The potential of AVM and AI – Opportunities and risks for appraisers

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SUMMARY

The utilization of Automated Valuation Models (AVMs) in real estate appraisal is becoming increasingly prevalent. Banks, for example, are increasingly using them in the financing process of standard properties such as apartments and single-family houses, while real estate investors frequently use them in investment decisions.
This has led to concerns among appraisers that their profession may become obsolete in the future. AVMs are often only utilized in conjunction with an overall automated valuation of a property, which can be imprecise, particularly for commercial properties or specialized properties such as schools with less transaction data. AVMs are also criticized for their "black box" nature, as it is difficult to understand the factors that lead to a specific valuation.
However, there are ways to combine the strengths of AVMs and human appraisers. AVMs can be used as a supporting tool for appraisers by extracting key insights and opening the black box to answer questions about how individual property characteristics are valued by the AVM.
In the context of regression analysis, a model was developed that uses AVMs to support appraisers in determining inputs for the appraisal process in a transparent way, thus improving efficiency and transparency and making the appraisal more fact-based.
This model allows the appraiser to verify the results of the AVM and adjust them if necessary to improve the accuracy of the estimates.
Overall, the combination of AVMs and AI offers the opportunity to improve the efficiency and accuracy of real estate appraisals without undermining the role of the human appraiser.
It is crucial to view AVMs as a supportive tool rather than a threat to the profession and to integrate the benefits of AVMs and AI into the appraisal process.

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1. INTRODUCTION

Automated Valuation Models (AVMs) are algorithms used in the real estate industry to estimate the value of properties. This paper provides a comprehensive overview and analysis of the current state of AVM technology and its potential impact on the real estate appraisal industry.
The paper explores the background and development of AVMs, the technologies used in AVMs, and the concerns and opportunities that arise from their integration into the appraisal process. In the context of a specific regression analysis, a model was developed that uses AVMs to support appraisers in determining inputs for the appraisal process in a transparent way, thus improving efficiency and transparency and making the appraisal more fact-based. This example is applied for the German residential real estate market to discuss the potential of the technology.
Additionally, the paper proposes development areas for combining AVMs with human appraisal expertise to enhance the accuracy and efficiency of the appraisal process.

2. AUTOMATED VALUATION MODELS (AVMs) IN REAL ESTATE

Automated Valuation Models are computer-based algorithms used to estimate the value of a property. They have become increasingly popular in the real estate industry due to their ability to quickly and efficiently provide property valuations. AVMs use statistical models and algorithms to analyze data on a property, such as its location, size, age, and recent sales of comparable properties. The algorithms then generate a predicted value for the property. AVMs are commonly used in the financial industry to assess the value of collateral for loans, but they can also be used by real estate professionals to determine the market value of a property. While AVMs are generally accurate and efficient for standard properties in strongly populated areas, they may not be as effective for unique or highly specialized properties that lack sufficient comparable sales data. Additionally, AVMs are often criticized for their lack of transparency, as the specific factors and weightings used in the models are typically not disclosed.
In fact, the first AVM was developed in the late 1960s by the United States Federal Home Loan Mortgage Corporation (Freddie Mac) to assist in valuing mortgage portfolios. However, it was not until the 1990s that AVMs began to be used more widely in the residential real estate market, and their use has continued to increase with advancements in technology and access to data. Despite this, AVMs are still not widely used in some countries, such as Germany, where traditional appraisal methods remain prevalent.
Despite these limitations, AVMs have the potential to be valuable tools for real estate professionals if used properly. Rather than replacing human appraisers, AVMs can

supplement their work by providing data and insights that can inform their valuations. The key is to use AVMs as a tool, not a replacement for human expertise.

2.1 Technological background of AVMs

Research shows there is no one specific technology used for AVMs, as different methods and algorithms can be employed depending on the specific AVM model and its application. However, some commonly used techniques include regression analysis, artificial neural networks, decision trees, and support vector machines. These methods use statistical models and algorithms to analyze large datasets of relevant features and historical sales data, in order to identify patterns and relationships that can be used to estimate the value of a property.

