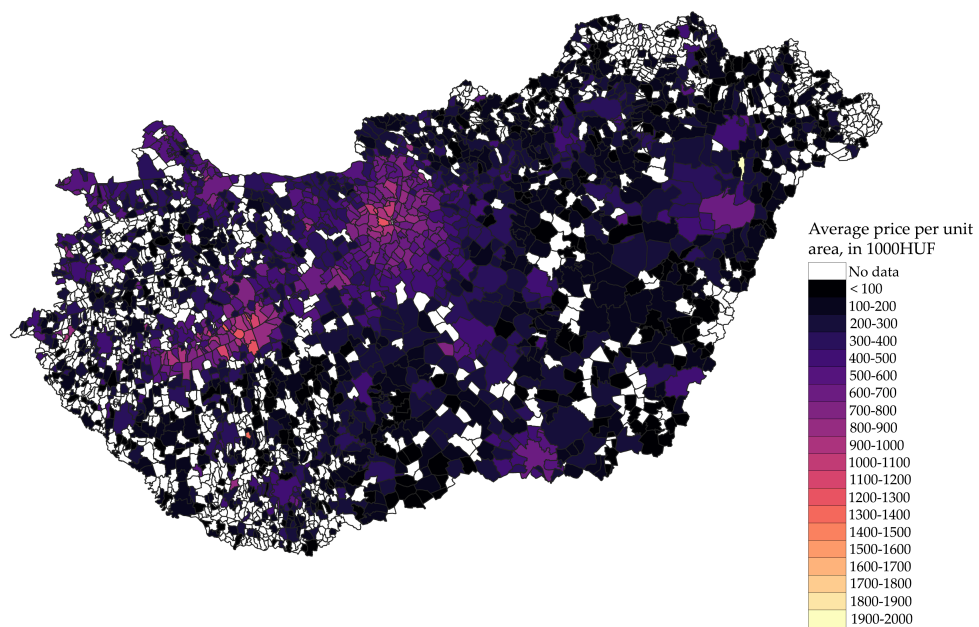


Figure 3: Average house and flat price per unit area

improve model performance and interpretability. By directly including these interactions, we aim to facilitate the model’s ability to learn complex relationships and provide clearer insights into the factors driving property valuations. For example, the value of garden space is likely to be amplified in densely populated urban areas like Budapest compared to less densely populated regions, where outdoor space is more readily available. The following interaction terms were constructed:

- **age · condition:** Captures the interaction between a property’s age and its condition. A well-maintained older property might be more valuable than a poorly maintained newer one.
- **subtype · floors_in_building:** Accounts for how the number of floors in a building affects the price differently for brick and panel constructions. For instance, higher floors in brick buildings might be more desirable due to perceived better quality and less noise, while this effect could be less pronounced in panel buildings.
- **subtype · floor:** Captures the combined effect of construction type and floor level on price. Lower floors might be less desirable in panel buildings due to concerns about dampness or security.
- **subtype · balcony:** Considers how the presence of a balcony influences price differently for brick and panel buildings. A balcony might be more valued in panel constructions where access to private outdoor space might be limited.
- **subtype · land_area:** Accounts for the varying importance of land area based on construction type. While both brick and panel buildings can have associated land, its impact on price could differ.
- **subtype · quality:** Captures the interaction between construction type and overall quality rating. The impact of a given quality level may differ between brick and panel buildings. For example, a high-quality rating might command a greater price premium for a brick building.
- **in_budapest · land_area:** Considers the premium placed on land area within Budapest, where space is often more expensive.
- **in_budapest · view:** Captures the added value of a desirable view specifically within Budapest.
- **in_budapest · lift:** Accounts for the importance of having a lift (elevator) in Budapest’s potentially taller buildings.
- **in_budapest · garden_connection:** Considers the value of direct garden access specifically within Budapest.
- **in_budapest · highway_noise_500_IntegratedWays:** Captures the negative impact of highway noise, which might be more pronounced in certain areas of Budapest (highway noise 500 integratedways aggregates the highways with weight exponentially decaying with distance)
- **comfort · quality:** Accounts for the interaction between comfort level and overall state of the property. High quality might enhance the perceived comfort of a property.

These interaction terms are subsequently treated as intrinsic features in our analysis.

2.4 Model comparison

To evaluate the efficacy of various modeling approaches for property price prediction, we trained and compared several supervised learning models using the cleaned dataset, incorporating all intrinsic, economic, location-based, and LLM-generated features. This comparative analysis allows us to assess the performance of different model architectures and identify the most suitable approach for this specific task. The following supervised learning models were tested: Elastic Regression (Linear regression with combined L1 and L2 priors as a regularizer, from Scikit-Learn), Extreme Gradient Boosting (from Chen *et al.*, [32]) and TabNET (from Arik *et al.*, [33]). For this purpose, we used the libraries *sklearn*, *xgboost* and *pytorch-tabnet*, to include a model from each larger architectural category, like linear, tree/forest based and neural network based.

For the gradient boosting model, the variables with less than 9 different values were treated as categorical variables. To better understand the effectiveness the more advanced algorithms, three baseline models were implemented as benchmarks:

Baseline I: Returns the mean price, regardless of input

Baseline II: Returns *mean price per unit area* $\cdot$ *floor area*

Baseline III: Returns *mean price per unit area in the settlement* $\cdot$ *floor area*

For the tests, the data was split into 2 parts: a training set (80%) and one test set (20%). To tune the hyperparameters of the models, 5-fold cross-validation was applied within the training set. Finally, the model’s performance was assessed by calculating errors on the test set, which was kept entirely separate for unbiased evaluation.”

To evaluate the models’ performance, we use three metrics: Root Mean Squared Error (RMSE), Mean Absolute Percentage Error (MAPE) and the coefficient of determination (R^2). Errors are always calculated by first transforming the prices back to their original form (reversing the log transformation and/or multiplying by floor area), to retain consistency. RMSE was chosen as the objective function for all models.

To illustrate the incremental predictive power of the features we add (location-based, economic and llm-based), and to gain a more nuanced understanding of the individual contributions they make, the models were tested on all sensible combinations of the feature groups.

2.4.1 The target variable: price and its variations

Logarithmic transformations of price are frequently employed in property valuation, offering several advantages, including the normalization of skewed distributions (evident in Figure 4) and mitigation of the impact of outliers on model training. To determine the optimal modeling strategy for our dataset, we systematically evaluated various transformations of the target variable, including:

- *Price*
- $\log(\text{Price})$
- $\frac{\text{Price}}{\text{Area}}$
- $\log\left(\frac{\text{Price}}{\text{Area}}\right)$
- $\frac{\log(\text{Price})}{\text{Area}}$

From our tests in Section 3.5.1, we concluded that utilizing $\log(\text{Price})$ is the most reasonable choice, so going forward, all tests will be using $\log(\text{Price})$ as the target variable.

The distribution of the described target variables can be seen in Figure 4.

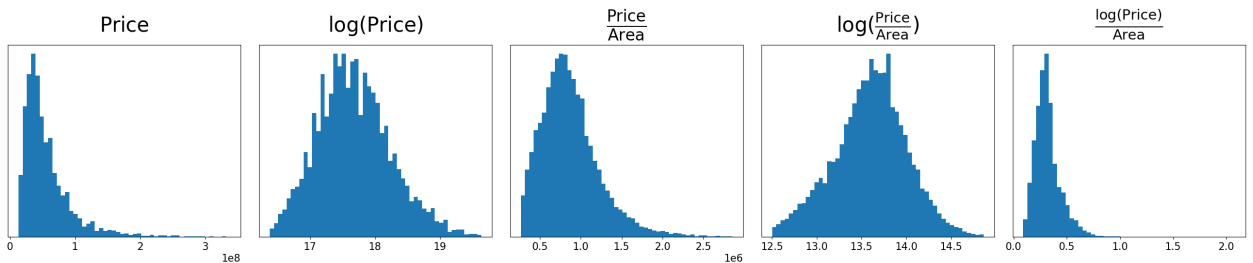


Figure 4: Histograms for different price metrics

2.4.2 Testing different feature groups and composite variables

In the full dataset, there are a large number (150+) of features, and four feature groups: intrinsic, locational, economic, and LLM-generated. To test which group is the most important for making precise price estimations, we investigate what incremental predictive power the groups have over each other. Since different

feature groups could improve on predictions for flats in different price categories, we split the listings into five quintiles, based on the price of the property, and investigate them separately.

We hypothesize that the dimensionality of feature groups can be reduced with minimal information loss. To test this, model performance was evaluated using lower-dimensional composites rather than full feature groups.

Single-variable composite features were generated using XGBoost, where the model predicted house prices based on the feature group investigated. Three- and sixteen-variable composites were similarly created using neural networks, with the values from the penultimate layer of the neural network extracted and treated as output for multi-variable composites.

To aid interpretation, SHAP plots were generated from the single-variable composites, which help make the numerical values more comprehensible to a human observer, potentially assisting with purchase decisions.

To further demonstrate the relatively low effective dimensionality of the data, we applied Singular Value Decomposition (SVD) to the location features. The EMPCA algorithm [34] was employed to handle missing values natively.

2.4.3 Comparing LLMs with conventional text processing methods

To validate our LLM-based free-text description processing method, we compared it with an alternative BERT embedding based approach of Baur *et al.* [30]. A key difference is that our descriptions are written in Hungarian, for which language processing methods work less effectively, simply because there is not as much text on the internet in Hungarian, and these tools are mainly developed in English. We used the Hungarian pre-trained BERT model of Devlin *et al.* [29]. The hungarian pretrained version was made by Nemeskey *et al.*, [35]. To account for the language difference, we also tried translating the descriptions to English, and tried using a multilingual pretrained BERT model from Google (bert-base-multilingual-cased), made by Devlin *et al.* [29].

2.4.4 Regression with only text input

Because the descriptions usually also contain most of the needed information for prediction, we also experimented with predicting house prices using BERT, based solely on free-text descriptions supplemented with textual representations of key features: floor area, quality, address, number of rooms, bathrooms, WC, orientation, location, and economic composites (normalized to a 1-10 scale and rounded). These details were integrated into coherent sentences. The BERT model was trained on 80% of the data, with 20% reserved for evaluation.

2.5 Model explanation

We employed SHapley Additive exPlanations (SHAP) and the built-in explanation functions of gradient boosting models to gain insights into the factors contributing to accurate price predictions. Additionally, partial dependence plots were generated for several key features to visualize their impact.

To better understand the LLM features introduced via Gemini, we trained a surrogate model on the output generated by the LLM, simulating its original decision process. This surrogate model was necessary as Google does not disclose the inner workings of their LLM. We used the BertForSequenceClassification model from the Transformers library as the surrogate. The integrated gradients method, an interpretability technique for neural nets based on the gradient of the network described in [36], was then applied to identify the three most important tokens for each description, followed by the creation of histograms to assess the frequency of these tokens across samples.

Furthermore, to gain additional insights into the factors driving the LLM’s luxury level predictions, we directly queried the Gemini model, prompting it to identify the most influential keywords within the property descriptions.

We aimed to investigate how much the performance of the models improves with the use of free-text-based LLM features, and whether there are specific characteristics of properties where these LLM features have the most impact. Our hypothesis was that LLM features would most significantly improve price estimates for properties where, without utilizing the free-text descriptions, the model would tend to underestimate

the listed price. We further hypothesized that while in the higher price category, these underestimations are justified because there are factors which could only be extracted from the descriptions, but in the lower price categories, the underestimation just represents the seller putting an unjustifiably high price on the property. This unjustifiable overrating of the property will also likely be present in the descriptions, which could fool the LLM into giving a higher rating to the listing, driving up the price in the predictions utilizing LLM-based features. To quantify this phenomenon, we calculated the following quantities:

We are considering the percentage error of every property in this section, because it is less dependent on the actual price of the flat. y_i denotes the actual listing prices, while $\hat{y}_i$ is the predictions made by the model, untransformed.

$$\varepsilon = 100 \frac{y_i - \hat{y}_i}{y_i}$$

We consider the improvement between the absolute error model utilizing LLM and the absolute error of the one that does not utilize the LLM-based feature for each property

$$Improvement = |\varepsilon_{LLM}| - |\varepsilon_{noLLM}|$$

And the value by which the non-LLM model underestimates the actual price is defined to be the *underestimation*

$$Underestimation = \varepsilon_{noLLM}$$

	BL 1	BL 2	BL 3	XGBoost	Tabnet	Elastic Regression
Intrinsic + economic + LLM + location	60.21	37.48	21.35	8.82	13.70	17.35
Intrinsic + economic + location	60.21	37.48	21.35	9.06	15.80	18.10
Intrinsic + location + LLM	60.21	37.48	21.35	9.21	14.83	19.74
Intrinsic + location	60.21	37.48	21.35	9.40	14.95	21.01
Intrinsic + economic + LLM	60.21	37.48	21.35	9.19	13.95	17.81
Intrinsic + economic	60.21	37.48	21.35	9.52	15.27	18.62
Intrinsic + LLM	60.21	37.48	21.35	9.72	16.35	21.96
Intrinsic	60.21	37.48	21.35	9.94	20.03	21.91

Table 2: MAPE of different models on different datasets

	BL 1	BL 2	BL 3	XGBoost	Tabnet	Elastic Regression
Intrinsic + economic + LLM + location	3.823e7	2.680e7	2.011e7	0.876e7	1.480e7	2.107e7
Intrinsic + economic + location	3.823e7	2.680e7	2.011e7	1.027e7	1.496e7	2.251e7
Intrinsic + location + LLM	3.823e7	2.680e7	2.011e7	0.903e7	1.542e7	2.176e7
Intrinsic + location	3.823e7	2.680e7	2.011e7	1.047e7	1.450e7	2.343e7
Intrinsic + economic + LLM	3.823e7	2.680e7	2.011e7	0.912e7	1.451e7	2.065e7
Intrinsic + economic	3.823e7	2.680e7	2.011e7	1.077e7	1.534e7	2.177e7
Intrinsic + LLM	3.823e7	2.680e7	2.011e7	0.943e7	1.874e7	2.186e7
Intrinsic	3.823e7	2.680e7	2.011e7	1.100e7	1.827e7	2.272e7

Table 3: RMSE of different models on different datasets

3 Results and discussion

This section presents the results of our experiments, analyzing the performance of different machine learning algorithms and feature combinations in predicting property prices. We evaluate the predictive accuracy of each model using various metrics, including MAPE, RMSE, and R-squared. We then delve into the relative importance of different feature groups, exploring their individual and combined contributions to prediction accuracy. Furthermore, we analyze the interpretability of the models, employing SHAP values and partial dependence plots to understand the relationships between features and predicted prices. Finally, we investigate the effectiveness of our proposed LLM-based features, comparing them to traditional text processing methods and exploring their impact on model performance across different price ranges. Additional experiments focusing on target variable transformations and the use of composite variables are also presented and discussed.

