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ABSTRACT

Automated Valuation Models (AVMs) have been used by mortgage industry participants for a number of years with a limited degree of success. A lack of comprehensive data and thus restricted reliability has prevented AVMs from being fully adopted by governments, lenders, brokers, and the like. This paper presents a framework for building an intelligent property valuation model that overcomes these problems. An overview of AVM research, a survey of current AVM products and several interviews with industry participants were conducted. The findings revealed a number of important elements for optimal AVMs. This paper also provides a description of a unique dataset combining both appraisal data and public record data. This information combined with well established data mining techniques including clustering, geocoding, and ensembles provides the basis for further research towards building a new property valuation method that better meets industry needs.

Keywords

Automated valuation model (AVM), Collateral database, Neighborhood, Spatial correlation

INTRODUCTION

Business intelligence (BI) refers to applications and technologies that enable decision makers to make more informed business decisions by improving the timeliness and quality of information. BI tools that help many mortgage lenders make a decision to accept or deny each loan application have been developed and tested with limited success. Collateral assessment has been the core of mortgage loan decision making because industry authorities and academicians have agreed that the most important determinant for loan default is the loan-to-value ratio (von Furstenberg, 1969). As a consequence property appraisals have played a key role in assuring lenders that collateral value is sufficient to avoid losses once a loan has been originated. Lenders rely upon appraisals for assurance that collateral value is sufficient to avoid losses in the case of non-repayment. Agents and brokers also rely upon appraisals to guarantee the completion of a transaction and ultimately their own compensation. Unfortunately, the professionals who generate appraisals are under a great deal of pressure from all sides of the transaction, which makes it difficult to generate an objective appraisal report (Ferguson, 1988). For example, a loan officer's compensation is tied to the success of the deal, leaving them with a natural incentive to make sure appraisals are high enough to satisfy loan-to-value requirements. In the same vein, appraisers who are concerned about maintaining regular business relationships and a steady stream of income have an incentive to make sure appraisals meet these expectations.

Various automated valuation models (AVMs) have been developed in the past 20 years to satisfy the needs for an innovative way of assessing a specific property while eliminating any human factors (see Table 1). AVMs are computer programs that use information such as property characteristics, sales price, and market trends to determine a value for a specific property. Most AVMs employ a variety of valuation techniques including both model-driven (e.g., multiple regression analysis) and data-driven (e.g., neural networks) techniques, and often use multiple techniques together to estimate market values of a property. From a cost perspective, AVMs are very attractive to lenders who typically pay upwards of $250 for a traditional appraisal and also offer significant time savings leading to customer service enhancements (Waller, 1999). Despite the promises of cost and time savings, AVM's have been slow to gain widespread acceptance, which motivates this study.

The remainder of this paper is organized as follows. We first highlight several research questions and why they are important to look at. We also explain two different research methodologies used for this study. Then, we discuss the implications, advantages and disadvantages of AVMs, and present a summary of many AVMs. Next, we present our findings from formal and informal interviews with an appraiser, a broker, and a bank manager. Based on our findings from several interviews, reviews on various AVMs, and literature reviews, we identify a list of core elements that an optimal AVM should have. In the following section, we introduce our data set and our approach to build such an AVM. Finally, we conclude the paper with some suggestions for possible future research.

LITERATURE REVIEW

Literature Review of Real Estate Valuation Method

In our study, we divide real estate valuation methods into three main categories, traditional, model-driven, and data-driven methods. One of the most widely used traditional methods is the comparable method. In this approach, the appraiser first selects several similar properties (i.e. comparables) from among all the properties that have recently been sold assuming that the value of the property being appraised (i.e. the subject) is closely related to the selling prices of similar properties within the same market area. The appraiser estimates the current value of the subject by adjusting the selling price of each comparable to account for differences in size, age, quality of construction, selling date, and the surrounding neighborhood. Note that the comparable method is heavily dependent on the availability, accuracy, completeness, and timeliness of sale transaction data from public records, data vendors, and the appraiser's network of local contacts. Further, the process of finding comparables and weighting the differences in characteristics between the subject and the comparable can ultimately change the outcome of the appraisal (McCluskey et al., 1997). Other traditional evaluation methods include the income method (using the present value of the predicted cash flow from rental income), profit method (assessing the potential revenue and costs), development method for plots and sites (using the difference between the value of comparable vacant land sales and the value of the land after fully developed), and simple statistical regression models (Des Rosiers et al., 2000).