Regression analysis is a widely used technique in AVMs. This method uses historical sales data to identify patterns in the relationship between the property's characteristics and its sale price. The algorithm then creates a linear model that can be used to predict the value of a property based on its characteristics. It involves analyzing the relationship between a dependent variable (such as property value) and one or more independent variables (such as square footage or number of bedrooms). While regression analysis is relatively simple and transparent, it may not capture all of the complex factors that affect property value.

Artificial neural networks (ANNs) are another commonly used technique in AVMs. ANNs are modeled after the structure of the human brain and consist of a network of interconnected nodes. Each node processes information and sends it to the next layer of nodes until the output layer produces a final prediction of the property's value. ANNs are particularly useful for AVMs because they can learn and adapt to new data inputs over time, improving the accuracy of their predictions. While neural networks can capture complex patterns and relationships in the data, they are often criticized for their lack of transparency. The weights assigned to each node are determined through a trial-and-error process, making it difficult for end-users to understand how the model arrived at its estimate.

Decision trees are another technique used in AVMs, which use a tree-like structure to model the decision-making process. The algorithm divides the data into smaller subsets based on their characteristics and assigns a value to each subset. These values are then used to create a tree-like structure that can be used to predict the value of a property based on its characteristics. Decision trees can be more transparent than other methods because they are easy to visualize and understand. However, decision trees can also be prone to overfitting, which occurs when the model is too complex and fits the training data too closely, leading to poor generalization to new data.

Support vector machines (SVMs) are a type of machine learning algorithm used in AVMs to identify patterns in data and make predictions. SVMs are based on the idea of finding a hyperplane that best separates the data into different classes. In AVMs, SVMs can be used to predict the value of a property based on its features. SVMs can be highly accurate in predicting property values, but they can also be opaque, as the inner workings of the model are difficult to interpret. This lack of transparency can make it challenging for users to understand how the model arrives at its predictions.

The specific inputs and weighting of features can vary depending on the AVM model. Some models may place more emphasis on certain features, such as the number of bedrooms or the age of the property, while others may consider a broader range of characteristics. Different AVM models may perform better in certain market segments or types of properties, depending on the specific data inputs and algorithms used.

2.2 Concerns regarding the use of AVMs in the appraisal indutry

Automated Valuation Models (AVMs) have been a point of concern for many in the appraisal industry, particularly due to their potential to replace human appraisers, especially for standard properties. This is a valid concern because appraisers fear that their expertise and experience could be devalued, and the quality of valuations could suffer if AVMs become the norm. AVMs are designed to provide an estimated value for a property based on data inputs, but they may not take into account important factors that could affect the value, such as property condition or specific market trends. Consequently, AVMs may not always provide an accurate valuation for complex or unique properties.

One of the significant concerns is the lack of transparency and interpretability of AVMs. The algorithms used to generate valuations are not always disclosed, which can make it difficult for appraisers to understand how the valuations were generated or to challenge them if they seem inaccurate. AVMs are often referred to as a "black box" because it is not easy to understand the factors that lead to a specific valuation. The lack of transparency in AVMs could lead to skepticism and distrust in the appraisal industry, particularly when the valuations provided by AVMs differ significantly from those generated by human appraisers.

The black box nature of AVMs is primarily due to the complexity of the underlying algorithms that generate valuations. These algorithms use sophisticated statistical techniques, machine learning models, and predictive analytics to analyze large datasets of relevant features and historical sales data. This results in a highly accurate and automated valuation process. However, it also means that the models are too complex for the average user to understand fully. The algorithms take into account numerous variables, such as the location, size, and type of property, as well as historical sales data, market trends, and other economic indicators, to generate a valuation.

Furthermore, the lack of transparency and interpretability in AVMs also stems from the fact that the specific inputs and weighting of features can vary depending on the model, and different AVM models may perform better in certain market segments or types of properties. As a result, it is difficult for appraisers or other stakeholders to understand how the AVM arrived at a specific valuation, particularly when the valuation is significantly different from human appraisals.