3.1 Model comparison

We start by presenting the results of the experiments evaluating the prediction accuracy of different machine learning model (Baselines, XGBoost, Elastic Regression and Tabnet) on the different feature groups (Intrinsic, location-based, economic and llm-based). Tables 2, 3 and 4 contain the different errors metrics and scores for each feature group combination for each model.

The superior performance the gradient boosting model, XGBoost, is a noteworthy observation. This marked improvement in predictive accuracy likely stems from several factors, including their inherent ability to handle missing data and high multicollinearity effectively. Unlike some other models that require imputation, which can introduce bias or distort relationships within the dataset, XGBoost and LightGBM can directly incorporate instances with missing values during the training process. Given the prevalence of missing data in our dataset – a common characteristic of real estate data – this capability offers a significant advantage. Additionally, the tree-based nature of gradient boosting makes them robust to multicollinearity, a situation where predictor variables are highly correlated. This is often present in real estate datasets, where

	BL 1	BL 2	BL 3	XGBoost	Tabnet	Elastic Regression
Intrinsic + economic + LLM + location	0	0.509	0.724	0.945	0.849	0.695
Intrinsic + economic + location	0	0.509	0.724	0.927	0.845	0.651
Intrinsic + location + LLM	0	0.509	0.724	0.944	0.836	0.675
Intrinsic + location	0	0.509	0.724	0.945	0.855	0.622
Intrinsic + economic + LLM	0	0.509	0.724	0.943	0.855	0.707
Intrinsic + economic	0	0.509	0.724	0.920	0.838	0.674
Intrinsic + LLM	0	0.509	0.724	0.934	0.758	0.671
Intrinsic	0	0.509	0.724	0.917	0.770	0.645

Table 4: R^2 score of different models on different datasets

features like the number of bedrooms and bathrooms, or proximity to various amenities, can be inter-related. While multicollinearity can inflate the variance of coefficients in linear models, making interpretation difficult, gradient boosting algorithms are less susceptible to this issue. Furthermore, gradient boosting methods are well-suited to capturing complex non-linear relationships between features and target variables, often crucial in accurately modeling real estate prices. Their ensemble nature, combining multiple decision trees, allows them to learn intricate patterns and interactions within the data, potentially contributing to their superior performance compared to linear models or individual decision trees. Finally, the sophisticated regularization techniques employed by gradient boosting algorithms help prevent overfitting, further enhancing their generalization ability and improving performance on unseen data.

3.2 Feature groups

Our analysis reveals that all three feature groups—intrinsic, location, and economic—contribute meaningfully to predictive performance, although their impact varies across different metrics and price ranges. While the economic features appear slightly less influential overall, both location and LLM-derived features demonstrate substantial predictive power. Interestingly, location features exhibit a stronger improvement on the MAPE score, suggesting their importance in accurately pricing typical or average properties. MAPE is more sensitive to smaller errors in numerous predictions, in the sense that one expensive property does not affect as much as for example, RMSE. So its improvement indicates a consistent benefit for more properties where prices do not deviate significantly from the average. Conversely, LLM features yield a more pronounced reduction in RMSE, implying their effectiveness in capturing the nuances of higher-value or unique properties, where accurate pricing is more challenging. RMSE is more sensitive to larger errors in absolute value, which might occur more frequently for high-priced outliers. The LLM features reduce these potentially large errors, improving the model’s accuracy on the more exceptional properties within the dataset. This observation is further supported by Figure 5, where location and economic features demonstrate consistent improvement across all price quintiles. In contrast, LLM features primarily benefit the lowest (Q1) and highest (Q5) price quintiles, potentially reflecting their ability to capture unique characteristics or market dynamics that disproportionately affect these segments. This non-uniform impact suggests that LLM features may be particularly valuable in addressing the challenges of pricing properties at the extremes of the market, where standard features might be less informative. Further investigation into the specific properties within these quintiles could shed light on the precise mechanisms through which LLM features contribute to improved accuracy.

3.3 Explaining the output of gradient boosting models

To gain insights into the black-box behavior of our models and identify the most influential features driving price predictions, we employed SHAP (SHapley Additive exPlanations) values along with the built-in feature importance tools provided by XGBoost and LightGBM. Given the superior predictive performance of gradient boosting models demonstrated in our earlier analysis, we focused our interpretability efforts on this class of algorithms. To ensure robustness of our findings, we employed two distinct gradient boosting

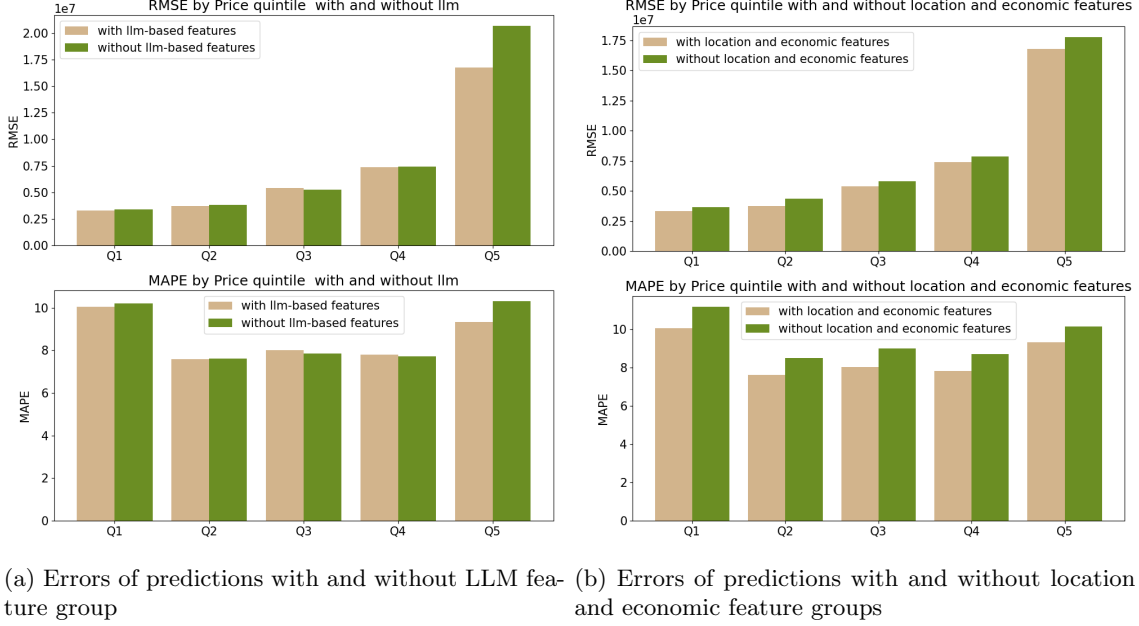


Figure 5: Errors by price quintiles

implementations: XGBoost and LightGBM, comparing the feature importance rankings generated by each method.

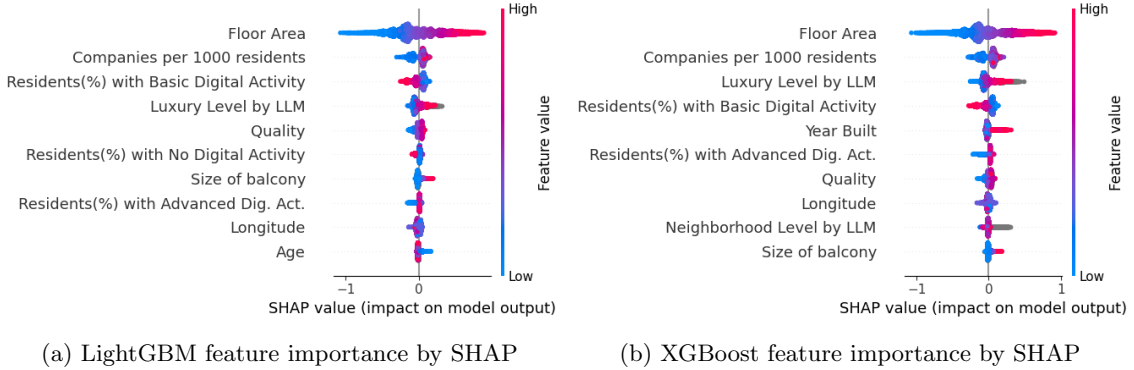


Figure 6: SHAP explanations

Analyzing the feature importance rankings depicted in Figures 6 and 7, several key observations emerge. Across both XGBoost and LightGBM models, and using both SHAP values and built-in feature importance measures, *floor area* consistently ranks as the most influential predictor, exhibiting a positive correlation with price. While prior studies have rarely identified floor area as the most significant factor, its importance in property valuation is widely recognized [25, 26, 27, 30, 37, 38, 39, 40], which is also represented in the literature review table (Table 1). Among other intrinsic features, *floor* and *quality* (the current state of the property, for example, *like-new* or *needs renovation*) also emerge as highly relevant. Low floor values, indicative of basement or lower-level units, are associated with lower prices, while higher quality ratings contribute positively to predicted values. Interestingly, *year built*, a feature often deemed important in previous research [30, 39], does not appear to be a strong predictor in our models.

Regarding location-based features, both *longitude* and *latitude* exhibit substantial influence, although their relative importance varies. The SHAP plots suggest that central locations, corresponding to the ap-

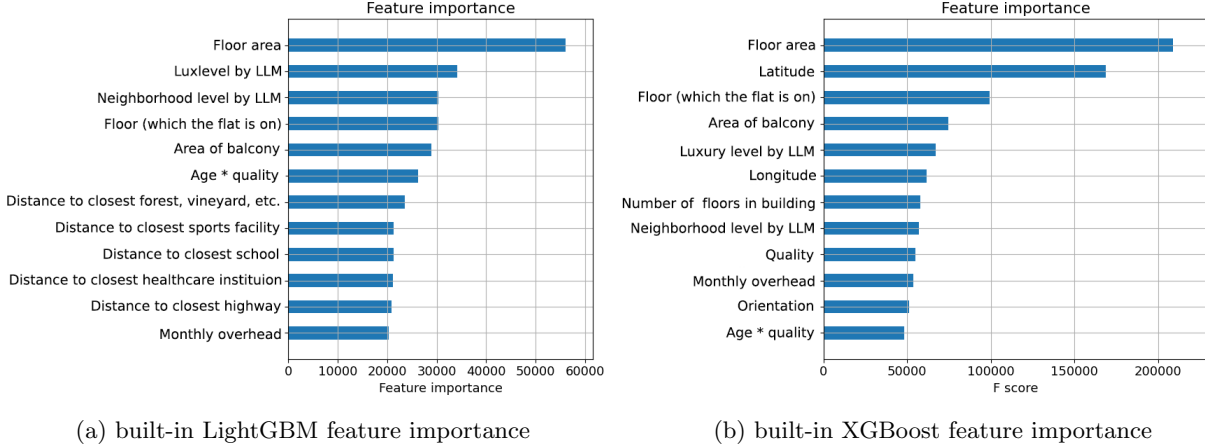


Figure 7: Built-in feature importances

proximate longitudinal center of Hungary and the location of Budapest (Figure 3), command price premiums. This aligns with the general trend of higher property values in western Hungary compared to the east, and a positive correlation between price and northerly latitude. Notably, the economic indicator *companiesperthousand* (number of limited liability companies per thousand residents) also ranks highly, indicating a positive relationship between local business density and property prices. Within the location feature group, proximity to *unorganized green area* (Forests, vineyards, meadows, etc.) appears as a key driver of valuations. The LLM-generated features also demonstrate considerable predictive power across all models. Specifically, *LLM luxury level* emerges as the most influential LLM-derived feature, followed by *LLM neighborhood level*, while features related to specific property oddities appear less impactful. This underscores the potential of leveraging unstructured textual data, such as property descriptions, for enhanced price prediction. Our findings suggest that substantial untapped information resides within these non-tabular data sources, warranting further exploration in future research. While this study focuses on description-derived features, we acknowledge the rich information content of property images, which represent another promising avenue for future investigation. A more detailed analysis of the impact of LLM-generated features is presented in a subsequent section.

To get a clearer picture of the relationship between the attributes and the target variable, we present Partial Dependence Plots in Figure 8. For this purpose, we selected the most important features from different groups to explore the different behaviour. The non-linear nature of some feature could be deduced, which also serves as an explanation why linear regression models showed poor performance in our research and in related works.

