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A Comparison of Regression and Artificial Intelligence Methods in a Mass Appraisal Context

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Abstract This paper describes a comparative study where several regression and artificial intelligence (AI)-based methods are used to assess properties in Louisville, Kentucky. Four regression-based methods [traditional multiple regression analysis (MRA), and three non-traditional regression-based methods, Support Vector Machines using sequential minimal optimization regression (SVM-SMO), additive regression, and M5P trees], and three AI-based methods [neural networks (NNs), radial basis function neural network (RBFNN), and memory-based reasoning (MBR)] are applied and compared under various simulation scenarios. The results indicate that non-traditional regression-based methods perform better in all simulation scenarios, especially with homogeneous data sets. AI-based methods perform well with less homogeneous data sets under some simulation scenarios.

The need for unbiased, objective, systematic assessment of real property has always been important, and never more so than now. Misleading prices for so-called level-three assets, defined as those classified as hard to value and hard to sell, have reduced confidence in balance sheets of financial institutions. Lenders need assurance that they have recourse to actual value in the event of default. Investors in large pools of asset-backed securities must have the comfort of knowing that, while they cannot personally examine each asset, those assets have been valued reliably. As always, valuations determined for real property have significant tax implications for current and new owners and must be substantiated in the courtroom in extreme cases. Annual property tax at the local level, as well as the occasional levy of estate and gift tax at the federal and state levels, is a function of the assessed value. Furthermore, the dissolution of a business or a marriage and the accompanying distribution of assets to creditors and owners require a fair appraisal of any real property.

In the United States, county/municipal tax assessors perform more appraisals than any other profession. Customarily they rely on a program known as Computer-

Assisted Mass Appraisal (CAMA). This affords them defense against accusations of subjectivity. Assessed values, initially based on sales price, are normally required by local law to be revised periodically with new data about more recent sales in the neighborhood. Conscientious assessors evaluate the quality of their operations by analyzing the degree to which their system's assessed values approximate actual sales prices.

The traditional approach to mass assessment has been based on multiple regression analysis (MRA) methods (Mark and Goldberg, 1988). MRA-based methods have been popular because of their established methodology, long history of application, and wide acceptance among both practitioners and academicians. The limitations of traditional linear MRA for assessing the value of real estate have been recognized for some time (Mark and Goldberg, 1988; Do and Grudnitski, 1992). These limitations result from common problems associated with MRA-based methods, such as the inability of MRA to adequately deal with interactions among variables, nonlinearity, and multicollinearity (Larsen and Peterson, 1988; Mark and Goldberg, 1988; Limsombunchai, Gan, and Lee, 2004). More recently artificial intelligence (AI)-based methods have been proposed as an alternative for mass assessment (Do and Grudnitski, 1992; Worzala, Lenk, and Silva, 1995; Guan and Levitan, 1997; McGreal, Adair, McBurney, and Patterson, 1998; Krol, Lasota, Nalepa, and Trawinski, 2007; Taffese, 2007; Guan, Zurada, and Levitan, 2008; Peterson and Flanagan, 2009).

The results from these studies have so far been mixed. While some studies show improvement in assessment using AI-based methods (Do and Grudnitski, 1992; Peterson and Flanagan, 2009), others find no improvement (Limsombunchai, Gan, and Lee, 2004; Guan, Zurada, and Levitan, 2008). A few studies even find neural networks (NN)-based methods to be inferior to traditional regression methods (Worzala, Lenk, and Silva, 1995; Rossini, 1997; McGreal, Adair, McBurney, and Patterson, 1998). Given the recognized need to improve accuracy and efficiency in CAMA and the great potential of AI-based methods, it is important for the assessment community to more accurately understand the ability of AI-based methods in mass appraisal. However, though there have been a number of studies in recent years comparing MRA with AI-based methods, meaningful comparison of the published results is difficult for a number of reasons. First, in many reported studies, the models have been built on relatively small samples. This tends to make the models' predictive performance sample specific. Moreover, data sets used for analysis have often contained different numbers and types of attributes and the predictive performance of the models has been measured using different error metrics, which makes the direct comparison of their prediction accuracy across the studies difficult. Finally, most of the studies have either focused on the predictive performance of a single method or compare the predictive accuracy of only a few methods such as MRA (or its linear derivatives), NN, and occasionally k-nearest neighbor.

Though AI-based methods have drawn a lot of attention in recent years in the appraisal literature, there is relatively little mention of another class of prediction methods that have been developed to avoid the common problems in the traditional MRA regression-based approach. In particular, Support Vector Machines using sequential minimal optimization regression (SVM-SMO), additive regression, and M5P trees are among the most well-known such methods (Quinlan, 1992; Wang and Witten, 1997; Witten and Frank, 2005). These methods have been successfully tested in fields outside the mass assessment literature and merit attention.

This paper attempts to address the above-mentioned comparative issues in previous studies by conducting a more comprehensive comparative study using a large data set. The data set contains over 16,000 transactions of recent sales records and has 18 attributes per record commonly used in mass appraisals. The data set is also very heterogeneous in terms of features and number of neighborhoods. Seven different models are built and tested. In addition to the traditional MRA model and an NN model, this study also introduces models such as M5P trees, additive regression, SVM-SMO regression, radial basis function neural networks (RBFNN), and memory-based reasoning (MBR). Five different simulation scenarios are used to test the models. These scenarios are designed to test the effect of a calculated input to capture the locational dimension and the effect of clustering/segmentation of the data set into more homogeneous subsets. The results are compared and analyzed using five different error measures. In general, the simulation results show that non-traditional regression-based methods (additive regression, M5P trees, and SVM-SMO) perform as well as or significantly better than AI-based methods by generating lower error estimates. In particular, non-traditional regression-based methods tend to perform better in simulation scenarios where the data sets are more homogeneous and contain more recently built properties. The results for non-traditional regression-based models are not as impressive for low-end neighborhoods, as these houses represent more mixed, older, and less expensive properties.