In conclusion, AVMs have the potential to revolutionize the appraisal industry, providing efficient and accurate valuations. However, there are legitimate concerns about their accuracy, transparency, and potential to replace human appraisers. It will be crucial for the industry to continue to monitor and regulate the use of AVMs to ensure that they are used appropriately and in a way that benefits all parties involved in the appraisal process.

3. DEVELOPMENT OF A TRANSPARENT AVM (Schlachter 2019)

As described, AVMs present a valuable opportunity to gain deeper insights into the real estate market. While AVMs are primarily used to predict the value of a property, they also offer a window into the inner workings of the market, both directly and indirectly. By analysing the parameters of the AVMs, we can better understand the trends and patterns that shape the market, including factors like supply and demand, economic conditions, and consumer preferences. These insights can be used to inform real estate investment decisions, improve pricing strategies, and identify new opportunities in the market.

3.1 Method

The classical models are based on the assumption of spatial homogeneity, i.e., spatial independence and thus the global validity of the coefficients. This would imply, regarding the real estate market, that the properties of an asset have a spatially constant coefficient. By considering the interactions between object and location properties, differences in the height of the coefficients of the object properties are taken into account depending on the location properties. Accordingly, the model presented does not assume spatial homogeneity.

This allows to use a large-scale market model which in this case was created for Germany and that has certain advantages over local models. If local models are used to predict the value of a property, the number of observations is restricted to the local market. Consequently, only models with limited degrees of freedom can be used. Those models are often not sufficient to provide deeper insights in the complexity of the real estate market.

A large-scale model for which the nation-wide dataset can be used can overcome some of these limitations. For such a model the differences in the submarkets need to be included in the model as well.

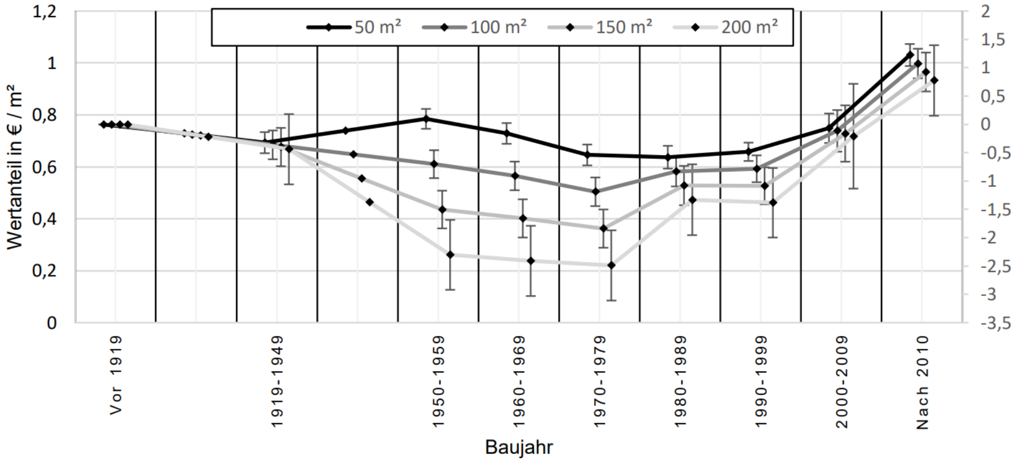
The value is obtained as the sum of the individual value components that depend on the respective object and location properties. In addition to linear influences, interaction effects between the object and location properties must also considered.

$$Wert = \alpha + \sum_{k=1}^{K} \beta_k OE_k + \sum_{j=1}^{J} \beta_{K+j} SE_j + \sum_{i=1}^{K}\sum_{l=1}^{K} \beta_{K+J+il}(OE_i * OE_l) + \sum_{o=1}^{J}\sum_{p=1}^{J} \beta_{K+J+KK+op}(SE_o * SE_p) + \sum_{m=1}^{J}\sum_{n=1}^{K} \beta_{K+J+KK+JJ+mn}(OE_n * SE_m) + \varepsilon$$

mit
$OE: Objekteigenschaft$
$SE: Standorteigenschaft$
$\alpha: Regressionskonstante$
$\beta: Regressionskoeffizient$
$\varepsilon: Störterm$