The partial dependence plots (Figure 8) provide further insights into the relationships between key features and predicted prices. As anticipated, the relationship between *floor area* and price exhibits a logarithmic trend, reflecting the logarithmic transformation applied to the target variable and the inherently linear relationship between these two quantities. Notably, the partial dependence plot for the LLM-generated luxury level feature demonstrates a remarkably clear and non-noisy relationship, particularly at the higher end of the scale. This suggests that the LLM effectively captures the characteristics of luxury properties from textual descriptions, enabling the model to differentiate them from standard offerings. The distinction between luxury levels 9 and 10, and levels 1 through 4, appears less pronounced, indicating that the LLM primarily excels at identifying properties at the extremes of the luxury spectrum. This observation aligns with our previous findings regarding the impact of LLM features on RMSE, where their contribution was most significant for high-value properties, which are likely to be those with exaggerated descriptions.

The partial dependence plot for *companiesperthousand* reveals a distinct step-like pattern, resembling the behavior of a categorical variable. High values of this feature, indicative of dense business activity, are associated with a clear price premium. Interestingly, this distinction does not align perfectly with the Budapest/non-Budapest divide, as some cities outside Budapest exhibit high *companiesperthousand* values,

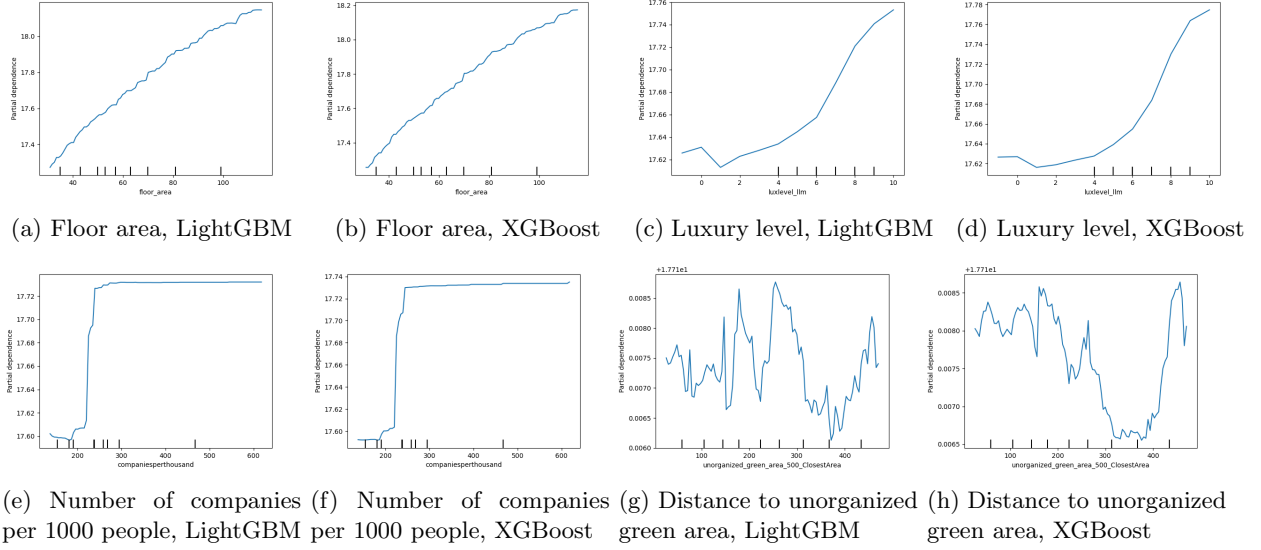


Figure 8: plots of partial dependence

while certain districts within Budapest have lower values.

Finally, the partial dependence plot for *unorganized green area 500 ClosestArea*, which captures the distance to the closest of the following places: forests, vineyards, meadows, etc. The dependence on this feature exhibits considerable noise and low dependence values, suggesting that this individual feature contributes relatively little to the overall prediction in isolation. However, as demonstrated in our feature group analysis, the collective contribution of location-based features, including this one, remains substantial.

3.3.1 A case study of one property

To get further insight into the workings of the pipeline, we analyzed a few individual properties and assessed the validity of feature contributions. Figure 9 summarizes our findings about a certain flat in the old town of Pécs. It is a newly built, luxurious home in a touristic area. If one examines the area around the property, the abundance of hotels, religious places and restaurants is immediately obvious, signaling that this location is often visited by tourists. This is reflected in the respective location features about these amenities. These all have a considerable contribution by themselves, and as a group, location features together is the biggest positive factor in the price according to SHAP. This indicates that the model can detect an exclusive location like this, and this is reflected accordingly in the prediction. If we shift our focus to the description (Appendix C in full), we found that it is completely new, equipped with smart home technology and a heat pump, with other premium features. Therefore, we can conclude that it is probably quite luxurious. The LLM corroborates this assessment, assigning a luxury rating of 8 out of 10. This high luxury score is seen as the high-impact factor driving up the price beside the location, both individually and in feature groups. The case study effectively demonstrates the synergistic interplay between location-based and LLM-derived features, enabling a more comprehensive and nuanced property valuation. Figure 9 visually captures this synergy, showcasing how the different components of our model combine to produce a well-rounded and accurate price estimate.

3.4 Explaining LLM features

To investigate the decision-making process of the Gemini LLM and understand which elements within the property descriptions contribute most significantly to the generated luxury ratings, we employed a surrogate model approach. Since the internal workings of Google’s Gemini are not publicly available, we trained a BERT-based surrogate model to mimic Gemini’s behavior. This allowed us to apply interpretability

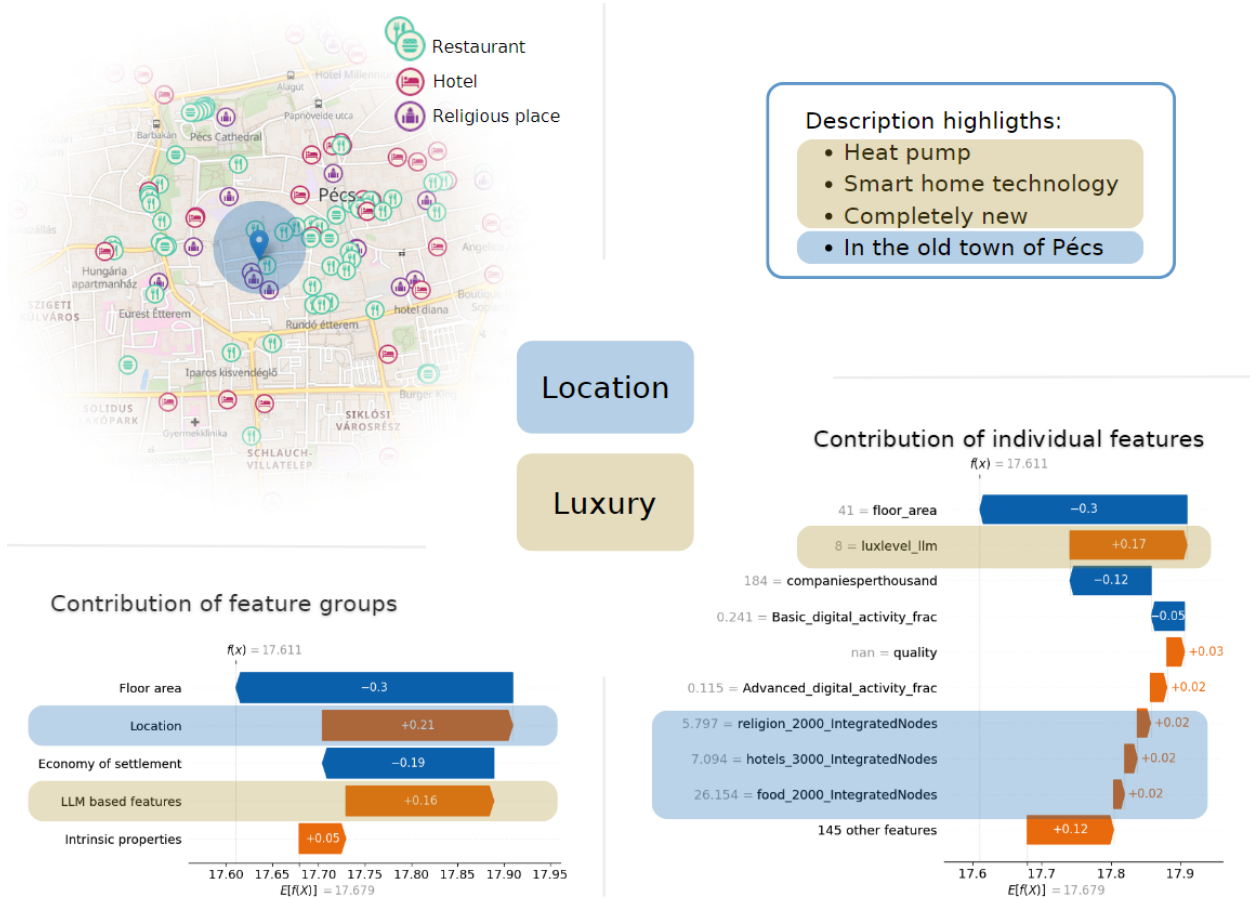


Figure 9: Effects of location and luxury in the pipeline

techniques, specifically the integrated gradients method, to the surrogate model. Having the output of the integrated gradients, we identified the three most influential tokens in each property description according to the surrogate model. The frequency distribution of these top tokens across the entire dataset is presented below, with a translations and our theories explaining their importance:

- ű, 7840 (a general affix)
- világos, 7834 (bright)
- WC, 5913
- ób, 4610 (general affix)
- uci, 4295 (general affix)
- kerület, 3907 (district, mainly in Budapest)
- perc, 3759 (minute)
- i, 3430 (general affix)
- Közös, 3283 (common, for example a gym)
- alkalmas, 3270 (suitable, e.g. for a family)

Bright being important is quite self-explanatory. However, the other words capture information related to them in their embedding.

District probably captures the district of the flat if it is in Budapest.

minute is important because phrases like "the flat is N minutes from X place"

WC captures how many are of them

Common captures common facilities, like gyms or pools

suitable likely captures who is it suitable for, like for example a family

Analyzing the results of querying the LLM itself to identify the most important keywords for the evaluation of the luxury levels, we got the following frequency of keywords appearing in the answer:

- location,31766
- renovation,16209
- size,15612
- amenities,13763
- balcony,9618
- renovated, 8139
- small size,6280
- air conditioning,5985
- lift,5863
- storage,5187

It can be concluded that very few of the most important words match from the two approaches. That could be due to LLMs replicating the general view of humans on the subject in contrast to the Bert method, which seems to learn the more specific, or even adversarial aspects from the data.

Another aspect of the LLM features is that they depend very much on the quality of the description. We hypothesized that the LLM could not actually distinguish an actually luxurious flat from an average flat with above average description, where the owner likely overrates their property. We measure the owner overrating their property with the *underestimation* metric:

$$\varepsilon = 100 \frac{y_i - \hat{y}_i}{y_i}$$

where y_i is the true listing price and $\hat{y}_i$ is the predicted price by the model.

$$Underestimation = \varepsilon_{noLLM}$$

To test this, we utilize the *underestimation* metric based on estimating the prices without the inclusion of LLM-based features. In Figure 10, one can see this *underestimation* metric plotted against the price of the properties and the improvement that introducing luxury level makes on error in predicting individual prices. We draw two conclusions from this plot: the *underestimation* is fairly equally distributed along the price axis, and the major improvements only happen at the high price category, in which special attributes can drive up the prices more, so luxury levels can have higher impact. Therefore, the more likely scenario is that the model can actually distinguish actual luxury from a well-written description.

It has to be mentioned that this metric is a very loose and inaccurate proxy of overrating the property and writing an unreasonably good description, so our analysis is far from perfect and can be faulty.

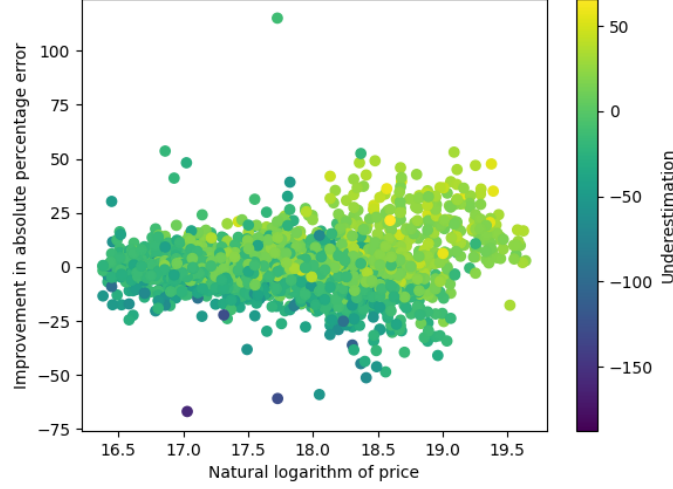


Figure 10: Improvement vs price

3.5 Additional experiments

This section explores several techniques to optimize the predictive performance and interpretability of our real estate price prediction model. First, we investigate the optimal transformation of the target variable (price) for regression. Next, we compare the performance of our LLM-based approach to traditional NLP methods for incorporating textual descriptions. Finally, we evaluate the impact of constructing composite variables from location and economic features, aiming to reduce dimensionality while maintaining predictive power and enhancing interpretability.

3.5.1 Target variable

Given the potential advantages of different target variable transformations, we evaluated five plausible variations for predicting property prices. Table 5 presents the performance of each transformation, measured by prediction error on the original (untransformed) prices.