This paper is organized as follows. The relevant literature is reviewed first. Next, there is a description of the data set and its descriptive statistics. After the data description there is a brief introduction to the four less commonly used models tested in this study. This is followed by a presentation of the error measures and performance criteria. The next two sections describe the computer simulation scenarios and present and discuss the results from the simulations. The paper closes with concluding remarks.

Literature Review

Multiple regression analysis (MRA) has traditionally been used as the main method of mass assessment of residential real estate property values (Mark and Goldberg, 1988). Methodological problems associated with MRA have been known for some time and they include non-linearity, multicollinearity, function form misspecification, and heteroscedasticity (Larsen and Peterson, 1988; Mark and Goldberg, 1988; Do and Grudnitski, 1992). Several AI methods, such as NN, have been introduced into mass assessment research to address these problems in

MRA. The most commonly studied methods are NN-based (Do and Grudnitski, 1992; Byrne, 1995; Worzala, Lenk, and Silva, 1995; Guan and Levitan, 1997; Rossini, 1997; McGreal, Adair, McBurney, and Patterson, 1998; Nguyen and Cripps, 2002; Guan, Zurada, and Levitan, 2008; Peterson and Flanagan, 2009). Some studies have reported that NN-based approaches produce better results when compared with those obtained with MRA (Do and Grudnitski, 1992; Nguyen and Cripps, 2002; Peterson and Flanagan, 2009) while others have reported comparable results using NN-based methods but have not found NN-based methods to be superior (Guan and Levitan, 1997; Limsombunchai, Gan, and Lee, 2004). Authors of other studies, however, are more skeptical of the potential merits of the NN-based approaches (Rossini, 1997; Worzala, Lenk, and Silva, 1995; McGreal, Adair, McBurney, and Patterson, 1998; Limsombunchai, Gan, and Lee, 2004). The main criticisms include the black box nature of NN-based methods, lack of consistency, and difficulty with repeating results. Worzala, Lenk, and Silva (1995) find that NN-based methods do not produce results that are notably better than those of MRA except when more homogeneous data are used. McGreal, Adair, McBurney, and Patterson's (1998) study leads their authors to express concerns similar to those by Worzala, Lenk, and Silva (1995). Rossini (1997) finds MRA yields consistent results, while NN results are unpredictable.

In addition to NN-based methods, other AI methods have also been explored in real estate valuation, including fuzzy logic, MBR, and adaptive neuro-fuzzy inference system (ANFIS) (Byrne, 1995; Bagnoli and Smith, 1998; Gonzalez and Formoso, 2006; Guan, Zurada, and Levitan, 2008). Fuzzy logic is believed to be highly appropriate to property valuation because of the inherent imprecision in the valuation process (Byrne, 1995; Bagnoli and Smith, 1998). Bagnoli and Smith (1998) also explore and discuss the applicability of fuzzy logic to real property evaluation. Gonzalez and Formoso (2006) compare fuzzy logic to MRA and find that fuzzy logic produces slightly better results. While fuzzy logic does seem to be a viable method for real property valuation, its major disadvantage is the difficulty in determining fuzzy sets and fuzzy rules. A solution to this is to use NN to automatically generate fuzzy sets and rules (Jang, 1993). Guan, Zurada, and Levitan (2008) apply this approach, called Adaptive Fuzzy-Neuro Inference System (ANFIS), to real property assessment and show results that are comparable to those of MRA.

In addition to NN and ANFIS there have also been a few studies that explore the use of other AI-based methods. Case-based reasoning (i.e., memory-based reasoning) is one such method. It intuitively appeals to researchers because of its closeness to the use of sales comparables in real estate appraisals (Bonissone and Cheetham, 1997; Soibelman and Gonzalez, 2002; Taffese, 2007). Gonzalez and Laureano-Ortiz (1992) introduce the case-based reasoning approach to real estate appraisal. They believe the case-reasoning approach closely resembles the psychological process a human appraiser goes through in assessing prices. Their results indicate that case-based reasoning is a promising approach. Bonissone and Cheetham (1997) point out a major shortcoming of the case-based reasoning approach. They show that in the typical case-based reasoning process, the steps of selecting the comparables have not captured the intrinsic fuzziness in such a process. Their proposed solution is to select similar cases for a given property using a weighted aggregation of the decision-making preferences, expressed as fuzzy membership distributions and relations. McCluskey and Anand (1999) use a hybrid technique based on NN and a genetic algorithm to improve the prediction ability of NN. Their approach is enhanced by the use of a nearest neighbor method for selecting comparables. The hybrid method produced the best results when compared with those by MRA and NN.