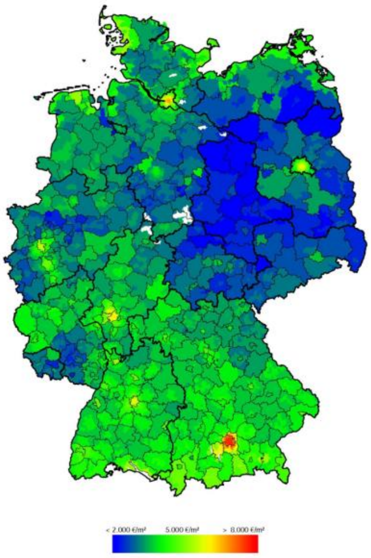
3.2 Results

The resulting model gives us the one hand the possibility to make predicts for a specific property. On the other hand, it allows us to understand and visualise the effect and the interaction of certain characteristics and how these have a combined effect on the overall value. As an example the combined influence on the rental income of construction year and living can be seen below.

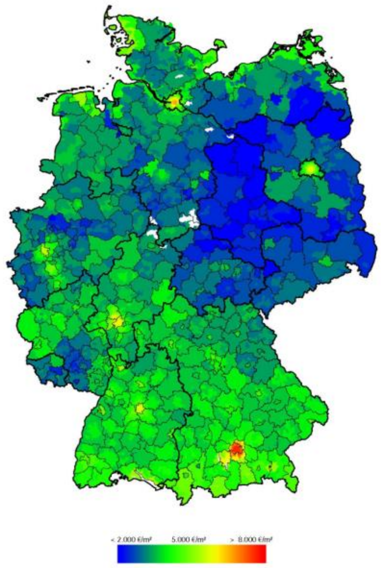


Regarding the year of construction, a non-linear relationship can be observed. Additionally, for the years of construction between 1950 and 1999, the living space is valued differently. For all categories, the values of larger apartments are lower than those of smaller ones. There is a significant difference for the years of construction from 1950 to 1999.

Based on the nation-wide model, the value of a property can be calculated for every location regardless of the presents of observations in that region if all locations characteristics are known. The direct and indirect influence of the location on the value is explicitly modelled with the interaction between the property and location characteristics. The following maps show the predicted rent and market value of a specific apartment for every zipcode in Germany. This demonstrates the potential for such models in regions with only few transactions as it allows data driven insights.



House Prices in Germany



Appartement prices in Germany

4. CONCLUSION

AVMs have the potential to be valuable tools for real estate professionals if used properly. Rather than replacing human appraisers, AVMs can supplement their work by providing data and insights that can inform their valuations. The key is to use AVMs as a supportive tool, not a replacement for human expertise. For example, the use of AVMs can significantly accelerate the appraisal process and reinforce and support the in-depth analysis of the appraiser with additional explanatory approaches of the AVM.
This approach allows appraisers to have a better understanding of how individual property characteristics are being evaluated by the AVM and incorporate this information into their own analysis.

One main contraint of using AVMs in the appraisal process is the lack of transaprency and interpretability because of the ”black box” nature of AVMs due to the complexity of the underlying algorithms that generate valuations, which make it hard to understand the factors that lead to a specific valuation.

Therefore, our approach is to explicitly model the relationships in the AVM and by this, using the fast analysis power of AVMs to identify the value influencing factors and the strength of their influence on the property's value instead of using it to predict the final value of the property.
The appraiser can then use this information to gain deeper knowledge on all influences and tosignificantly improve the efficiency and accuracy of real estate appraisals. This approach can improve efficiency and transparency in the valuation process, while also ensuring that the valuation remains based on factual information and professional judgment and without undermining the role of the human appraisers.

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BIOGRAPHICAL NOTES

Dr. Christina Mauer and Dr. Maximilian Schlachter started their research on real estate valuation during their PhD at Technical University Munich in 2015. During that time, they published several papers about valuation methods and their difficulties in renowned journals. Dr. Mauer then worked as a fund manager for a large international real estate fund while Dr. Schlachter worked as a Senior Data Scientist at one of the largest real estate data providers in Germany. Both were confronted with the practical problems of the valuation industry during this time and therefore decided to found their company, einwert, to create new solutions based on digital tools.

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