	<i>MAPE</i>	<i>RMSE</i>	<i>R</i> ²
<i>Price</i>	9.06	0.877e7	0.947
<i>log(Price)</i>	8.82	0.876e7	0.947
<i>log($\frac{Price}{Area}$)</i>	9.29	0.906e7	0.944
$\frac{\log(Price)}{Area}$	10.03	0.992e7	0.932
$\frac{Price}{Area}$	9.46	0.906e7	0.943

Table 5: Performance while predicting different price metrics

Among the evaluated target variable transformations, $\frac{\log(Price)}{Area}$ exhibited the poorest performance. This

is likely attributable to the transformation of the target variable to a skewed distribution, as visualized in Figure 4, which can hinder the model’s ability to effectively capture subtle variations in price. Consequently, $\log(\text{Price})$, highlighted in bold, emerged as the most effective transformation, outperforming both the untransformed *Price* and all variations involving normalization by area. The inferior performance of area-normalized targets could be due to the presence of non-linear relationships between price per unit area and other features, which are not adequately captured by these transformations.

3.5.2 Comparing LLMs with conventional text processing methods

To assess the viability of our LLM-based description processing method, we compared its performance against established techniques using BERT embeddings, as proposed by *Baur et al.* [30]. Their research demonstrated the effectiveness of integrating BERT embeddings into regression models for improved price prediction. Table 6 summarizes the performance of our LLM approach compared to several BERT-based models.

Table 6: Performance with different text techniques

	<i>MAPE</i>	<i>RMSE</i>	<i>R</i> ²
<i>With LLM</i>	8.82	0.876e7	0.947
<i>Hungarian bert</i>	10.41	0.991e6	0.930
<i>Descriptions translated, english bert</i>	10.42	0.989e7	0.932
<i>Multilingual bert</i>	10.12	0.974e7	0.932

A key distinction between our study and *Baur et al.* is the language of the property descriptions. Our descriptions are in Hungarian, a less resource-rich language compared to the English descriptions used in their study. The relative scarcity of Hungarian training data for NLP models could potentially explain the lower performance observed for the BERT embeddings in our experiments. To address this potential language-related disparity, we also evaluated BERT models trained on English translations of our Hungarian descriptions, as well as a multilingual BERT model. However, these variations did not yield substantial improvements, leading us to conclude that our LLM-based approach significantly outperforms existing state-of-the-art techniques for this specific task, using Hungarian property descriptions.

We conducted several additional experiments to further explore the impact of embedding dimensionality and alternative modeling approaches. To address the potential issue of high dimensionality associated with BERT embeddings, we constructed composite features using both XGBoost and neural networks. However, these composite features did not lead to improved prediction accuracy.

Furthermore, we experimented with a multimodal transformer architecture designed to handle both tabular and free-text data simultaneously. While this approach offered some improvement in RMSE compared to using only intrinsic, economic, and LLM-generated features, its overall performance was considerably worse than that of the gradient boosting models. This suggests that, for this particular task, the benefits of a unified multimodal architecture are outweighed by the superior performance of gradient boosting methods, especially when combined with LLM-generated features.

Finally, we evaluated a BERT-based regression model trained solely on the free-text property descriptions, augmented with textual representations of key numerical and categorical features. This model achieved an *RMSE* of 0.8246e7, comparable to the gradient boosting models. However, its performance on other metrics, such as: *MAPE*: 10.00, *R*²: 0.922, was notably inferior. This reinforces the value of incorporating structured tabular data alongside the text descriptions for optimal predictive accuracy.

3.5.3 Testing composite variables

As there are a substantial amount of features both in the location-based and in the economic feature groups (62 and 37, respectively). We hypothesize that the dimensionality of feature groups can be reduced with minimal information loss, as they present large multicollinearity. To test the multicollinearity first, PCA was performed on the feature groups. The results of the location-based group is presented in Figure 11.

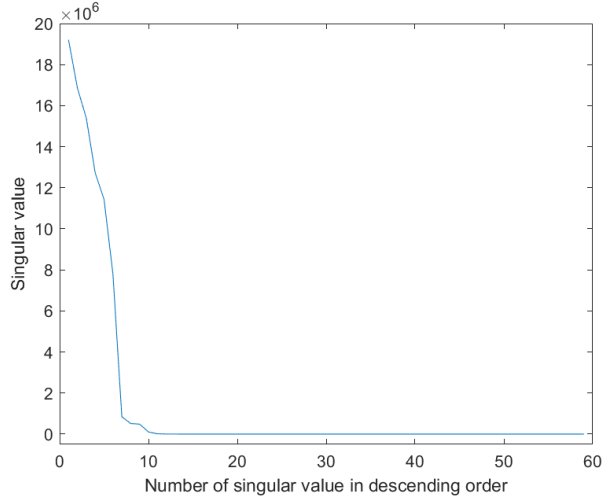


Figure 11: Singular values in location features

Figure 11 shows that the first 7 singular values account for more than 98% of the whole variance, which indicates high multicollinearity.

Next, we test whether the feature groups are reducible to lower-dimensional composite features without significant performance degradation. The performance metrics presented in Table 7 demonstrate that we lose relatively little predictive power when introducing these composite variables while gaining much interpretability – especially with the single-variable composites, highlighted in bold. For example, on a website it could inform the buyer how the location (or economic state of the region) contributes to the price of the real estate with a single number.

To further explore the composition and interpretability of our composite features, we applied SHAP analysis to the one-dimensional composites generated by XGBoost. This allowed us to identify the underlying features that contribute most significantly to the composite values.

Figure 12 illustrates the SHAP values for both the economic and location composites. The description of the variables are found in Table 9 and Table 10, for location-based and economic features, respectively. In the economic composite, measures of digital activity emerge as prominent drivers. Specifically, the proportion of residents with “no digital activity” or “basic digital activity,” as defined by the Hungarian Central Statistical Office (<https://www.ksh.hu/ffi/1-23.html>), exhibits a strong negative relationship with the composite value. These measures serve as proxies for the developmental state of a settlement, reflecting levels of technological infrastructure and potentially correlating with economic prosperity and living conditions, all of which can influence property values. The presence of a higher proportion of residents with limited digital literacy suggests potential economic challenges within a given area, negatively impacting property prices.

The location composite is heavily influenced by the proximity of financial and sports institutions. A high density of financial institutions likely indicates a well-developed business district, while the presence of sports facilities often signals access to green spaces and recreational opportunities. Both of these factors are generally associated with higher property values, aligning with the observed positive contribution of these features to the location composite.

Table 7: Performance with different composites

	MAPE	RMSE	R^2
<i>All full</i>	8.82	0.8763e7	0.947
<i>Location 16 variables, rest original</i>	9.00	0.897e7	0.945
<i>Location 6 variables, rest original</i>	9.07	0.9044e7	0.944
<i>Location 3 variables, rest original</i>	9.08	0.9040e7	0.944
<i>Location 1 variable, rest original</i>	9.13	0.9103e7	0.943
<i>Economic 3 variable, rest original</i>	9.19	0.9040e7	0.944
<i>Economic 1 variable (XGB), rest original</i>	8.89	0.8860e7	0.946
<i>Economic 1 variable (XGB), location 1 variable</i>	9.23	0.9192e7	0.942

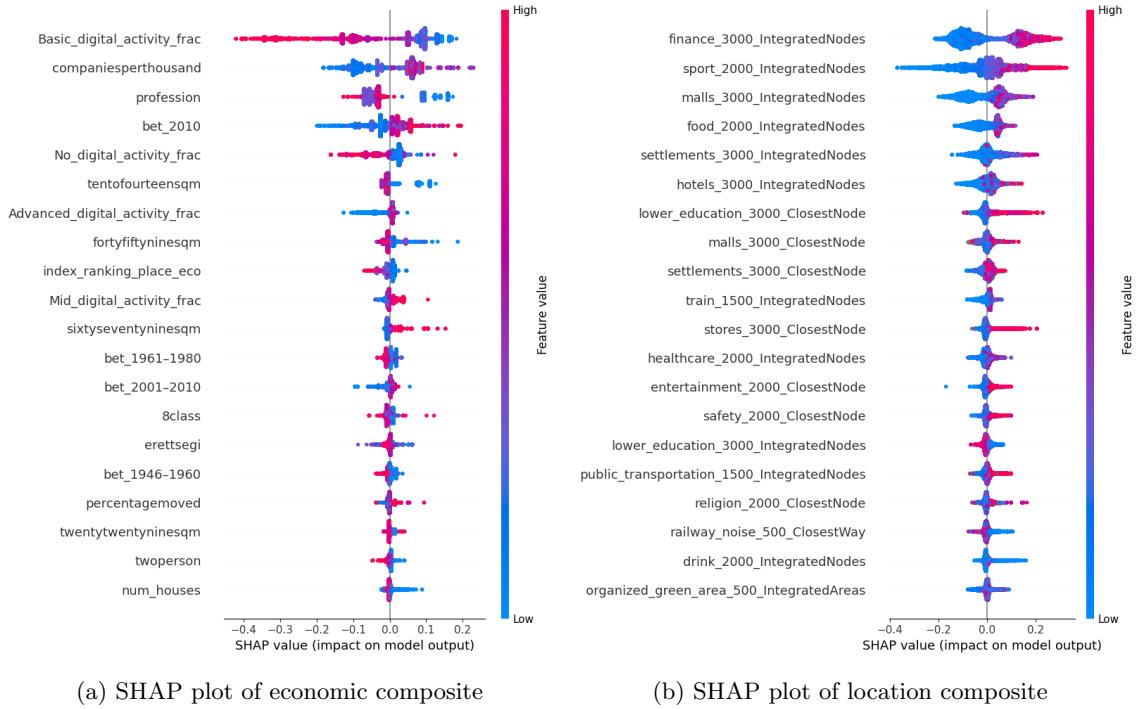


Figure 12: Interpretations of composites

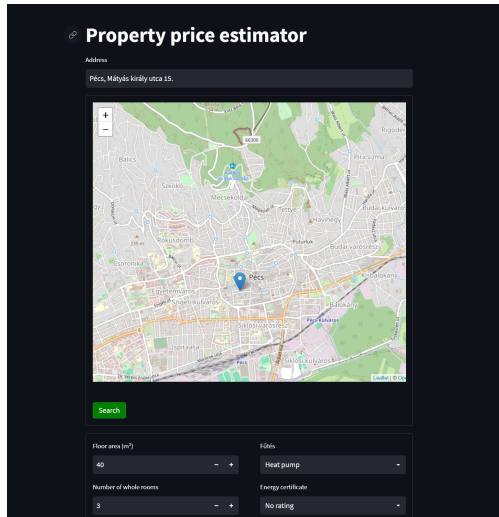
4 Web application

To bridge the gap between research and practical application, we developed a user-friendly web application for real estate valuation. This tool leverages the power of our trained machine learning models, incorporating both traditional structured data and insights derived from property descriptions via our innovative LLM-based processing.

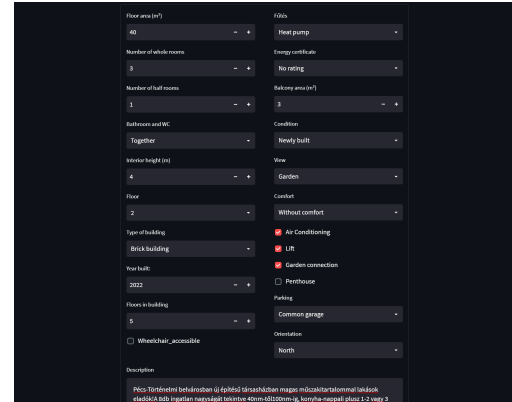
As illustrated in Figure 13, our web application offers a comprehensive and intuitive interface. Users can input property details through a structured form (Figure 13b) or by simply pasting a property description. The integrated map feature (Figure 13a) facilitates convenient location input and visualization. Critically, our application provides explanations for the generated predictions (Figure 13c), detailing the contributions of different features to the final estimated value. This transparency, based on the SHAP analysis described earlier, is a unique feature of our application, setting it apart from existing commercial solutions.

The web application was developed using Streamlit, a Python framework well-suited for interactive data applications. The application incorporates a map interface powered by Streamlit-Folium, a library that

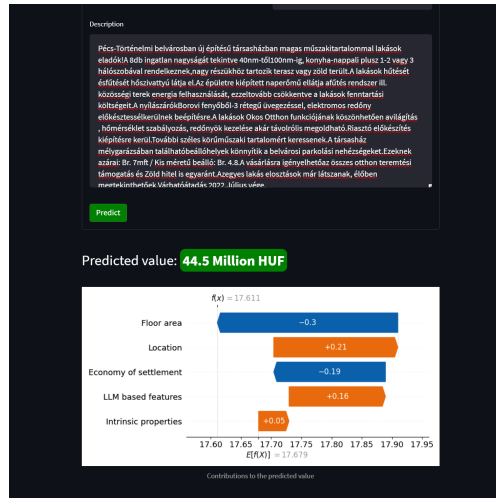
leverages the Folium API for convenient geospatial visualization. To facilitate geocoding, we employed a self-hosted instance of Nominatim, an open-source geocoding software deployed within a Docker container. Similarly, the calculation of location-based features relies on Overpass, accessed via API calls to another Docker container. This containerized approach ensures reproducibility and simplifies deployment.



(a) Map integration



(b) Input form



(c) Prediction and explanation

Figure 13: Screenshots of the developed web application

(a) Commercial estimator 1: link

(b) Commercial estimator 2: link

(c) Commercial estimator 3: link

Figure 14: Examples of existing commercial real estate estimators

In contrast to our application, existing commercial real estate price estimators (Figure 14) often lack the depth and breadth of features considered in our model. They typically rely on a limited set of structured inputs and do not incorporate the rich information available in property descriptions. Furthermore, none of the existing solutions offer the transparency and explainability provided by our SHAP-based approach.