Most of the reported studies are based on relatively small sample sizes, with the exception of a couple of studies (Gonzalez and Formoso, 2006; Peterson and Flanagan, 2009). Studies with a small sample size tend to make the resulting error estimates sample specific and less realistic and do not allow one to generalize the prediction results, especially when k-fold cross-validation or a similar technique is not used in building and testing the models. The current study uses a large and diverse sample. A 10-fold cross-validation is applied and each experiment repeated from 3 to 10 times (described in the section on simulation scenarios) (Witten and Frank, 2005). Consequently, the data subsets used to train the models are fully independent from the data subsets used to test the models. The error estimates are then averaged over all folds and runs to obtain reliable, realistic, and unbiased error measures.

Description of Data Sample

The chief tax assessment official in Louisville, Kentucky granted access to the complete database of over 309,000 properties and 143 variables. About 222,000 properties were identified as residential properties. The database represents properties belonging to about 20 Tax Assessor (TA) districts, divided into more than 400 TA neighborhoods, which are in turn divided into about 8,000 TA blocks. For each property, attributes include the most recent sale price and date, the current assessed value, and significant characteristics such as square feet on each floor, garage size, and presence of air conditioning. The data set was reduced to only those properties with actual sales dates and prices within the most recent five years, 2003–2007, which was approximately 20,000 records. Vacant lots and properties being used commercially were then excluded. Next, the records were cleansed to eliminate obvious errors, repeated records representing group sales, inconsistent coding, and missing values common in any database that large, eventually reducing the size to 16,366 observations and 18 variables that were used for analysis.

One of the most important input variables in the real estate valuation context is the location of the property. Location of the property could be captured by implementing its spatial *x-y* coordinates in the model (Bourassa, Cantoni, and Hoesli, 2010). This paper introduces an approach based on the available assessment data set. In the original data set, location has been represented by a set of the three nominal variables representing a relatively small TA block within a larger TA neighborhood within an even larger TA district. Representing the property location in this manner is infeasible as each value of the nominal variables is encoded as a separate input variable. This approach would increase the dimensionality of the data set by introducing hundreds of additional dummy variables, thereby substantially diminishing the predictive capability of the models. Thus, the location is presented as a calculated variable, i.e., as the mean sale price of all properties within a particular neighborhood within a district. This attribute and/or the median sale price would normally be available to property tax assessors, appraisers, real estate agents, banks, home sellers, realtors, private professional assessors, as well as potential buyers. According to the information provided by the tax assessment official in April 2009, one of the ways to assess (or reassess) the value of a property for tax purposes in the area in which these data were collected is to sum the sale prices of all similar properties sold recently in the immediate neighborhood of the house, divide it by the total square footage of these properties and multiply by the square footage of the property to be assessed.

The basic descriptive statistics of this data set, including frequency counts and percentages, are presented in Exhibits 1 and 2. Each variable in Exhibit 1 (measured on the ratio scale or interval scale) represents an input to the models. In Exhibit 2, each of the ordinal variables, *Number of baths* and *Lot type*, represents an input. For the variable *Construction type*, each level represents a dummy variable. As a result, three dummy variables are created as input, one for each construction type level. For nominal variables, each distinct level of the variables is represented by a dummy variable. For example, since the *Garage type* variable has six levels (0–5), six dummy variables are created as input to the models, one for each level. One can see that the data set is diverse in terms of neighborhoods, sale prices, lot types and sizes, year built, square footage on the floors, number of bathrooms, etc.

Description of Methods

Seven different models are built and tested. In addition to the traditional MRA model and an NN model, this study also employs models such as M5P trees, additive regression, SVM-SMO regression, RBFNN, and MBR. Because MRA, NNs, and MBR have been used quite extensively and are well-known in the assessment research community, this research examines the four remaining methods, i.e., M5P trees, additive regression, SVM-SMO regression, and RBFNN in this section. Exhibit 3 contains a brief summary of the four new methods.

MRA, which is a useful linear model, suffers from some well-known problems. MRA, however, forms a foundation for more sophisticated, nonlinear models. Like NNs, the three MRA-based methods described in this section are able to approximate nonlinear functions and can capture more complex relationships between attributes in many practical applications.

Exhibit 1 | Descriptive Statistics for the Ratio and Interval Variables

Attribute	Mean	Std. Dev.	Max.	Min.	Median
Sale price ($)	159,756	98,686	865,000	17,150	134,925
Year property sold	2005	1.2	2007	2003	2006
Quarter of sale	2.48	1.04	4	1	2
Land size (acres)	0.27	0.48	17.34	0.15	0.21
Year built	1968	31.2	2006	1864	1967
Square footage in basement (feet)	831.9[a] 190.1[b]	416.7[a] 402.1[b]	2,952[a] 2,952[b]	30[a] 0[b]	753[a] 0[b]
Square footage on floors (feet)	1,582.1	649	7,459	556	1,404
Number of fireplaces	0.51	0.5	1	0	1
Garage size (number of cars)	1.14	0.87	2	0	1
Mean sales prices ($) *of all properties within TA_ District in TA_Neighborhood*	159,756	88,398	535,000	31,150	133,894

Notes:

[a] Only 3,739 houses that contain a basement are included in the calculations. For some other houses ,the area of a full basement may be included in the total square footage.

[b] All 16,366 houses are included in the calculations. (If a property does not have a basement, its feature value is represented by a 0.)