Model-driven methods include advanced statistical models such as the hedonic pricing method (Janssen et al., 2001), autoregressive integrated moving average (ARIMA) (Tse, 1996), Monte Carlo simulation method (Hoesli et al., 2006), and various spatial statistical models with geographical information system (GIS) tools (Peterson 1998). These methods are model-driven because all of them are mathematical and statistical models based on certain assumptions on parameters and error terms of underlying pattern structures. To study the effects of the uncertainty of valuation parameters for real estate valuation, Hoesli et al. (2006) used Monte Carlo simulations and presented the entire distribution of estimated values. Spatial analysis methods try to identify a spatial distribution and relationship that best represents real estate markets and use it to predict values. Since the process of identifying spatial relationships requires the detection of neighborhoods that show spatial relationships, this approach may not work well with unsold properties.

Data-driven methods make no assumptions on parameters and error terms in finding a mapping function that best represents the relationship between the property attributes and the market price of the subject. Data-driven methods include artificial neural networks (ANNs) (Borst, 1992) and fuzzy logic (Pagourtzi et al., 2006). Note that ANNs are capable of approximating non-linear functions and can replace multiple regression methods for multi-parametric comparative assessments. It is the universal approximation property of ANNs that makes ANNs one of the most popular algorithms for temporally correlated data. The universal approximation property implies that with an infinite number of hidden nodes, multi-layer neural networks can approximate any function arbitrarily close. Recently, a new architecture based on GIS techniques integrated with fuzzy theory and spatial analysis has been presented and evaluated for a prediction task of house sale prices (Pagourtzi et al., 2006).

Preliminaries of AVMs

AVMs are computer programs that determine a market value for a specific property by using various techniques and information. Several AVMs available on the Internet are presented in Table 1. AVMs emerged in the early 1980's to validate human appraisals by eliminating the possibility of subjective human factors and the tendency to justify loan amounts rather than delivering objective price estimates. Note that eliminating human factors in real estate appraisal is important to minimize the risk to a wide variety of stakeholders. For example, borrowers or home buyers who have purchased a home at an overstated price are susceptible to losing a significant amount of equity and more serious consequences like bankruptcy if they have to sell in the case of a market downturn. Investors are also exposed to a significant amount of risk. Banking systems and even whole economies are vulnerable to market changes when they use overvalued property as collateral for loans. The property crash in the United Kingdom during the 1970's and the savings and loans crisis in the United States during the 1980's have both been directly tied to improper valuation practices and fraudulent appraisals (Gilbertson and Preston, 2005). Since most AVMs use only objective information such as property characteristics, sales prices, and market trends, they are relatively free from human factors. AVMs cost less and can be completed quickly, often in seconds, which leads to customer service enhancements and further cost reductions.

Despite the promises of cost and time savings, AVMs have been slow to gain widespread acceptance. One of the possible reasons is that AVMs are inherently black-box models, making it difficult to understand how they determine the value of a subject. However, the most important reason for their slow adoption is lack of comprehensive data and hence limited reliability (Waller, 1999). Note that AVMs do not work well in an area where public records information is poor and tax assessments are very inaccurate as in a nondisclosure state or rural areas. In terms of accuracy, AVMs are also limited because they cannot make value adjustments beyond property characteristics. AVMs cannot fully consider subjective but important factors such as a superior view and the neighborhood environment. Further, AVMs cannot automatically consider new remodels without updated information and cannot distinguish between finished space and unfinished space.