The key features of the web application, reflecting these advantages, include:

- **LLM-Enhanced Valuation:** Leverages the power of Gemini to extract nuanced information from descriptions.

- **Interactive Map Integration:** Facilitates convenient and visual location input.
- **Explainable Predictions:** Provides transparent insights into the factors driving the valuation.
- **Economic Contextualization:** Incorporates economic indicators for a broader market perspective.

This webapp demonstrates the potential of combining advanced machine learning techniques with LLMs to provide accurate and interpretable property valuations, making this complex process more accessible to a wider audience. The ability to utilize free-text descriptions, a readily available source of information, significantly enhances the usability and value of this application for both buyers and sellers in the Hungarian real estate market.

5 Conclusion

Our study had a dual purpose. Having prepared our scraped dataset, we first compared the performance of several supervised learning models on the dataset of flat and house advertisements. We concluded the clear superiority of LGBM and XGBoost followed by Random Forest Regressor, leaving Elastic Net Regression and Decision Tree Regressor behind. The performance of the model which returned the mean price of the given settlement was also noteworthy.

Second, we detected how each feature contributes to the prediction using SHAP method. We observed that apart from floor area, the number of companies per thousand people in a settlement, and luxury levels were the most important in predicting asking price, while the year the property was built in had less impact, contradicting previous studies.

We tested a novel approach for generating tabular data from the descriptions of the house listings and also explored how one can create a representative single variable for human interpretation from a large amount of related features, and how much information it can capture. We tested what contributes to a Large Language Model giving a high luxury level to a description, and what other information it could capture apart from the real luxury level.

Beyond these, we also aimed to provide a clearer picture of the Hungarian real estate market. Our research has some limitations: since our dataset spans only six months, our methods were incapable of capturing long-term trends. For the same reason, potential changes in the economic environment are not reflected in our model. It's important to note that our model predicts listing prices, not actual sale prices, due to the lack of transaction data. While predicting listing prices has practical value, for example, assisting sellers in setting competitive asking prices or aiding buyers in assessing initial offers, it doesn't necessarily reflect the final transaction value. Listing prices can be influenced by seller expectations and market dynamics, and may not perfectly align with the property's true market value. Therefore, our predictions should be interpreted as estimates of advertised prices rather than definitive valuations. Another topic for further consideration would be using both pictures, descriptions and tabular data in a multimodal model and looking at the improvement that it provides.

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Appendix

A Abbreviations

- RF: random forests
- LGB: Ligth Gradient Boosting
- XGB: Xtreme Gradient Boosting
- GB, GBM: Gradient Boosting Machine
- SVR: Support Vector Regression
- NN: Neural Network
- GRNN: General Regression NN
- BPNN: Back Propagation NN
- LR: Linear Regression
- kNN: k-Nearest Neighbors
- ETR: Extra Trees Regressor
- ET: Extra Trees
- DT: Decision Trees
- MLP: Multi-layer perceptron
- OLS: Ordinary Least Squares
- NB: Negative Binomial Regression
- SGD: Stochastic Gradient Descent
- CART: Classification and Regression Trees
- GBDT: Gradient Boosted Decision Trees

B Features

Table 8: Intrinsic features and their properties

Feature Name	Description	Mean
Feature Name	Description	Mean
geocoder latitude	Latitude * 1e6	4.73794e+7
geocoder longitude	Longitude * 1e6	1.91969e+7
price	The listed price of the flat	17.68
floor area	Floor area of the flat	63.77
rooms	number of whole rooms + 0.5 * number of half rooms	2.35
land area	Area of land that comes with the flat	385.67
subtype	0 means brick building, 1: built from concrete panels, 2 means slip-formwork construction	0.26
wheelchair accessible	0 for no wheelchair access, 1 for access	0.34
height	0 for less than 3m inner height, 1 for more	0.41
floor	0: semi basement, 1: ground floor, 2: mezzanine, 3: 2nd floor, 4: 3rd floor etc.	4.31
energy certificate	Energy certificate required in Hungary, 0 is not rated, 1 through 22 are the levels higher is better.	14.63
year built	Approximate year in which the flat was built	1971.08
floors in building	Number of floors in the building	3.97
balcony	Floor area of the balconies combined	9.85
bathroom and WC	0: bathroom and WC in one room, 1: separated, 2: both in distinct rooms and in one room	0.61
quality	integers from 0 to 6, higher is better	3.4
garden connection	0 for no connection, 1 for connection	0.18
view	window facing the 0: street, 1: yard, 2: garden, 3: panorama	1.11
comfort	comfort level, integers from 0 to 5	3.11
air conditioning	0: no AC, 1: has AC	0.61
lift	0: no elevator, 1: has elevator	0.59
panelprogram	Panelprogram is a Hungarian program for making flats more energy efficient 0: not in, 1: in	0.64
parking	0: on the street 1: in the garden 2: common garage 3: private garage	0.54
parking place price	Price of parking place	8.5815e+9
overhead	Avg price of monthly overhead	5.2928e+6
orientation	0: north 1: northeast 2: east etc.	3.87
roof	0: Not roof floor, 1: roof floor	0.42
whole rooms	Number of whole rooms	2.17
half rooms	Number of half rooms	0.35
no heating	Booleans considering each heating type 0: no 1: yes	0.12
tile stove		0.01
other heating		0.01
other boiler		0
electronic heating		0.05
wall heating		0
fan coil		0.01
gas central heating		0.26
gas convector		0.16
gas boiler		0.02
house central heating		0.13
house central heating with individual measurement		0.08
heat pump		0.04
renewable energy heating		0.01
ceiling cooling heating		0.03
underfloor heating		0.02
district heating		0.19
district heating with individual measurement		0.1
mixed fuel boiler		0
in_Budapest	0 if the flat is not in Budapest, 1 if it is	0.67
parking price relation	Parking place 0: included 1: can be rented 2: must be rented 3: can be bought 4: must be bought	1.84

Table 9: Location variables

<i>variable name</i>	<i>key words</i>	<i>radius</i>
organized green area	park, playground, pitch, garden, golf course, grass village green	100, 500
unorganized green area	allotment, forest, meadow, orchard, vineyard, greenfield, heath, scrub, grassland, wood	100, 500
mountains	peak, castle, viewpoint	100, 500
water	water, river, lake	100, 500
industrial area	railway, military, industrial	100, 500
drink	bar, biergarten, cafe, pub	2000
food	fast food, food court, restaurant	2000
entertainment	cinema, theater, museum	2000
sport	gym, swimming pool, water park, sports centre	2000
lower education	kindergarten, school	3000
higher education	college, university	3000
religion	place of worship, mosque, synagogue	2000
safety	fire station, police	2000
healthcare	clinic, doctors, hospital	2000
other public service	post office	2000
building noise	night club, aerodrome, industrial	500
highway noise	motorway, trunk, primary, secondary, tertiary	500
railway noise	tram, rail, subway	500
hotels	hotel	3000
settlements	city, town	3000
finance	atm, bank	3000
stores/malls	supermarket, marketplace, shop, store	3000
shopping area	commercial, retail	3000
private traffic	motorway link, trunk link	1500
public transportation	bus station, bus stop, platform, tram stop, subway entrance	1500
train	train station, halt, station, stop	1500

Table 10: Economic variables and their descriptions

Feature Name	Description	mean	median
No digital activity frac	% of people not doing digital acitvty on the settlement	0.11	0.1
Basic digital activity frac	% of people only doing basic digital activity	0.23	0.22
Mid digital activity frac	% of people doing medium digital activity	0.47	0.47
Advanced digital activity frac	% of people doing advanced digital activity	0.15	0.17
companiesperthousand	Number of listed companies per thouasand people	258.67	239
num houses	Number of houses on the settlement	49031.8	45675
bef 1919	% of houses built in the given period	0.22	0.07
bet 1919–1945		0.12	0.13
bet 1946–1960		0.07	0.06
bet 1961–1980		0.28	0.34
bet 1981–2000		0.16	0.15
bet 2001–2010		0.1	0.1
bet 2010		0.06	0.05
num ppl	Number of people living in the settlement	83036.5	70048
no8class	% of people who have not completed primary school	0.07	0.07
8class	% of people with a highest education level of primary school	0.12	0.12
profession	% of people with highest education level of profession school	0.11	0.09
erettsegi	% of people with highest education level of matura exam	0.31	0.31
university	% of people with university degrees	0.34	0.34
lessthan10sqm	% of houses in the given floor area range	0.02	0.01
tentofourteensqm		0.05	0.05
fifteentonineteensqm		0.09	0.09
twentytwentyninesqm		0.21	0.22
thirtythirtyninesqm		0.18	0.18
fortyfiftyninesqm		0.26	0.26
sixtyseventyninesqm		0.11	0.1
morethaneightysqm		0.08	0.07
family	% of family households	0.48	0.5
notfamily	% of non-family households	0.52	0.5
oneperson	% of households with n people	0.46	0.46
twoperson		0.27	0.27
threeperson		0.13	0.13
fourperson		0.08	0.08
fiveperson		0.03	0.03
sixormoreperson		0.02	0.02
2010pop	2010 population of the settlement	85609.7	71633
percentagemoved	Percentage moved from settlement in the last 10 years	-0.04	-0.04

C Case study description

Pécs-Történelmi belvárosban új építésű társasházban magas műszaki tartalommal lakások eladók! A 8db ingatlan nagyságát tekintve 40nm-től 100nm-ig, konyha-nappali plusz 1-2 vagy 3 hálósobával rendelkeznek, nagyrészükhöz tartozik terasz vagy zöld terület.A lakások hűtését és fűtését hőszivattyú látja el. Az épületre kiépített naperőmű ellátja a fűtésrendszer ill. közösségi terek energiafelhasználását, ezzel tovább csökkentve a lakások fenntartási költségeit.A nyílászárók Borovi fenýőből-3 rétegű üvegezéssel, elektromos redőny előkészítéssel kerülnek beépítésre.A lakások Okos Otthon funkciójának köszönhetően a világítás , hőmérsékletszabályozás, redőnyök kezelése akár távolról is megoldható. Riasztó előkészítés kiépítésre kerül.További széles körű műszaki tartalomért keressenek.A társasház mélygarázsában található beállóhelyek könnyítik a belvárosi parkolási nehézségeket .Ezeknek az árai: Br. Xmft / Kis méretű beálló: Br. X.A vásárlásra igényelhető az összes otthonteremtési támogatás és Zöld hitel is egyaránt.Az egyes lakáelosztások már látszanak, előben megtekinthetőek. Várható átadás 2022.Július vége.

D Prompt Templates

In the following section, you can see the prompt templates used for generating the LLM generated features. All prices were blurred out in order to prevent data leakage, and if the llm did not output a usable numerical value, NaN was put in the dataset.

All examples used in these templates are from the training set, and were hand-picked, generally to represent as diverse information as possible. One could theoretically improve the performance by a large amount by picking better examples and also by several prompt-engineering techniques.

D.1 Oddities

Can you please tell me if this flat has anything that would make it particularly expensive, like a pool, a home theater or gym, being waterfront or having historical significance? Description: Panorámás lakás kiadó a DunaPest Rezidenciákban. Az épület szolgáltatásai is széleskörűek: - fitness terem, úszómedence, gyermekmedence, szauna, szolárium, termál medence, masszázs, parkosított tetőkert napozóval és játszótérrel, squash, biliárd- és játékszoba, könyvtár, 24 órás portaszolgálat és recepció. Egyéb lakásokért az épületben is érdeklődhet nálunk, várjuk érdeklődését. Részletes információt üzenetben/ telefonon tudunk adni. medence, fitness terem Again, anything, not just what I wrote for example. Please output a 1 if yes and a 0 if no! 1

Can you please tell me if this flat has anything that would make it particularly expensive, like a pool, a home theater or gym, being waterfront or having historical significance? Description: A Budai Vár alatt. Szuper Lakás. A Vörösmarty parkkal szemben eladó egy különleges adottságokkal rendelkező, 81 nm-es, 2 szoba-hallos, konyha+étkező, erkélyes lakás. Az ingatlan Bauhaus típusú, lifttel rendelkező ház 1. emeletén helyezkedik el, Délkeleti tájolású, napfényes és szellős. Az ablakai és az erkély egy csendes, tele zöld fákkal és virágzó bokrokkal, rendezett kertre néz. . A lakáshoz tartozik a földszinten egy kis lakás amit a társasház kezel. A kis lakás nagyobb tulajdoni hányada a lakáshoz tartozik. A lakásba belépve kellemes otthon fogadja! Tágas előszoba, külön és egybe nyíló napfényes szobák, beépített konyhabútorral rendelkező konyha étkezővel, ablakos fürdőszoba, külön mellék helység (lichtófra szellőző lehetőséggel), beépített gardrób szekrénnel ellátott közlekedő biztosít komfort érzetet. A lakás fűtéséről, távfűtés gondoskodik, egyedi mérővel. A meleg vizet, a fürdőben bojler, a konyhában elektromos kis bojler biztosítja. A közös költség X Ft, ami a korlátlan víz és fűtés használatot is tartalmazza. Ablakai redőnnel rendelkeznek, a lakás riasztó berendezéssel is el van látva. Átlagos állapotú, némi felújításra szorul, de megkímélt, akár azonnal költözhető. A lakáshoz egy önálló, kb. 6 m²-es pincerész is tartozik. Párok, kisgyerekes családok ideális otthona lehet, de bérbeadásra is tökéletes választás. A lakóközösség rendezett, kedves, segítőkész szomszédokkal. A környék ellátottsága kiváló, kis boltok, bevásárlóközpontok, óvodák, iskolák és gimnáziumok, sportolási lehetőségek a közelben találhatóak. Szabadidő eltöltésére a Vár, a Vörösmarty, Tabán, Horváth-kert, a közeli fürdők, Gellért-hegy és a Duna-part ad lehetőséget. Tömegközlekedése a pár percrenyire található Széll Kálmán térről és Attila útról a város minden pontja felé remek, metró, buszok, villamosok segítségével, éjszaka is megoldott. Parkolás nem csak a ház előtt, ha nem az egész területen ingyenes első kerületi lakcímmel rendelkezők számára. Amennyiben felkeltette érdeklődését a lakás, vagy további információra van szüksége, várom megtisztelő hívását. Again, anything, not just what I wrote for example. Please output a 1 if yes and a 0 if no! 1

Can you please tell me if this flat has anything that would make it particularly expensive, like a pool, a home theater or gym, being waterfront or having historical significance? Description: V. kerület Városház utca - Bútorozott lakás Budapest belvárosában kiadó

Hosszú távú bérletre bútorozott és gépesített lakás kiadó az V. kerületben a Városház utcában.