Exhibit 2 | Frequencies for the Nominal and Ordinal Variables

Attribute	Values Taken	Frequency	Percent	Type of Attribute	Label
Number of baths	0	11	0.07	Ordinal	Sub-standard
	1	5,562	33.99		1 Bath
	2	1,635	9.99		1½ Baths
	3	4,445	27.16		2 Baths
	4	3,073	18.78		2½ Baths
	5	751	4.59		3 Baths
	6	889	5.43		>3 Baths
Presence of central air	0	2,214	13.53	Nominal	None
	1	14,152	84.67		Present
Lot type	1	14,150	86.46	Ordinal	Small (≤0.25 acre)
	2	1,706	10.42		Medium (0.25–0.5 acre)
	3	246	1.50		Large (0.5–0.75 acre)
	4	264	1.61		Tract (>1 acre)
Construction type	1	9,579	58.83	Ordinal	1.0 Story
	2	3,146	19.22		1.5 Story
	3	3,641	22.25		2.0 Story
Wall type	1	6,862	41.93	Nominal	Frame
	2	9,268	56.63		Brick
	3	236	1.44		Other
Basement type	0	6,214	37.97	Nominal	None
	1	1,691	10.33		Partial
	2	8,461	51.70		Full or Complete
Basement code	0	6,211	37.95	Nominal	None
	1	10,155	62.05		Standard
Garage type	0	5,001	30.56	Nominal	None
	1	132	0.81		Carport
	2	4,279	26.15		Detached
	3	6,435	39.32		Attached
	4	448	2.74		Garage in basement
	5	71	0.43		Build in garage

Notes: The values taken for the variables in this table are the way that they appear in the raw data, as well as the way that they are used for estimation purposes.

Broadly speaking, an additive regression technique combines the output of multiple models that complement each other and weighs a model's contribution by its performance rather than by giving equal weights to all models (Friedman, Hastie, and Tibshirani, 2000). For example, a forward stagewise additive model starts with an empty ensemble and incorporates new members (models) sequentially, maximizing the predictive performance of the ensemble as a whole. The technique is often called a boosting method because the performance of the

Exhibit 3 | Summary Description of the New Methods

M5P Trees	Additive Regression	SVM-SMO Regression	RBFNN
M5P trees are ordinary decision trees with linear regression models at the leaves that predict the value of observations that reach the leaf. The nodes of the tree represent variables and branches represent split values. Model tree induction algorithms derive from the divide-and-conquer decision tree methodology. Unlike classification trees, which choose the attribute and its splitting value for each node to maximize the information gain, model trees choose them to minimize the intra-subset variation in the class values down each branch and maximize the expected error reduction (standard deviation reduction). The fact that the tree structure divides the sample space into regions and a linear regression model is found for each of them makes the tree somewhat interpretable.	Additive regression is a way of generating predictions by combining contributions from an ensemble (collection) of different models. Additive regression usually starts with an empty ensemble and adds new models sequentially. Each new model, as it is incorporated into the ensemble, focuses on those instances / cases where the ensemble performs poorly to boost the overall performance of the ensemble. Each new model is added in such a way that it maximizes the performance of the ensemble without compromising the predictive abilities of the existing ensemble.	SVM is a classification and regression method based on the concept of decision planes. SVM's initial introduction suffered from having to rely on quadratic programming solvers for training, a problem which has since been solved through the use of sequential minimal optimization or SMO. SVM makes use of a (nonlinear) mapping function that transforms data in input space to data in feature space in such a way as to render a problem linearly separable.	RBFNN emerged as a variant of NN in late 1980s. An RBFNN is typically embedded in a two layer neural network with each hidden unit implementing a radial activation function. The output unit implements a weighted sum of the hidden unit outputs. RBFNNs are known for their excellent approximation capabilities and their ability to model complex mappings.

ensemble model is gradually enhanced by focusing repeatedly on the training patterns that generate large residuals that are given higher weights. It is clear that this technique, if not controlled by cross-validation, may lead to undesired overfitting because in each subsequent stage the model added fits the training data more closely.

Gradient boosting builds additive regression models by sequentially fitting a simple parameterized function (base learner) to current pseudo-residuals by least squares at each iteration. The pseudo-residuals are the gradient of the loss function being minimized, with respect to the model values at each training data point, evaluated at the current step. More formally the boosting technique can be presented as follows (Friedman, Hastie, and Tibshirani, 2000). Let y and $\mathbf{x} = \{x_1,..., x_n\}$ represent an output variable and input variables, respectively. Given a training sample $\{y_i, \mathbf{x}_i\}_1^N$ of known (y, $\mathbf{x}$)-values, the goal is to find a function $F^*(\mathbf{x})$ that maps $\mathbf{x}$ to y, such that over the joint distribution of all (y, $\mathbf{x}$)-values, the expected value of some specified loss function $\boldsymbol{\Psi}(y, F(\mathbf{x}))$ is minimized:

$$F^*(\mathbf{x}) = \arg\min_{F(\mathbf{x})} E_{y,\mathbf{x}} \boldsymbol{\Psi}(y, F(\mathbf{x})). \tag{1}$$