Table 1: Representative AVMs

Product	Company	Coverage	Description
ValuePoint	First American	National	One of the early pioneers in the AVM industry. Works well with limited (or no) property characteristics such as square footage, bedrooms, and bathrooms. Unique coverage that no other public records service provides.
PSAR	PSAR Systems	National	Considered the father of modern AVM products. Requires geographic and date of sale information only. Utilizes a two-pronged approach, sales comparison and regression analysis.
CASA	Fiserv	National	Combines analysis from many different approaches including hedonic, sales comparison, repeat sales, non-linear regression. Unique in that it utilizes home price forecasting to provide near real time valuation estimates.
HVE	Freddie Mac	National	15 year old product relies upon repeat sales and hedonic models. Provides a forecast standard deviation for determining reliability of confidence scores and suggests methods for validating against out of sample data.
HPA	First American	National	Considered the industry standard for index-based AVMs. Utilizes repeat sales and hedonic models for valuations. Indexes are constructed from 200 million historical records and 100 million properties.

DATA DESCRIPTION AND RESEARCH MODEL

Data Description[1]

Since the first credit reporting more than 100 years ago, lenders have shared their customers' credit information to minimize their risk which in turn benefited borrowers by ensuring more funds were available for them. To realize similar benefits by sharing of appraisal property information and to provide global access to this appraisal data, FNC Inc. created the National Collateral Database (NCD) in 2006. The NCD is based on two major sources, public record data from a national public record company and appraisal data from lenders, appraisal companies, government agencies, and individual appraisers. It consists of 138.5 million county assessor records (including residential, commercial, vacant land, etc.), over 2,700 assessor counties (87% of the counties in the country), over 1,330 deed counties (current sales information, sales prices where available), sales information for the past 3 ½ years (about 85 million records), and over 8 million appraisals, which is updated at least once a year. In terms of appraisal data, FNC receives and processes appraisals from over 2,940 counties (94% of all counties in the U.S.), and processes approximately 400,000 appraisals per month which contain information on over 1 million properties per month. In public recordings, FNC receives and processes deed/recording updates in 42% of counties in the US (1,334 out of 3,141 counties), which are received and updated daily. The process of combining these disparate data sources to create a unified database is shown in Figure 1. The data set for our study is a fraction of the NCD, a set of records in Orange County in Los Angeles.

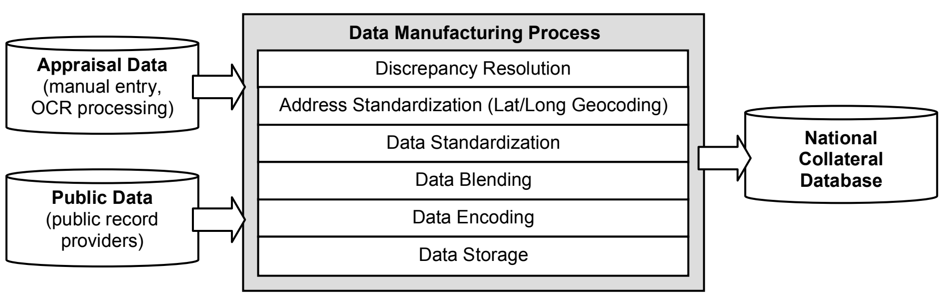

Figure 1: Manufacturing process for the National Collateral Database

[1] Data description in this section is a short summary of FNC report, "The National Collateral Database: Overview and Potential Applications," 2006.

Until FNC's NCD is made available, most lenders will be forced to rely on two sources of data for residential properties; regional multiple listing services (MLS) and public record data providers. However, appraisal information provides additional information about a property because appraisers utilize all available information from not only a combination of public record and MLS, but also physical property inspections and past appraisals that they have completed to create a valuation for the property. This process of combining data from various sources along with their local market knowledge and physical inspection of the property make the appraisal the best and most timely source of data. Further, there is information not only on the subject property but also sales and physical characteristic information on at least three comparable properties, which provides a great deal of cross verification information about the properties. Sharing appraisal data can provide timely and better detailed information on comparable properties handled by other lenders, allowing for more sound values with less complex valuation products. Shared, standardized, readily accessible collateral data also has positive implications for capital markets. Lenders would have access to the best possible analytics on collateral, thereby reducing their costs of processing and underwriting valuations.