-69 m² -1 nappali -1 hálószoba -1 konyha -1 fürdőszoba -3. emeleti lakás lifttel -légkondi, riasztó, mosógép, mikró, sütő, tűzhely, mosogatógép, hűtő

KÖZLEKEDÉS: -kiváló közlekedés -Deák Ferenc tér és Ferenciek tere közelében -M1, M2, M3 -47, 49 villamos -5, 7, 8, 9, 15, 105, 108E, 110, 112, 115, 133E busz

BÉRLETI DÍJ: -Bérleti díj: X Euró/hó -Közös költség: X X Ft/hó (fűtést tartalmazza) -Augusztustól költözhető -minimum 1 éves bérleti szerződés, 3 hónap depozittal és az első hónap bérleti díjával -Kisállatok tartása nem megengedett! -Dohányzás tilos!

KÉREM INGATLANOSOK NE KERESSENEK!

Vth district-Városház street - Equipped apartment in the centre of Budapest

For long term rental we are offering a completely furnished and equipped apartment in the Vth district of Budapest at Városház street.

-69 m2 -1 bedroom -1 living room -1 kitchen -1 bathroom with bathtub -3th floor with elevator -air conditioner, alarm, washing machine, microwave, oven, stove, dishwasher, fridge

TRANSPORTATION: -perfect transportation -closed to Deák Ferenc square and Ferenciek square -M1, M2, M3 -tram 47, 49 -bus 5, 7, 8, 9, 15, 105, 108E, 110, 112, 115, 133E

RENTAL: -Rental fee: X Euro/month -Common cost: X X HUF/month (including heating) -Availability: August -minimum 1 year rental period with 3 months deposit and 1st month rental fee -Pets are not welcomed! -Smoking is not allowed!" "Budapest belvárosában a Ferenciek terénél Városház utcában galériás, bútorozott, egyedi fűtésű, 2. emeleti albérlet hosszú távra tulajdonostól kiadó. Kiváló közlekedés a város minden pontjához busszal, metróval. Olcsó rezsivel, számlaképes, 1 havi kauciót kérek. Azonnal költözhető. Ingatlanközvetítők ne keressenek. Érdeklődés kizárólag telefonon. Again, anything, not just what I wrote for example. Please output a 1 if yes and a 0 if no! 0

Can you please tell me if this flat has anything that would make it particularly expensive, like a pool, a home theater or gym, being waterfront or having historical significance? Description: 13. kerület, Újlipótvárosban, frissen felújított garzon lakás francia erkéllyel eladó. További képekért és információkért keressen bizalommal! Again, anything, not just what I wrote for example. Please output a 1 if yes and a 0 if no! 0

Can you please tell me if this flat has anything that would make it particularly expensive, like a pool, a home theater or gym, being waterfront or having historical significance? Description: EZ EGY ÉLETÉRZÉS! MARINA PART legelegánsabb és legmagasabb színvonalú épületegyüttesében, a Prestige Towers-ben kiadó amerikai konyhás nappalival és egy hálósobával rendelkező, Dunai panorámás, nagy erkélyes, bútorozott, gépesített apartman.Gyönyörű , világos, DNY-i fekvésű, panorámás lakás exkluzív élettér lehet igényes bérlők számára.Új bútorokkal, konyhával (legmodernebb beépített gépekkel- 6. érzékes Samsung sütő-micro- indukciós főzőlap..)12 személyes mosogatógép, szárítós mosógép, hatalmas gardrób szekrény, klíma, padlófűtés szolgálja majd az itt élők kényelmét.Bérleti díjban korlátlanul használható Önnek és családjának a ház wellness-fitness részlege: - edzőterem, szauna, külső medence, napozó kertA lakás bérleti díja X ezer Ft + rezszi (közös költség fűtéssel, hűtéssel , fitnessszel X ezer)Garázs bérelhető plusz költségért.Igényes bérlők jelentkezését várjuk minimum 12 hónapos szerződéssel és két havi biztosítékkal.Szívesen adok bővebb információt, várom hívását Again, anything, not just what I wrote for example. Please output a 1 if yes and a 0 if no! 1

Can you please tell me if this flat has anything that would make it particularly expensive, like a pool, a home theater or gym, being waterfront or having historical significance? Description: VI. kerület Izabella utcában eladó egy 82 nm-es világos három szobás földszinti téglá építésű nagypolgári lakás.ÉPÜLET:-1850 körül épült 2 emeletes régi polgári stílusú társasház-35 lakás található benne normális lakóközösséggel-felújított kapualj LAKÁS:-82 négyzetméteren, 3,8 m belmagassággal, tágas terekkel ideális családi otthon- három szobás- melyből két szoba az Izabella utcára néz, - ennek köszönhetően mindkét szobája világos- konyha és étkező tágas és világos udvari nézetű-fürdő-wc, + wc elrendezéssel.MŰSZAKI JELLEMZŐK és FELSZERELTSÉG-a lakás fűtéséről és meleg víz ellátásáról (kondenzációs) gáz cirkó gondoskodik-a lakást négy évvel ezelőtt felújították-a fürdőszoba és WC helyiségekben új szaniter burkolatok kerültek- ekkor került beépítésre a galéria is-új beépített konyha került ekkor a lakásbaKÖLTSÉGEK:-közös költség X Ft felújítási alappal, biztosítással-fűtés költség átlagosan X Ft- vízfogyasztása külön mérőóra alapján-elektromos áram szintén fogyasztás alapjánKÖRNYÉK:-Városliget, Hősök tere, Állatkert a közelben-72-es, 75-ös és 79-es trolibuszok, 105-ös és X-as buszok járnak a környéken-M1-es földalatti és az Andrássy út is szintén gyorsan elérhető-óvodákkal, bölcsődékkel és iskolákkal jól ellátott a környék-parkolási lehetőség, utcánHa megtetszett Önnek a hirdetés kérem hívjon bizalommal akár hétvégén is! Again, anything, not just what I wrote for example. Please output a 1 if yes and a 0 if no! 0

Can you please tell me if this flat has anything that would make it particularly expensive, like a pool, a home theater or gym, being waterfront or having historical significance? Description: A Lehel piac közelében a Bulcsú utcában kiadó 55nm-es, amerikai konyhás nappalis és hálós. ERKÉLYES lakás. Az ingatlan

berendezett és gépesített. GYERMEKBARÁT AZ INGATLAN. Közös költség XFt. 2 havi kaucióval és 1 havi bérleti díjjal, minimum 1 évre, AZONNAL költözhető. — Hívjon bizalommal, reggeltől estig, és NE maradjon le róla, tekintse meg mihamarabb a bérleményt.

Ügyfeleink számára a közvetítés díjtalán.

Amennyiben nem tudom felvenni a telefont, visszahívom! Again, anything, not just what I wrote for example. Please output a 1 if yes and a 0 if no! 0

Can you please tell me if this flat has anything that would make it particularly expensive, like a pool, a home theater or gym, being waterfront or having historical significance? Description: Új építésű társasházban, a belváros szívében eladóvá vált egy 42 négyzetméteres, erkélyes, másfél szobás ingatlan, jöjjön el, tekintse meg, és találja meg itt következő otthonát!Tömegközlekedés szempontjából a lakás elhelyezkedése kiváló, a 4-es és 6-os villamos, 5-ös, 7-es, 110-es, 112-es, 133-as busz, valamint az M2-es és M4-es metró egyaránt 5 perc sétával elérhető. Az ingatlan és környezete csendes, az ablakok és az erkély a zárt belső kertre néznek.A lakás teljesen gépesített (hűtő, mosógép, mikro, légkondicionáló) és bútorozott (egyedileg a lakáshoz készítettet premium minőségű keményfa bútorok a nappaliban és a gardróbban).A lakásban turbós gázkazán található, amit ideiglenesen elektromos panelek helyettesítenek. A melegvizet villanybojler biztosítja. A rezszi és a közös költség a téli hónapokban X X Ft körül mozog.Az épület alsó szintjein teremgarázs található, ahol igény esetén állandó parkolóhely bérelhető.A lakás akár azonnal költözhető. Amennyiben ajánlatom elnyerte tetszését, hívjon bizalommal, előre egyeztetett időpontban tudom mutatni az ingatlant.Irodánkban hiteltanácsadást, hiteligyintézkést és kedvezményes ügyvédi közreműködést biztosítunk. Again, anything, not just what I wrote for example. Please output a 1 if yes and a 0 if no! 0

Can you please tell me if this house has anything that would make it particularly expensive, like a pool, a home theater or gym, being waterfront or having historical significance? Description: Közvetlen Balatonparti ingatlan!!Balatonboglár központjában, a Balatontól mindössze 150 m-re eladó egy 145 m²-es házrész, mellette egy 52 m²-es kis ház előtt 10 m²-es terasszal. Az udvaron egy 20 m²-es fedett terasz van, mely a nyári minden napokat teszi kellemessé a szabadban. Itt lehet sütni-főzni, iszogatni-eszegetni akár rossz idő esetén is.Ezen kívül találunk még egy 21 m²-es ingatlant is,mely jelenleg garázként funkcionál. Mellette tárolók vannak.A kis ház szobája laminált parkettás, tusolós fürdőszobával, konyhával rendelkezik.A nagy házban a hatalmas konyha-étkező-nappali járólapos, a két nagyméretű szoba laminált parkettás, a fürdőszoba wc-vel és külön a wc helyiség hidegburkolatosak. Az egész ingatlannak megnyerő, ””jó itt lenni”” hangulata van.Minden helyiség klimatizált, műanyag ablakok, stílusos, szép faajtók jellemzik mindkét lakóingatlant. Teljes közművel rendelkezik az ingatlan, a melegvizet mindkét lakórészen 1-1 villanybojler biztosítja, a fűtést a kis házban konvektor, a nagy házban gázkazánról radiátorok.A kis házra került 6 kw-os napelem is, mely a nyári hónapok villamosenergia ellátását és a téli hónapok temperálását segíti elő, csökkentve ezáltal a rezsiköltségeket.A virágos, füves udvar keleti, majd déli fekvésének köszönhetően egész nap napos, világos, vidám arcát mutatja! Ha a Balatonpart közelségét keresi és csak át akar sétálni a strandra, ám mégis kényelmesen, otthonosan, kulturált környezetben, nagy terekkel akarja biztonságban tudni családját.....megtalált!! Again, anything, not just what I wrote for example. Please output a 1 if yes and a 0 if no! 1

Can you please tell me if this house has anything that would make it particularly expensive, like a pool, a home theater or gym, being waterfront or having historical significance? Description: Eladó! Hollókőn az ófaluban 1800 nm-es telken lévő 87 nm-es FELÚJÍTANDÓ valyog ház.A házban konyha, 2 szoba, fürdőszoba és egy kamra található.Fűtés egyedi fa tüzelés kályha. Again, anything, not just what I wrote for example. Please output a 1 if yes and a 0 if no! 1

Can you please tell me if this house has anything that would make it particularly expensive, like a pool, a home theater or gym, being waterfront or having historical significance? Description: *description of the house* Again, anything, not just what I wrote for example. Please output a 1 if yes and a 0 if no!