Boosting approximates $F^*(\mathbf{x})$ by an additive expansion of the form:

$$F(\mathbf{x}) = \sum_{m=0}^{M} \beta_m h(\mathbf{x}; \mathbf{a}_m), \tag{2}$$

where the functions $h(\mathbf{x}; \mathbf{a})$ (base learner) are usually chosen to be simple functions of $\mathbf{x}$ with parameters $\mathbf{a} = \{a_1, a_2,...a_m\}$. The expansion coefficients $\{\beta_m\}_0^M$ and the parameters $\{\mathbf{a}_m\}_0^M$ are jointly fit to the training data in a forward stage-wise manner. The method starts with an initial guess $F_0(\mathbf{x})$, and then for $m = 1, 2,..., M$:

$$(\beta_m, \mathbf{a}_m) = \arg\min_{\beta,\mathbf{a}} \sum_{i=1}^{N} \boldsymbol{\Psi}(y_i, F_{m-1}(\mathbf{x}_i) + \beta h(\mathbf{x}_i; \mathbf{a})) \tag{3}$$

and

$$F_m(\mathbf{x}) = F_{m-1}(\mathbf{x}) + \beta_m h(\mathbf{x}; \mathbf{a}_m). \tag{4}$$

Gradient boosting by Friedman, Hastie, and Tibshirani (2000) approximately solves (3) for arbitrary (differentiable) loss function $\boldsymbol{\Psi}(y, F(\mathbf{x}))$ with a two-step procedure. First, the function $h(\mathbf{x}; \mathbf{a})$ is fit by least-squares:

$$\mathbf{a}_m = \arg \min_{\mathbf{a},\rho} \sum_{i=1}^{N} [\tilde{y}_{im} - \rho h(\mathbf{x}_i; \mathbf{a})]^2 \tag{5}$$

to the current pseudo-residuals:

$$\tilde{y}_{im} = -\left[\frac{\partial \Psi(y_i, F(\mathbf{x}_i))}{\partial F(\mathbf{x}_i)}\right]_{F(\mathbf{x})=F_{\mathbf{m}-\mathbf{1}}(\mathbf{x})}, \tag{6}$$

Then, given $h(\mathbf{x}; \mathbf{a}_m)$, the optimal value of the coefficient β_m is determined:

$$\beta_m = \arg \min_{\beta} \sum_{i=1}^{N} \boldsymbol{\Psi}(y_i, F_{m-1}(\mathbf{x}_i) + \beta h(\mathbf{x}_i; \mathbf{a}_m)). \tag{7}$$

This strategy replaces a potentially difficult function optimization problem (3) by one based on least squares (5), followed by a single parameter optimization (7) based on the general loss criterion $\boldsymbol{\Psi}$ [adapted from Friedman, Hastie, and Tibshirani (2000)].

M5P tree, or M5 model tree, is a predictive technique that has become increasingly noticed since Quinlan introduced it in 1992 (Quinlan, 1992; Wang and Witten, 1997). Model trees are ordinary decision trees with linear regression models at the leaves that predict the value of observations that reach the leaf. The nodes of the tree represent variables and the branches represent split values. The fact that the tree structure divides the sample space into regions and a linear regression model is found for each makes the tree somewhat interpretable. Model tree induction algorithms derive from the divide-and-conquer decision tree methodology. Unlike classification trees, which choose the attribute and its splitting value for each node to maximize the information gain, model trees minimize the intra-subset variation in the class values down each branch. In other words, for each node a model tree chooses an attribute and its splitting value to maximize the expected error reduction (standard deviation reduction).

An M5P tree is built in three stages (Wang and Witten, 1997). In the first stage a decision tree induction algorithm is used to build an initial tree. Let T represent a set of training cases where each training case consists of a set of attributes and an associated target value. A divide and conquer method is used to split T into subsets based on the outcomes of testing. This method is then applied to the resulting subsets recursively. The splitting criterion is based on the standard deviation of the subset of values that reach the current node as an error measure. Each attribute is then tested by calculating its expected error reduction at the node. The attribute that maximizes the error reduction is chosen. The standard deviation reduction is calculated as follows:

$$SDR = sd(T) - \sum_i \frac{T_i}{T} \times sd(T_i), \tag{8}$$

where T is the set of training cases and T_i are the subsets that result from splitting the cases that reach the node according to the chosen attribute. Splitting in M5P stops when either there is very little variation in the values of the cases that reach a node or only a very few cases remain.

In the second stage of the tree construction process the tree is pruned back from each leaf. The defining characteristic of an M5P tree is in replacing a node being pruned by a regression model instead of a constant target value. In the pruning process the average of the absolute differences between the target value and actual value of all the cases reaching a node to be pruned is calculated as an estimate for the expected error. This average will underestimate the expected error because of the unseen cases so it is multiplied by the factor:

$$p' = \frac{(n + v)}{(n - v)}, \tag{9}$$

where n is the number of training cases that reach the node and v is the number of parameters in the model that represents the class value at that node.

The last stage is called smoothing to remove any sharp discontinuities that exist between neighboring leaves of the pruned tree. The smoothing calculation is given as follows:

$$p' = \frac{np + kg}{n + k}, \tag{10}$$

where p' is the predicted value passed up to the next higher node, p is the predicted value passed to this node from below, g is the predicted value of the model at this node, n is the number of training cases that reach the node below, and k is a constant (the common value is 15). The above described process of building a model tree by Quinlan (1992) is improved by Wang and Witten (1997) and this study uses the improved version referred to as M5′ or M5P.

SVM is a relatively new machine learning technique originally developed by Vapnik (1998). The basic concept behind SVM is to solve a problem, i.e., classification or regression, without having to solve a more difficult problem as an intermediate step. SVM does that by mapping the non-linear input attribute space into a high dimensional feature space. A linear model constructed in the new feature space represents a non-linear classifier in the original attribute space. This linear model in the feature space is called the maximum margin hyperplane, which provides maximum separation into decision classes in the original attribute space. The training cases closest to the maximum margin hyperplane are called support vectors.