Research Questions and Methodology

This study intends to provide answers (or at least provide a framework) to several research questions. First, this study intends to find answers to the questions such as what are the minimum functionalities of an AVM and how can we design an intelligent and reliable AVM. For this purpose we conducted interviews with three main business partners (an appraiser, mortgage broker, and lender) in the mortgage market to provide a consolidated overview on AVMs. Then, we claim that it is in our best interest to combine the expertise of human appraisers and the convenience of AVMs, and present a conceptual and theoretical framework to design such a system that is intelligent and reliable. Our analysis is not possible without full access to the consolidated database. One of authors is a co-founding member of FNC. Inc and is currently helping us obtain a segment of NCD for this study. We believe that once our automated appraisal model is calibrated and tested on a consolidated database, after rigorous model building phases, it can significantly improve the performance and reliability of traditional AVMs. For the conceptual framework for our proposed model, please refer to the subsequent section entitled Conceptual Framework Toward an Intelligent Property Valuation Model.

Another interesting research question is what characteristics define good neighborhoods (or comparables) and how can we select them among possibly hundreds of thousands of candidates? Note that most human appraisers and AVMs estimate a market value of the subject by adjusting their initial estimates after comparing interior and exterior characteristics of the subject to similar comparables. Since a real estate property is a geographically determined commodity, location or distance from the subject would be an important factor in identifying good neighbors. In addition, subjective attributes that are important to buyers and human appraisers can be considered to narrow the list down further. Finally, temporal correlations between the subject and the neighboring properties should be also considered. We intend to identify these neighborhood factors through three different approaches. First, we conducted an interview with an appraiser to directly learn about appraisal procedures. According to our findings, few temporal and physical characteristics such as age of the dwelling, lot size, square footage, and the number of bedrooms and bathrooms are considered important. Second, we surveyed what information AVMs utilize for their appraisals considering them as possible candidates. Finally, we will identify other key factors such as spatial relationships and distributions from existing literature.

Knowledge Discovery in Appraisal Database

For the purpose of finding interesting but unexpected patterns from the appraisal database, we will take a reverse engineering approach to find common appraisal practices and how important each attribute is in the appraisal process. This knowledge discovery process will provide insights on whether human appraisers misrepresent the value of the subject because of the pressures coming from externalities. With our access to the appraisal database, we will be able to validate whether or not the appraisal was completed in accordance with the relevant regulations (e.g., in the Uniform Standards of Professional Appraisal Practice (USPAP)) and detect potential areas of fraud. The appraisal database can also be mined to create a clear picture of regional economic activity by providing answers to questions such as what modifications are people making to their houses, what characteristics are now appearing in new houses that are different than older houses, what locations are in the highest demand, and what home variables are the most effective in quickly selling a house (FNC, 2006).

We also expect to develop a clear status of the current residential mortgage market. Note that each appraisal provides information on both the neighborhood and the status of the market. While it is true that appraisers tend to be optimistic about the current condition of each market, as a whole, the favorable ratings tend to decrease as the market gets weaker. As the market begins to weaken, the transaction dates for the comparable properties on the appraisal tend to get older and their proximity to the subject gets further away. This provides a quantifiable and very timely measure of the strength of each market. In particular, we will also reverse engineer the appraisal database to find common patterns of appraisal practices, how important physical and locational variables are in the process of determining a final appraisal value of a specific property, how human experts resolve conflicts of interest, and how they respond to pressures coming from externalities. Several research questions related to appraisal practices are summarized as follows:

- On average, how many comparables are used in each appraisal and how many comparables are under-valued or over-valued compared to the chosen subject? For each appraisal, we expect three comparables, an under-valued comparable, a similar-valued comparable, and an over-valued comparable in terms of market price.
- What is the distribution of higher and lower prices of comparables? We may represent it in terms of the ratio of subject price to comparable price. This will give a rough estimate of neighborhood in terms of price.
- Which attributes (physical, price, and distance) are the most critical to determine the candidacy of comparables and how important are they in the process of determining the final estimate of the subject?
- In how many cases, is the estimated value of the subject lower than loan amount, resulting in denial of loan application?
- How do appraisers adjust a market price of the subject from market prices of comparables? In particular, how do appraisers adjust their estimates based on subjective factors such as superior views and neighborhoods?
- Is it worth it to employ human experts to evaluate subjects when 15% of error margins are acceptable?