D.2 Neighborhood levels

Address: VI. kerület, Teréz körút Csak 1 van belőle! Ne maradjon le róla! Csak az OTP Ingatlanpont kínálatában! RITKA LEHETŐSÉG! VILLAHÁZBAN eladó egy alagsori, különleges hangulatú lakás. Sétátávolságra rengeteg látnivalóval találkozhatunk. A Hősök terével szemben, a Városliget szomszédságában, a Szépművészeti múzeum közelében, Diplomata övezetben, egy reprezentatív házban, 57 nm-es; tulajdoni lapon 1 szobás, de két szobássá alakított lakás. Akár üzlethelyiségnek vagy irodának is alkalmas! Házközponti fűtéses, alacsony rezszi költséggel! A közösköltségben, mely X.-Ft, minden benne van; kivéve a villany! Amennyiben hirdetésem felkeltette az érdeklődését, kérem, hívjon most! Szükség esetén teljeskörű ügyintézés (kedvezményes hitelkonstrukcióval, megbízható ügyvédi közreműködéssel) állok a rendelkezésére! Referenciaszám: M212009 Rate the neighborhood of this flat on a scale of 1 through 10! Reply with a single number! If you are accurate, I will tip you 500\$ dollars! 10

Address: Salgótarján, Zöldfa út Salgótarjánban, a Zöldfa utcában 4. emeleti, 48 nm-es, 2+1 félszobás, gázkonvektoros, redőnyös, szépen felújított, jó állagú lakás eladó. A fürdőszobában sarokkád, a szobákban laminált padló van. Közös költség 5 ezer Ft/hó. Négyemeletes téglaház. Lift nincs. Szegény környék. Az utcában sok szegény ember lakik. Üzletek, orvos, gyógyszerár a városrészben elérhető közelségben található. A Budapest felé vezető 21-es számú 4 sávós főútvonal 800 méterre található, melyen kb. 75 perces autóútra van a főváros. A két város közt állandó távolsági buszjárat indul minden órában, kb. 80 perces menetidővel. Irodánkban ingatlanja adás-vételéhez teljes körű ügyintézészt biztosítunk, ideértve a kedvezményes hitellehetőséget is. Minden eladó ingatlan értékesítése előtt annak tulajdoni lapját beszerezünk és ellenőrizzük. Ingatlant csak azonosított ügyfélnek mutatunk be, vételi ajánlat esetén az ingatlan tulajdoni lapját a vevőnek bemutatjuk. Tevékenységünket kamarai nyilvántartás alapján végezzük. Eladó ingatlanja reális árú értékesítésében is tudunk együttműködni, forduljon hozzánk bizalommal! Amennyiben az ingatlan nem nyerte el tetszését, kérem tekintse meg további hirdetéseimet. Idegen anyanyelvű vevők részére is állok rendelkezésre. If you are foreign citizen, please do not hesitate to contact me via email. Rate the neighborhood of this house on a scale of 1 through 10! Reply with a single number! If you are accurate, I will tip you 500\$ dollars! 1

Address: VII. kerület, Rákóczi út Megvételre kínálok VII. kerületben ERZSÉBETVÁROS részén az Astoria közelében, gyönyörű szép SINGER házban magas emeleti, nagy terekkel rendelkező 4 szobás közepes állapotú nagyszerű elosztású lakást! LAKÁS-Gyorsan költözhető-tehermentes-csendes-4.emeleti-130 nm, 4 szoba+ 1 hall -nagy terekkel rendelkező és kitűnő elosztású-dupla wc és külön fürdő-erkélyes HÁZ-1937/38-ban a Singer Varrógép Rt. megrendelésére Málik József tervei alapján épült hatemeletes Singer-ház, amely két utcai homlokzattal (Rákóczi út 16. - Dohány u. rendelkezik. A kivitelező/építő Havas Sándor cége volt. Travertin burkolatos Rákóczi úti és téglaburkolatos Dohány utcai homlokzat; vörösmárvány burkolatú előtér/lépcsőház, igényes asztalos- és fémmunkák-új lifttel rendelkezik-kamerával felszerelt-gazdálkodása rendezett-zárt lépcsőház KÖRNYÉ- A méltán népszerű, közkedvelt része a kerületnek a remek infrastruktúra és tömegközlekedés miatt - Óvodák, iskolák, éttermek és kávézók szolgálják a környéken élők kényelmét! Nyerte tetszését hívjon, rugalmasan mutatható! Rate the neighborhood of this flat on a scale of 1 through 10! Reply with a single number! If you are accurate, I will tip you 500\$ dollars! 8

Address: X. kerület, Cserkesz utca Description: OLCSÓ TÉGLAGARZON ELADÓ! Kőbánya-Óhegyen falújítandó garzonlakás eladó.

29 m²-es, egyszobás – a fűtés cirkó.

Beosztása praktikus: szobája csendes, a fürdő zuhanyzós, a vécé külön helyiségben.

A lakás felújítandó, leszámítva a fűtésrendszert: ez 3 éve lett korszerűsítve, BOSH kombi cirkó kazán került beszerelésre, azóta mind a fűtést, mind a melegvizet ez biztosítja.

Nyugodt kis lakás, rendezett lakóközösségű, viszonylag kis lakásszámú tégláépület földszintjén.

Gyorsan fejlődő környék, ahol az itt lakók összetételét mindinkább meghatározzák az egyre szaporodó új építésű házak; hangulatos környék, sok zölddel (az Óhegy park sétátávolságra található. Kiváló közlekedés

és infrastruktúra: Köki, kék metró pár perc alatt elérhető, Liget tér, városközpont ugyancsak. Ideális befektetésnek: a környékbeli ingatlanok könnyen, gyorsan kiadhatóak – de saját lakásnak is kitűnő.

Rezsije reális: közös költség 8.000, minden egyéb (víz, villany, gáz) mérhető, minden saját mérőórával rendelkezik.

Az ingatlan tehermentes, megbeszélés szerinti határidővel költözhető.

Írányár: X millió (!).

Érdeklődni a hét minden napján, akár hétvégén is. Rate the neighborhood of this flat on a scale of 1 through 10! Reply with a single number! If you are accurate, I will tip you 500\$ dollars! 3

Address: Gárdonyi, Szabadság utca Description: Gárdonyi központi részén, új építésű társasházi lakások lefoglalhatóak. Állandó lakás céljára, nyaralónak, vagy befektetési céllal is kiváló lehetőség. Tervezett átadás: 2023 tavasz.

-CSOK és hitel igénybe vehető! -Zöld hitel igényelhető!

Az ingatlan 4 db teljesen különálló épületből/lakásból áll. A duplakomfortos lakásokhoz saját terasz, kertterület, valamint 2 autó számára telken belüli parkoló tartozik. Az épület téglalapítású, profi - több évtizedes tapasztalattal rendelkező - csapat által minőségi anyagokból kerül kivitelezésre. A házak 15 cm-es grafitos szigeteléssel, cserépfedéssel, az antracit színű, műanyag nyílászárók 3 rétegű üvegezéssel kerülnek beépítésre. A lakások (padló) fűtését és melegvíz ellátását a legmodernebb hőszivattyús rendszer biztosítja. A lakások H-tarifás mérőórákkal kerülnek átadásra, így az alacsony rezsiköltség garantált, a gázszámlával sem kell bajlódni.

A1 lakás – belső 2 szintes. A lakás hasznos lakóterülete nettó 111 nm. A földszinten amerikai konyhás nappali-étkezővel, kamrával, kényelmes fürdővel, külön mellékhelyiséggel, az emeleten 3 hálószobával, tágas fürdővel (zuhany és kád is található) valamint egy külön mellékhelyiséggel. A hozzá tartozó terasz mérete: 10,5 nm. A saját kertrész területe: 214 nm. Ára: X M Ft.

A2 lakás – belső 2 szintes. A lakás hasznos lakóterülete nettó 111 nm. A földszinten amerikai konyhás nappali-étkezővel, kamrával, kényelmes fürdővel, külön mellékhelyiséggel, az emeleten 3 hálószobával, tágas fürdővel (zuhany és kád is található) valamint egy külön mellékhelyiséggel. A hozzá tartozó terasz mérete: 10,5 nm. A saját kertrész területe: 179 nm. Ára: X M Ft.

A3 lakás belső 2 szintes. A lakás hasznos lakóterülete nettó 111 nm. A földszinten amerikai konyhás nappali-étkezővel, kamrával, kényelmes fürdővel, külön mellékhelyiséggel, az emeleten 3 hálószobával, tágas fürdővel (zuhany és kád is található) valamint egy külön mellékhelyiséggel. A hozzá tartozó terasz mérete: 15,76 nm. A saját kertrész területe: 378 nm. Ára: X M Ft.

A4 lakás – belső 2 szintes. A lakás hasznos lakóterülete nettó 111 nm. A földszinten amerikai konyhás nappali-étkezővel, kamrával, kényelmes fürdővel, külön mellékhelyiséggel, az emeleten 3 hálószobával, tágas fürdővel (zuhany és kád is található) valamint egy külön mellékhelyiséggel. A hozzá tartozó terasz mérete: 15,76 nm. A saját kertrész területe: 428 nm. Ára: X M Ft.

Aldi áruház 100 m-es körzetben, a tópart és a vasútállomás pár perces távolságban helyezkedik el. A 7-es út 100 m-es távolságon belül van, így akár Budapest, akár Székesfehérvár kényelmesen, rövid idő alatt elérhető.

Amennyiben a Velencei-tó környékén keres kényelmes, igényes, minőségi anyagokból épült, korszerű ingatlant jó elhelyezkedéssel, megtalálta.

Ingatlanközvetítők kérem ne keressenek! Rate the neighborhood of this flat on a scale of 1 through 10! Reply with a single number! If you are accurate, I will tip you 500\$ dollars! 6

Address: VIII. kerület, Illés utca Description: Illés utcában 3. emeleti, udvari, fekvő galériás, klímás, igényesen felújított, stúdiólakás eladó. Víz, villanyvezeték, 7 éve felújítva, darálós wc. Rendőrségre bekötött riasztó. Közös költségben felújítási alap. Rate the neighborhood of this flat on a scale of 1 through 10! Reply with a single number! If you are accurate, I will tip you 500\$ dollars! 2

Address: Pécs, Mecsekoldal Description: Pécssett, a Mecsekoldalban, mindössze egy perc sétára a Szent István tértől, családi házas övezetben, minimál stílusú, összesen 6 db lakásból és garázsokból álló, szigetelt, lépcsőházanként külön-külön lifttel szerelt, hőszivattyús, téglalapítású társasházban, komoly szakmai múltjáról és referencia munkáiról ismert beruházó által megvalósított, pécsi viszonylatban is egyedülállóan

modern, exclusive kivitelezésű és rendkívül korszerű belső elrendezéssel és felszereltséggel bíró, nagyon elegáns, teraszos, valamint saját kertes kialakítású, új építésű lakások 2022. június havi kulcsrakész átadással még eladók. Külső nyílászáróként műanyag/fém szerkezetű, 3 rétegű üvegezéssel ellátott, nemesgáz töltetű prémium minőségű ablakok kerülnek beszerelésre. A teraszokat ún. WPC faburkolattal látják el. A lakások hőtermelését és melegvízellátását egyedi hőszivattyú biztosítja. A fűtést részben padlófűtéses, illetve Fan Cool beltéri egység, míg a hűtést levegő/víz hőszivattyú Fan-Cool látja el a gépészeti kiviteli terveknek megfelelően. A hirdetésben szereplő I. emeleti, belső kétszintes ingatlan összesen 118,59 m² alapterületű lakótérrel, 64,54 m² nagyságú - nagyrészt zöldtetős kialakítású - terasszal és loggiával, valamint még külön 78,5 m²-es saját kerttel rendelkezik. A lakótér alsó szintjén előtér, tágas konyha-étkező-nappali, zuhanykabinnal szerelt fürdőszoba, kamra, közlekedő, előtér, míg a felső szinten három darab, külön nyíló, kényelmes hálószoba, minőségi burkolatokkal és szaniterekkel ellátott, káddal szerelt fürdő-WC, ezen felül még zöldtető és terasz is kialakításra kerül. Fontos, hogy a lakás belső elrendezésén még lehet változtatni, ezen felül a minőségi szaniterek, csaptelepek, a belső nyílászárók, a hideg és meleg burkolatok a beruházó által közölt magas műszaki tartalommal foglalt árkategórián belül még szabadon választhatók. Az épület városban belüli elhelyezkedése, tájolása, a kialakított szobaszám, a belső terek kialakítása, valamint a modern hangulat mind-mind a kényelmes és elegáns lakhatást biztosítja akár egy nagyobb létszámú család számára. A hirdetési összegnek ugyanakkor nem része a teremgarázs ellenértéke, ami további bruttó X Mft. Rate the neighborhood of this flat on a scale of 1 through 10! Reply with a single number! If you are accurate, I will tip you 500\$ dollars! 10

Address: *address description* Rate the neighborhood of this flat on a scale of 1 through 10! Reply with a single number! If you are accurate, I will tip you 500\$ dollars!

D.3 Luxury levels

On a scale of 1 to 10, how luxurious is this flat in Budapest? Description: PANORÁMA, TISZTA LEVEGŐ, ERDŐ, LIFTES, GARÁZSOS FELÚJÍTOTT VILLAÉPÜLET!!! Budapest II kerület, Máriaremete II/A, Ördögárok utca Eladó II. kerületben a Francia iskolához közel az Ördögárok utcában egy 3 lakásos, 3 szintes ház teljes első emelete, 128 nm (3db terasszal). Gyönyörűen körbe napozott, ősfás, kertvárosi övezetben. Csendes. A lakás felépítése: előszoba, gardrób, mosókonyha, ablakkal ellátott fürdőszobák (zuhany, mosdó, WC), dolgozószoba, nagy, tágas étkező-nappali, 2 darab hálószoba, ablakkal ellátott nagy fürdőszoba (sarokkád, WC, bidé, mosdó). Fűtés: házközponti fűtés (Modern, hatalmas Viessmann kazán, víztárolóval!) egyedi méréssel padló és falfűtésen keresztül. A közös költség tartalmazza: fűtés, szemét, társasházi alap, kertész, hideg víz, közös fogyasztók. Csak meleg víz, áram és egyéni igények (Tv, internet, riasztó) van ezen felül. A lakás fő tájolása Dél-nyugati. 3 nagy méretű terasz tartozik hozzá. Saját tároló kb.Xnm, közös tároló, garázs, és felszíni beálló(Együttes értéke:XMft). Öntözővel ellátott hatalmas, parkosított kert, közös grillezővel és gyerekek játszótérrel. A ház lifttel felszerelt. Az ablakokon automata redőny és szúnyogháló van. A klíma igényes LG típusú, képeretként funkcionáló beltéri egységgel. Riasztó van beépítve. A konyha tömör cseresznyefából készült, ólom üvegezéssel. A konyhalap öntött gránitból lett kialakítva. Bosch beépített hűtő. Zanussi a sütő és a kerámialapos főző. IGAZI KANDALLÓ A NAPPAL-IBAN!!! Budapest District X, Máriaremete X/A, Ördögárok street On the first floor of a renovated, bright, villa house overlooking Csatlós Street, a 128 sqm + three balconies, three rooms (all rooms have a balcony), air-conditioned, apartment for sale. There's two bathroom with toilet (one of them has bath the other has shower), living-room with american kitchen, hall, wardrobe and laundry room. Heating: central-heating with own measurement (wall and floor heating), there isn't any radiators! Water meter available! One large garage and a storage belongs to the apartment. The plot is beautifully well maintained. The condominium has three floors, an elevator and an apartment on each level. As the apartment overlooks Csatlós Street, it is not loud, there is only a pedestrian entrance from Ördögárok Street, by car the entrance is from Csatlós Street! Its