As an example suppose there are data from an input/attribute space ***x*** with an unknown distribution $P(\boldsymbol{x}, y)$, where y is binary, i.e., y can have one of two values. This two-class case can be extended to a k class classification case by constructing k two-class classifiers (Vapnik, 1998). In SVM a hyperplane separating the binary decision classes can be represented by the following equation:

$$y = \mathbf{w} \cdot \mathbf{x} + w_0, \tag{11}$$

where y is the output, ***x*** is the input vector, and ***w*** is the weight vector. The maximum margin hyperplane can be represented as follows (Cui and Curry, 2005):

$$y = b + \sum a_i y_i \mathbf{x}(i) \cdot \mathbf{x}, \tag{12}$$

where y_i is the output for the training case $\boldsymbol{x}(i)$, b and a_i are parameters to be determined by the training algorithm, and ***x*** is the test case. Note that $\boldsymbol{x}(i)$ and ***x*** are vectors and $\boldsymbol{x}(i)$ is the support vectors. Though the example given above is for the binary classification case, generalization to multiclass classification is possible. For an m class case, a simple and effective procedure is to train one-versus-rest binary classifiers (say, “one” positive, “rest” negative) and assign a test observation to the class with the largest positive distance (Boser, Guyon, and Vapnik, 1992; Vapnik, 1998). This procedure has been shown to give excellent results (Cui and Curry, 2005).

The above discussion has been restricted to the classification cases. A generalization to regression estimation is also possible. In the case of regression estimation, $y \in R$ and an attempt is made to construct a linear function in the feature space so that the training cases stay within an error > 0. This can be written as a quadratic programming problem in terms of kernels:

$$y = b + \sum a_i y_i K(\mathbf{x}(i), \mathbf{x}), \tag{13}$$

where $K(\mathbf{x}(i), \mathbf{x})$ is a kernel function.

Vapnik (1998) shows that, for linearly separable data, the SVM can find the unique and optimal classifier called the maximum margin classifier or optimal margin classifier. In practice, however, the data or observations are rarely linearly separable in the original attribute space, but may be linearly separable in a higher dimensional space specially constructed through mapping. SVM uses a kernel-induced transformation to map the attribute space into the higher dimensional feature space. SVM then finds an optimal linear boundary in the feature space that maps to the nonlinearly separable data in the original attribute space. Converting to the feature space may be time consuming and the result difficult to store if the feature space is high in dimensions. The kernel function allows one to construct a separating hyperplane in the higher dimensional feature space without explicitly performing the calculations in the feature space. Popular kernel functions include the polynomial kernel:

$$K(x, y) = (xy + 1)^d, \tag{14}$$

and the Gaussian radial basis function:

$$K(x, y) = \exp\left(\frac{-1}{\delta^2}(x - y)^2\right), \tag{15}$$

where d is the degree of the polynomial kernel and δ^2 is the bandwidth of the Gaussian radial basis function kernel.

Since its introduction SVM has attracted intense interest because of its admirable qualities, but it had been hindered for years by the fact that quadratic programming (QP) solvers had been the only training algorithm. Osuna, Freund, and Girosi (1997) show that SVMs can be optimized by decomposing a large quadratic programming problem into a series of smaller quadratic programming. Platt (1998) introduced sequential minimal optimization as a new optimization algorithm. Because SMO uses a subproblem of size two, each subproblem has an analytical solution. Thus, for the first time, SVMs could be optimized without a QP solver.

An RBFNN differs from a multilayer perceptron (a feed-forward NN with back-propagation) in the way the hidden neurons perform computations (Poggio and Girosi, 1990; Park and Sandberg, 1991). Each neuron represents a point in input space, and its output for a given training case depends on the distance between its point and the target of the training. The closer these two points are, the stronger the activation. The RFBNN uses nonlinear bell-shaped Gaussian activation functions whose width may be different for each neuron. The RBFs are embedded in a two-layer network. The Gaussian activation function for RBFNN is given by:

$$\phi(\mathbf{X}) = \exp\left\lfloor -(\mathbf{X} - \boldsymbol{\mu}_j)^T \sum_{j}^{-1} (\mathbf{X} - \boldsymbol{\mu}_j)\right\rfloor, \tag{16}$$

for $j = 1,..., L$, where $\boldsymbol{X}$ is the input feature vector and L is the number of neurons in the hidden layer. $\boldsymbol{\mu}_j$ and Σ_j are the mean and covariance matrix of the *jth* Gaussian function. The output layer forms a linear combination from the outputs of neurons in the hidden layer. The output layer implements a weighted sum of the hidden-layer outputs:

$$\psi_k(\mathbf{X}) = \sum \lambda_{jk}\varphi_j(\mathbf{X}), \tag{17}$$

for $k = 1,..., M$, where λ_{jk} are the output weights, each represents a connection between a hidden layer unit and an output unit and M represents the number of units in the output layer. For application in mass assessment, M will be 1. λ_{jk} shows the contribution of a hidden unit to the corresponding output unit. When $\lambda_{jk} > 0$, the activation of the hidden unit j is contained in the activation of the output field k. The output of the radial basis function is limited to the interval (0,1) by the sigmoidal function as follows:

$$Y_k(\mathbf{X}) = \frac{1}{1 + \exp[-\psi_k(\mathbf{X})]}, \tag{18}$$

for $k = 1,..., M$.