Once we identify useful and interesting patterns such as contribution of the subject's attributes to the final appraisal value, we would like to graphically represent them for easy interpretation and visualization. This visualization tool will also include graphical representation of housing price variations as the absolute location (longitude, latitude coordinates) changes in a specific housing market. Ultimately, much more accurate, timely and geographically specific indices will be developed in terms of sales price, market and neighborhood conditions and physical property characteristics. This will make it possible to have the opportunity to quantify the collateral risk and will enable pricing to incorporate the collateral risk.

EXPLORATORY STUDY ON PERCEPTION AND BIAS OF AVM

Three Perspectives from an Appraiser, Mortgage Broker, and Bank Manager

Three interviews with different industry participants—a professional appraiser, a loan officer who worked for a mortgage broker and a bank manager from a major national lender—were conducted in January and February of 2007. The interviews followed a loose format whereby questions about general processes, understanding of AVMs and their use were asked. Participants also discussed some of the difficulties they faced and needs that were not being met. The main objective of an interview with an appraiser is to understand the general process, from initial request to delivery of appraisal report. Our interview revealed that human appraisers heavily rely on their own knowledge of the local market and a physical inspection of the outside perimeter and interior room dimensions to determine a market price of the subject. In particular, during the physical inspection, our interviewee mentioned that he noted any negative and positive items (e.g., superior front view and clean and well maintained neighborhoods), drew up property structural characteristics, and actually calculated square footage, rather than simply quoting a public record. For the purpose of defining neighborhoods to select comparables, our interviewee first used MLS to look up similar properties based on key characteristics such as number of bedrooms, number of bathrooms and square footage within a one mile radius of subject. When good comparables were not found within a one mile radius of the subject, he continuously expanded the radius until suitable comparables were found. From this observation we conclude that physical distance from the subject is the most important criteria in determining neighborhoods and, within the given distance limit, differences in physical characteristics of comparable candidates are used to adjust the value of the subject.

Another interesting observation made from this interview is that the human appraiser feels an enormous amount of pressure from all parties from real estate agents or lenders. Through this interview, we found out that, on average, the lender disputed appraisals 25% of the time and that the appraiser conforms by making adjustments. Note that due to many subjective items like a superior front view, an adjusted value may be still acceptable, and whether or not the appraiser stands firm with any party is purely up to his own judgment. However, appraisers have a strong motivation to adjust the estimated value of the property because everyone has a vested interest in seeing the loan go through underwriting. Our interviewee does not consider an AVM as an additional option for making property assessments.

In contrast, both the loan officer and bank manager showed positive attitudes on AVMs, indicating that they sometimes conducted their own property assessments in addition to the professional appraiser's report. The loan officer made an assessment based on a quick look at comparable listings pulled from local MLS data or employed an AVM strategy. The loan officer considered physical characteristics such as square footage and number of bedrooms and bathrooms important to define comparables. In the event that the variance between the different assessments seemed outside accepted norms, both interviewees indicated they simply requested an adjustment by the original appraiser or they ordered completely new assessments from different appraisers whom they knew from experience produced results more in line with their expectations. The bank manager indicated that AVMs were a key part of their overall business strategy, and roughly 35-40% of booked loans are decided based on AVM results alone. However, due to government stipulations, AVMs can only be used for loans less than $250,000. Overall, AVMs are an attractive choice to lenders in terms of reduction ($10 vs. $250), time savings (seconds vs. days), and a customer service and general competitiveness point of view. For these reasons, they have a whole team to study the best usage of AVMs and employ one industry expert on AVMs to lead that effort.

Human vs. Machine Appraisals

Many professional appraisers, home owners, and some major risk-assessment firms point out several limitations of AVMs such as incapability for considering subjective factors (e.g., neighborhood and view), possibility of using an unreliable and faulty database of comparables, limited flexibility and inadaptability of incorporating new information related to interior and exterior renovation of the properties, and lack of visual inspection. In an extreme case, they claim that AVMs always indiscriminately compare the subject to incompatible neighborhoods because computers cannot see the difference between them. However, similar arguments can be made on appraisals by human appraisers. It is well known that appraisers are under pressure from loan applicants and loan officers, and it is tempting for appraisers to adjust the estimated value of the property to avoid a cut-off in supply of future work. Note that if valuation was an exact science, there would be no need for independent, third-party, arbitrators to settle rent review disputes. Note also that real estate price information managed by state and federal government based on a survey of professional appraisals can be inaccurate when there are fundamental structural changes in real estate markets. Shimizu and Nishimura (2006) point out that significant discrepancies exist between actual transaction prices and appraisal land price information in Japanese Government's published land price information system (PLPS, so-called Koji-Chika).