price includes the garage and the storage. Please output a single number! 8

On a scale of 1 to 10, how luxurious is this flat in Budapest? Eladó II.kerületben, Csatlós utcában, X lakásos társasház, első emeletén lévő 128m²-es, világos, tágas elrendezésű, rendszeresen karbantartott, duplakomfortos, kertkapcsolatos, panorámás lakás. A társasház telke1600m²- öntözőrendszer, játszótér, grillezésre alkalmas hely is kialakításra került. Lift van. Társasház legalsó szintjén található közös helységek: tárolók, zuhanyzó, Wc, kazánház, garázs stb...Lakás paraméterei: 3 szoba, 1 nappali étkező-amerikai konyha, közlekedő, gardrób, mosókonyha, 2 fürdőszoba, 3 erkély. Fűtés: fal és padlófűtésLakásban található külső-belső nyílászáró fa típusú Lakásban található összes ablakon és erkélyajtón elektromos redőny és szúnyogháló is van. Nappaliban található kandalló fatüzelésű, olasz márvány burkolattal lett kialakítva. Használata közben egyáltalán nincs füst.Klíma, riasztó van.Minden szoba külön nyílik. Burkolat:parketta: fa/tölgy Lakásban többi helységében a burkolat- olasz kerámia járólap. Beépített konyhabútor: tömör cseresznyefa. Az ingatlanhoz tartozik saját zárható tároló. Parkolási lehetőség zárt garázsban X autó számára, illetve a társasház telkén belül több autó számára is van lehetőség. Kapu elektromos.Közös költség XeFt/hó, amely tartalmazza a fűtés, hidegvíz, kertész, szemétszállítás, csatorna, társasház összes közös fogyasztását, a társasház biztosítási díját is. Melegvíz, villany saját fogyasztás szerint. Lakásban található beépített bútorok az ingatlan vételárát képezik. Az ingatlan tehermentes. Azonnal költözhető. Irány ár: XM Ft. Garázs az ingatlanhoz tartozik, benne van az árban. Please output a single number! 9

On a scale of 1 to 10, how luxurious is this house in Sződliget? Sződligeten jó infrastruktúra mellett ELADÓ egy Dél-Nyugati fekvésű,68 m²-es 2 szobás, gázcirkós családi ház garázzsal, fűt kúttal, 540 m²- es kerttel. A jó műszaki állapotú ingatlan palatetős, betonfödemes, téglá építésű. Kész tervrajz van a házhoz, melyen egy kényelmes, emeletes, teraszos ház alakítható ki. Az utca, aszfaltozott. A szomszédok kedvesek. Vácra és a fővárosba ingázóknak nagy előny a vasút közelsége. Busz 5 percre, a vonat 10 percre található.

Jellemzői:

- az ingatlan 1960-ban épült, és 2005-ben lett felújítva - burkolatok: kerámialap, parketta - Fűtése: gázcirkóval, - tárolásra alkalmas melléképület, ami garáznak is használható - külső szigetelés - fűt kút - műanyagnyílászárók - jó állapotú épület - parkolás az udvarban - kilátás: kertre néző - padlás

Irányára: X M Ft Please output a single number! 8

On a scale of 1 to 10, how luxurious is this flat in Budapest? Budaliget csendes részén a Honfoglalás lakóparkban, eladó egy 12 lakásos, szinteltolós társasház földszintjén található 51 nm-es, 1 szobás, nagy teraszos ingatlan.A lakáshoz tartozik egy teremgarázs, és kizárólagos használatú tároló, ami benne van az árban. A környéken az infrastruktúra kiváló, uszoda, Francia iskola és óvoda. A lakópark előtt buszmegálló 157 és 157 A melyek a Hűvösvölgybe visznek le. Néhány perc autózással bevásárlóközpontok Hűvösvölgy, Solymár Auchan, Lidl, stop-shop, posta 5-10 perc alatt elérhetőek. Please output a single number! 3

On a scale of 1 to 10, how luxurious is this house in Szentendre? Szentendrén, kiváló helyen Pismány déli oldalán közel a központhoz, aszfaltozott, rendezett utcában, PANORÁMÁS, 6 szobás, bruttó 160 nm-es, klímás, felújított, családi ház, beépített bútorokkal eladó.A ház kiváló elosztású, elegáns, belsőépítész által tervezett enteriőrrel rendelkezik, minden helyiségben tervezett, magas minőségű alapanyagokból készült beépített bútorokkal lett kialakítva. Fa nyílászárók, igényes, egyedi beltéri, részben toló ajtók kerültek beépítésre.Fürdőszoba Villeroy szaniterekkel, Hans Grohe kiegészítőkkal, design cement burkolattal, üveg kabinnal kivitelezett. Az épület 2006-ban épült, 2022-ben fejeződött be a teljeskörű felújítása.Parkosított, 589nm-es, rendezett , Wellis süllyeszthető medencével, gyerek fajtájszótérrel, locsolórendszerrel ellátott , teraszos kialakítású kert.Bármely kérdés esetén forduljon hozzám bizalommal! Please output a single number! 10

On a scale of 1 to 10, how luxurious is this flat in Hajdúszoboszló? Hajdúszoboszló csendes utcájára néző 4. emeleti panellakás eladó. A lakás két éve felújításon esett át, a lakásban beépített konyhaszekrény és légkondicionáló is van. Az ingatlan közel van a fürdőhöz, gyógyszertárhoz, bolthoz, egészségházhöz, iskolákhoz és óvodához is. Bármilyen kérdés esetén hívjon bizalommal. Please output a single number! 5

On a scale of 1 to 10, how luxurious is this flat in Budapest? Budaliget kedvelt részén a Honfoglalás utcában, eladó ingatlan tulajdonostól, 19nm-es kertre néző terasszal, tárolóval és teremgarázzsal Irányár X millió Ft IN-GATLANKÖZVETÍTŐK SEMMILYEN MÓDON NE HÍVJANAK! Please output a single number! 2

On a scale of 1 to 10, how luxurious is this flat in Budapest? Igazán magas luxus szinten felújítás alatt álló, a terveknek tökéletesen megfelelő nagypolgári lakás, 4,5 méteres belmagassággal, hatalmas terekkel, mindenképp a legdrágább minőségben kivitelezve a teljes körű felújítást! A ház pár éve kívül-belül felújított, elegáns, liftes. A lokáció a lehető legimpozánsabb, a Bazilika és a Szabadság tér közé esik. Mélygarázs hely bérelhető közvetlenül ott!! Jelen állapotban meg bele is lehet szólni a kivitelezésbe, mert pár hónap mire teljesen elkészül! Please output a single number! 10

On a scale of 1 to 10, how luxurious is this flat in Budapest? FIX ÁR, HA ALKUDOZNI AKAR KÉREM NE KERESSEN! Újpest Városcsúcs Metró megállótól 250 méterre, teljes körű felújítást, komfortosítást igénylő garzon lakás tulajdonostól eladó. Több mint 10 éve áll üresen az ingatlan. Önálló helyrajzi számon van, tehermentes, azonnal birtokba vehető, tulajdoni lapon is lakás besorolású. Zuhanyzó és a wc kialakítandó, jelenleg komfort nélküli így lakáshitelt nem tud felvenni rá! A társasházban két lakásunk van, mindegyik eladó, akár össze is nyithatóak. A képeken látható barna és sárga ajtó. Mindegyik 15 m² és darabja X millió. Ha egyben veszi meg a 2 önálló helyrajzi számon lévő 15m² lakást akkor fix X millió a vételár, alkura nincs lehetőség. Befektetésnek is kiváló, jól bérebe adható az elhelyezkedése miatt. Mélyen piaci ár alatt tulajdonostól eladó. Közvetítők segítségét nem kérjük! Please output a single number! 1

On a scale of 1 to 10, how luxurious is this flat in Pécel? Eladó nettó 63 nm (+ 2 db 5-4 nm terasz) méretű társasházi lakás Pécel központjában. A lakás egy 24 lakásos, fejlődő társasház első emeletén helyezkedik el. (4 lépcsőház, 6-6 lakással) Helyiségek: nappali-étkező-konyha részben egybenyitva, 2 háló 1-1 nyugati terasszal, ablakos fürdő, ablakos wc melegvízes kézmosóval, előtér. "Rendhagyó" belső kialakítás, belmagasság 270 cm, fa ablakokkal. 2021-ben teljes villanyhálózat és tetőszigetelés csere történt. Téli hónapokban elég volt három konvektor (a négyből). Csendes zöldterület a kilátás nyugatra is és keletre is, reggeli és délutáni nap átjárja, keresztirányú és állandó légmozgás nyitott ablakoknál elérhető. Rendezett lépcsőház, csöndes szomszédok, saját udvar autó beállási lehetőséggel. Közvetlen madárcsicsergős patakpart, mégis minden közel, de zaj nélkül (Templom, általános- és középiskola 500 m, Penny, piac, posta, buszmegálló, ruhaüzlet, háztartási, barkácsbolt, cipész, cukrászda, virágos, gumis, dohánybolt, biobolt, bank, atm) 200 méterrel belül. Közvetlen kék buszjárat az Őrs vezér tere (35 perc), és vonatjárat a Keleti Pályaudvarra (25 perc). Vételár X M Ft. Ingatlanosok kérem ne hívjanak! Please output a single number! 7

On a scale of 1 to 10, how luxurious is this house in Bonyhád? Eladásra kínálom szeretett otthonunkat Bonyhád egyik központi utcájában, mégis csendes környezetben. A ház 3 éve esett át teljes körű belső felújításra, amikor is víz és hőszigetelés, az összes villanyvezeték és vízcső, valamint az összes belső burkolat cseréje lett elvégezve. A konyha teljesen felszerelt, egyedi méretre gyártott konyhabútorral. A munkák során kizárólag magas minőségű, tartós anyagok kerültek felhasználásra. További kérdéssel keressenek bizalommal. Please output a single number! 3

On a scale of 1 to 10, how luxurious is this flat in Budapest? Déli tájolású, csendes, erkélyes háromszobás lakás panelprogramos házban

XI. kerület Kelenföld kedvelt, központi részén, kiváló közlekedés mellett, csendes, parkra néző, jó elosztású, háromszobás, világos, 2. emeleti, erkélyes, bruttó 63 nm-es lakás eladó. Az erkélyfal és vele együtt az ablakok cseréjét, valamint a nappali és a két hálószoba laminált padlóval történő újra burkolását a jelenlegi tulajdonos az előző évben végeztette el. A lakás többi része átlagos állapotú. Az elektromos vezetékek felújítása 10 éven belül történt meg. Fűtése egyedileg mért távfűtés, a hálószobák ablakai műanyag redőnnel árnyékolhatók. A lakás további berendezési tárgyai (beépíthető mosogatógép, bútorok) megbeszélés tárgyát képezik.

A lakáshoz tartozik egy saját használatú pincerész és egy közös emeleti tároló is.

A ház külső szigetelése március közepén fejeződött be a nyílászárók cseréjével együtt, a tető szigetelésének munkálatai folynak jelenleg.

Személyes megtekintés és további kérdések megválaszolása érdekében a hét bármely napján várom megkeresését. Please output a single number! 5

On a scale of 1 to 10, how luxurious is this flat in Budapest? IX. kerület - Ferencváros szívében eladó egy kiváló adottságú, magas emeleti nagypolgári lakás. Az ingatlan 4. emeleti (nem zárószint), 115 m²-es, délkeleti tájolású, jelenleg 3 nagyméretű szobával és külön konyhával rendelkezik. Az előszobából egy világos nappaliba érkeziünk, melyből két külön bejáratú szoba nyílik. A szobákat és az előszobát parkettával burkolták, kialakításukat tekintve jól berendezhetők. A konyha a nappaliból és az előszobából is megközelíthető. Itt kialakításra került egy 2 m²-es kamra is. Fürdőszoba és a mellékhelyiség külön-külön vannak, szellőztetésük a lichthof felé történik. Egyedi mérőórák vannak felszerelve. A lakás fűtését gáz fűtésű cserépkályha illetve konvektorok adják. A hangszigetelést a jó minőségű nyílászárók és a redőnyök biztosítják. A társasház 5 emeletes, jó állapotú, liftes, kis lakóközösséggel rendelkezik, emeletenként csupán 3 lakás található. A közös költség X Ft, mely tartalmazza a felújítási alapot is. Az ingatlan lokációját tekintve kitűnő helyen található. Kiváló infrastruktúrával rendelkezik, a 4-es, a 6-os villamos, 3-as metró, a Boráros térről induló HÉV ill. számtalan buszjárat: 2, X, X, X pár lépésre elérhető. Közben több egyetem /ELTE, SOTE, CORVINUS, BME/, boltok, éttermek, óvodák, iskolák találhatóak. A lakás tehermentes, rövid időn belül birtokba vehető. Kérdés vagy megtekintés esetén keressen bizalommal! M208764 Please output a single number! 7

On a scale of 1 to 10, how luxurious is this flat in *city?* *description* Please output a single number!