The network learns two sets of parameters: the centers and width of the Gaussian functions by employing clustering and the weights used to form the linear combination of the outputs obtained from the hidden layer. As the first set of parameters can be obtained independently of the second set, RFBNN learns almost instantly if the number of hidden units is much smaller than the number of training patterns. Unlike multilayer perceptron, the RBFNN, however, cannot learn to ignore irrelevant attributes because it gives them the same weight in distance computations [adapted from Bors (2001)].

Exhibit 4 | Performance Measures for Numeric Prediction

Error / Performance Measure	Formula
Root Mean-squared Error (RMSE)	$\sqrt{\dfrac{\sum_{i=1}^{n}(p_i - a_i)^2}{n}}$
Mean Absolute Error (MAE)	$\dfrac{\sum_{i=1}^{n}\lvert p_i - a_i\rvert}{n}$
Root Relative Squared Error (RRSE)	$\sqrt{\dfrac{\sum_{i=1}^{n}(p_i - a_i)^2}{\sum_{i=1}^{n}(a_i - \overline{a})^2}}$, where $\overline{a} = \dfrac{\sum_{i=1}^{n} a_i}{n}$
Relative Absolute Error (RAE)	$\dfrac{\sum_{i=1}^{n}\lvert p_i - a_i\rvert}{\sum_{i=1}^{n}\lvert a_i - \overline{a}\rvert}$
Correlation Coefficient (CC) Goodness of Fit (R^2) = CC^2	$\dfrac{S_{PA}}{\sqrt{S_p S_a}}$, where $S_{PA} = \dfrac{\sum_{i=1}^{n}(p_i - \overline{p})(a_i - \overline{a})}{n-1}$ $S_p = \dfrac{\sum (p_i - \overline{p})^2}{n-1}$, $S_A = \dfrac{\sum (a_i - \overline{a})^2}{n-1}$, and $\overline{p} = \dfrac{\sum_{i=1}^{n} p_i}{n}$
Mean Absolute Percentage Error (MAPE)	$\dfrac{\sum_{i=1}^{n}\left\lvert \dfrac{p_i - a_i}{a_i}\right\rvert}{n}$

Notes: p_i is the predicted sale price, a_i is the actual sale price, n is the number of observations, $i = 1 \ldots n$.

Error Measures and Performance Criteria

Model performance measures are essential in evaluating the predictive accuracy of the models. Exhibit 4 presents the error measures used for numeric prediction (Witten and Frank, 2005). The RMSE is the most commonly used and principal measure; it is expressed in the same units as actual and predicted sale values (dollars). The disadvantage of RMSE is that it tends to aggregate the effect of outliers. The MAE, also expressed in dollars, treats errors evenly according to their magnitude. If the range of the actual property sale prices in the data set is large, i.e., $17,150; $865,000, relative error measures expressed as percentages can also be useful in evaluating the predictive effectiveness of the model. For example, a 10% error for $17,150 and $865,000 is $1,715 and $86,500, respectively. If this 10% error is equally important in predicting both sale prices, RMSE and MAE will not capture this effect, but relative errors such as RRSE and RAE will. The RRSE expresses the root of the total squared error normalized by the total squared error of the default predictor. In other words, this error is made relative to what it would have been if a simple predictor had been used, i.e., the average of the actual values from the training data. In the two mentioned relative error measures, the errors are normalized by the error of the simple predictor that predicts average values. The two relative error measures try to compensate for the basic predictability or unpredictability of the dependent variable. If it lies fairly close to its average value, one can expect prediction to be good and the relative measure compensates for this. The correlation coefficient (CC) measures the statistical correlation between the actual and predicted values. The squared correlation coefficient is the goodness of fit, R^2. The use of five error measures in one study represents a very comprehensive attempt to evaluate and compare performance of different methods in mass assessment. This set is used internally to compare the predictive performance of the seven methods in each of the five scenarios. The mean absolute percentage error (MAPE) is then used to compare the predictive accuracy of the best models to the Freddie Mac criterion, explained below.

Computer Simulation Scenarios

The simulations were performed with SAS Enterprise Miner (EM) and Weka (Witten and Frank, 2005). The former is a well-known data analysis software developed and maintained by the SAS company (www.sas.com) and the latter is an open source software product designed for data mining available from the University of Waikato, New Zealand (Witten and Frank, 2005). Each of these software products is equipped with a set of convenient tools for modeling. Computer simulation was performed under five different scenarios and the predictive effectiveness of the methods on the test set was measured by five performance measures: MAE, RMSE, RRSE, RAE, and R^2. Scenarios 1 and 2 tested the models on the entire data set, which contained very heterogeneous properties in terms of their sale prices and features. Exhibits 1 and 2 show the descriptive statistics, including frequencies of the features used. For example, the smallest and largest property sale prices are $17,150 and $865,000, respectively.

Scenario 1 uses the 16 original input variables (along with the dummy variables), whereas in scenario 2, in addition to the original 16 input variables (also with dummy variables), an additional calculated input variable is used to represent ‘‘location.’’ This variable is introduced to capture the location dimension and is defined as the mean sale price of the properties within the TA district within the TA neighborhood, which, depending on the neighborhood, contains between 10 and 50 properties. Adding location as an input, as any assessor would do, significantly lowered the error estimates. This need to cluster or segment the data set can minimize problems associated with heteroscedasticity (Mark and Goldberg, 1988; Newsome and Zietz, 1992). Newsome and Zietz (1992) suggest that location based on home prices can be used as a basis for segmentation.