Due to its convenience and timeliness, AVMs are growing in acceptance (Waller, 1999). However, the accuracy and reliability of an AVM becomes crucial for lenders when considering borrowers with marginal credit scores. While AVMs can be quite accurate, particularly when used in a very homogeneous area, AVMs are not accurate in rural areas or when the subject does not conform well to the neighborhood (e.g., when there is a renewal of a single city block, changing neighboring homes in poor condition to homes in excellent condition). An analysis of 10 leading AVMs by FNC for homes purchased in June and July of 2006 covering 48 states revealed that 50% of the valuations for each of the models were off by at least 20%. Therefore, extreme caution should be exercised when relying on AVMs, especially if the user is unfamiliar with modeling and the local markets. With improved accuracy of AVMs, it might be possible for lenders to offer the loan at a different interest rate to compensate for the risk they are taking.

CONCEPTUAL FRAMEWORK TOWARD AN INTELLIGENT PROPERTY VALUATION MODEL

Identification of Neighborhoods Based on Temporal and Spatial Correlations

The importance of identifying the neighborhood environment for property evaluations was recognized long ago. According to Solow (1946), real estate evaluation consists of two distinct parts, the appraisal of structures and dwellings of the property itself and the evaluation of environmental factors. The definition of neighborhood in real estate evaluation can be identified in terms of temporal and spatial correlations. Neighborhoods based on a temporal relationship (temporal neighbors) are basically real estate properties transacted within a pre-defined time window. Temporal correlation becomes more critical when housing prices change rapidly over the time dimension. Clearly, the last year's housing price is a better indicator of the current year’s housing price than that of many years ago. Statistical models developed for temporally correlated data analysis include autoregressive (AR), moving average (MA), autoregressive and moving average (ARMA), and autoregressive integrated moving average (ARIMA) models. These models are linear models and assume the constancy of the mean and standard deviation of a stochastic process. Algorithms based on ANNs (Riedmiller, 1994) and its variants have also been used to predict, classify, and describe temporally correlated data. Commonly multi-layer perceptrons with sigmoidal and radial basis function have been used to replace the linear stochastic model, AR (p) model. A different type of neural network, the recurrent neural network (RNN) (Elman, 1990), has also been proposed to model temporally correlated data sets.

Spatial stochastic processes are defined typically over longitude and latitude, and effects may diminish within relatively short distances. A variety of spatial statistical methods with proxies such as the average price of housing in surrounding areas or a spatial moving average of price have been used to uncover localized trends in housing prices. According to many prior studies, housing values are significantly affected by local environmental quality, neighboring nonresidential land uses and proximity to negative externalities. Besner (2002), among all physical variables, selected the age variable as the most effective measure of similarity to represent the spatial dependence of individual house prices because houses built during a particular period share specific technological and architectural characteristics. However, it is also known that proximity is a more important factor than similarity in determining spatial dependence (Besner, 2002). In Fik et al. (2003), the importance of absolute location is studied to explain housing price variations in an urban residential housing market.

Computerized Automated Mass Assessment (CAMA) Systems

Property appraisal is required for housing transactions, the governmental need to assess market values of properties for residential tax purposes, and the lenders' need to estimate the value of loans in their portfolio to assess loan loss reserves (Thrall, 1998). For real estate transactions, appraisal is typically done on a single-property basis by a certified appraiser. Perhaps the largest problem associated with human appraisals for mass assessment (e.g., residential tax assessment) is the prohibitive cost and therefore operational infeasibility of finding comparable properties when large numbers of properties are involved. Although the price of appraisal for a single-family dwelling may not be a large component of the overall closing costs, it may become a considerable administrative expenditure if it involves a large number of properties (Thrall, 1998). In addition, manual appraisal of large numbers of properties takes a long time to complete. Together these factors led to the use of computerized automated mass assessment (CAMA) systems to automate appraisal.

One of the problems of using CAMA systems for lending purposes is how to control inputs and outputs. Everyone in the loan origination process is interested in some way in making the loan. Modifying the inputs (boundary of comparable search, even size of building) to create a favorable answer is a mighty temptation. Even foreclosure is unlikely to result in regret if the mortgage has been securitized and the originator gets paid to service the loans in the package. In property tax assessment, by contrast, there are contesting interests and a quasi-legal dispute resolution process. The assessor, arguably, wants assessments as high as defensibly possible. The taxpayers, clearly, want their assessments low. Disputes are normally adjudicated in assessment appeal. The county assessor is frequently an elected office. The contest of interests tends to refine the accuracy of the valuation results.

Identification of Submarket Structure

It has been shown that residential property markets consist of multiple submarkets defined in terms of geographical boundaries, economic or environmental characteristics or the physical characteristics of the properties. Most researchers have used statistical techniques to define housing submarkets. Whether or not the recognition of submarkets can improve the reliability of out-of-sample predictions for a large housing market is studied in Bourassa et al. (2003). Following their suggestions, we would like to first divide the market into several submarkets using clustering algorithms. After identifying several submarkets, we will calibrate a prediction model for each submarket utilizing information on the sale prices and physical characteristics of the properties within a given segment. Each model then will be used to estimate values for the properties that did not transact. Bourassa et al. (2003) notes that the ultimate goal of clustering is to find submarket structure for accurate estimates of house values, not to find relatively homogeneous submarkets. It should be noted that prediction models based on very homogeneous submarkets of few samples are not very reliable because of large standard errors, which in turn makes prediction inaccurate for properties that did not transact because the properties that transacted may differ from those that did not.

Design of Ensemble Models for Property Evaluation

To accurately determine the market value of a given property, we will utilize a special type of predictive models, ensemble classifiers (or ensembles) that have been well studied in data mining community. An ensemble is a meta-classifier that combines the predictions of individual classifiers called base classifiers with the equal weight or weights based on estimated prediction accuracy. Ensemble models have demonstrated consistent—in some cases, remarkable—improvements in prediction accuracy over individual classifiers at the cost of model complexity. Bagging (Breiman, 1996) and Boosting (Freund & Schapire, 1996) are the most popular methods to create ensembles based on sampled records from the original data set. In Bagging, each classifier is calibrated on a randomly drawn training set with the probability of drawing any given example being equal, while Boosting (Freund & Schapire, 1996) produces a series of classifiers and new classifiers are constructed to better predict examples for which the current ensemble's performance is poor. Ensembles can also be constructed by having individual base classifiers built on a different subset of the original predictive variables (Ho, 1998) or by considering multiple ensembles simultaneously in an evolutionary environment (Kim et al., 2006).

Ensembles within the field of mass appraisal and valuation are investigated in McCluskey and Anand (1999) who recognized unique advantages of integrating multiple models to complement some of the discrete problems of individual techniques. The various hybrid architectures are considered to incorporate a k-nearest neighbor algorithm (k-NN), neural networks and genetic algorithms (Goldberg, 1999) to discover variable weights in the distance metric towards matching categorical variables to retrieve neighbors. In our study, we will test different ensembles by combining various evaluation methods (e.g., traditional multiple regression models, ANNs, and k-NN) to boost not only the accuracy but also reliability of predictive models. It is also possible to develop ensembles that combine single or different evaluation methods trained onto the subspace of selected variables such as physical and locational characteristics, sales history, and comparable sales.

CONCLUSION

Over the years a number of AVMs including traditional, model-driven, and data-driven variations have been developed to mitigate the effect of human factors on property valuation. However, despite the promise of convenience, timeliness, and lower costs, industry has been slow to fully adopt them. This is primarily due to a lack of comprehensive data and thus limited reliability. In this study we presented a framework for building an intelligent property valuation model that addresses these shortcomings. The proposed method relies upon a unique database provided by FNC Corporation. This dataset is a comprehensive combination of both appraisal data and public record data. This information combined with well established data mining techniques including clustering, geocoding, and ensembles will provide the basis for research in building a new property valuation method that better meets industry needs.

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