Since any given house may sell for a different price in a later year than it would in a previous year, even with no change in its attributes, sale prices have to be adjusted for general market inflation/deflation. Since the 16,366 records represent houses sold between 2003 and 2007, this study used the *Year of sale* and *Quarter of sale* variables to capture the general market macroeconomic effect in scenarios 1–4. As both variables are measured on the interval scale, they are treated as numeric variables and represent two inputs to the models. In scenario 5, the *Age* of the properties was calculated from the *Year of sale, Quarter of sale,* and *Year built* to capture the general market effect. The *Age* variable, which is clearly on the ratio scale, replaced the three mentioned variables in the models. The market effect could also be handled by a technique used in Guan, Zurada, and Levitan (2008). In that technique, the sale prices in the data set had been market-adjusted before they were used in the models. Another alternative would be to limit the sample to sales in a single year, although that would limit the validity and generalizability of the results due to the smaller data set size. It could be argued that the market-adjusted technique or just using the *Age* of the properties variable may have more merit as it reduces the number of input variables in the models and can make models simpler to explain.

In scenarios 3 through 5, automatic K-means clustering is used to group the properties into several more homogeneous clusters. K-means is one of the popular clustering procedures used to find homogeneous clusters in a heterogeneous data set. It works well with large data sets, and as most clustering algorithms, it is quite sensitive to the distance measures; however, the k-means algorithm may not work too well with overlapping clusters and may be sensitive to the selection of initial seeds, i.e., embryonic clusters. Euclidean distance was applied to measure the similarity between observations and the procedure was run for different initial seeds to ensure that they produced similar clusters. The models were tested on each cluster, and the models' performance measures were also examined. Grouping properties into clusters helped to identify that the models tested on segments containing more expensive and more recently built properties yielded better overall predictive performance, i.e., they produced significantly lower error estimates than models built on clusters consisting of mid-range and low-end properties.

In scenario 3, the clusters are based on all the 17 normalized input variables, including *Location,* and the normalized output variable, the *Sale price.* Exhibit 5 presents the features of the properties for the three clusters created. For example, one can see that cluster 1 includes 4,792 transactions representing more affluent properties with the mean *Sale price* of $269,388 and larger properties with the *Square footage on floors* of 2,261 sq. ft., as well as more recently built properties with the mean *Year built* = 1993. Clusters 2 and 3 represent less expensive properties, which are 50–60 years old.

Exhibit 5 | Feature Means and Standard Deviations for Three Clusters in Scenario 3

		Sale price	*Location*	*Square footage*	*Year*	*Number*		*Land*	*Garage*
	Observations	($)	($)	*on floors*	*built*	*of baths*	*Fireplace*	*size*	*size*
Cluster 1	4,792	269,388	256,852	2,261	1993	4.2	0.93	0.35	1.8
		94,593	80,167	621	18	1.1	0.25	0.57	0.4
Cluster 2	4,836	133,784	131,110	1,364	1955	2.2	0.50	0.24	1.1
		59,264	55,881	400	25	1.2	0.50	0.41	0.8
Cluster 3	6,738	100,426	111,261	1,256	1960	1.9	0.24	0.23	0.7
		47,109	50,231	407	32	1.1	0.43	0.45	0.8

Two variables were used creating the clusters for scenario 4: the normalized *Sale price* and *Location*; whereas scenario 5 utilized four attributes: *Sale price*, *Location*, *Age*, and *Square footage on floors*. In both scenarios 4 and 5, clusters 1 and 2 represent more affluent properties, while clusters 3, 4, and 5 contain mid-end and low-end properties located in less expensive neighborhoods in terms of property prices and their features. Exhibits 6 and 7 show the property features of each of the four and five clusters, respectively. For example, in Exhibit 6 one can see that cluster 1 includes 3,188 more affluent properties located in more affluent neighborhoods, with a mean *Sale price* of $318,399; larger properties in terms of the *Square footage on floors* (mean = 2,510 sq. ft.), as well as more recently built properties with the mean *Year built* = 1992. The five clusters in scenario 5 further discriminate properties in a more subtle way. The standard deviations of the features of the properties belonging to clusters 3 and 4 in scenario 4 and clusters 3 through 5 in scenario 5 show more variation, especially in terms of the sale price.

It appears that regardless of the number of attributes used for creating clusters for scenarios 3 through 5, in each of the three scenarios there is one or more distinct and homogeneous cluster that contains higher-end properties and other more heterogeneous and mixed clusters that include mid-range and less expensive properties. The means and standard deviations of the features presented in Exhibits 6 and 7 across all clusters confirm these observations. For example, in cluster l of scenario 5 (Exhibit 7), the percentage of the standard deviation of the actual sale prices to the mean of actual sale prices is $67,254/$521,429 = 12.9% and the same ratio for cluster 5 is $43,115/$108,804 = 39.6%.

A 10-fold cross-validation was used in all five scenarios and the experiments were repeated from 3 to 10 times to obtain true, unbiased, and reliable error measures of the models. In 10-fold cross-validation, a data set is first randomized and then divided into 10 folds (subsets), where each of the 10 folds contains approximately the same number of observations (sales records). First, folds 1–9 of the data set are used for building a model and fold 10 alone is used for testing the model. Then, folds 1–8, and 10 are employed for training a model and fold 9 alone is used for testing, and so on. A 10-fold cross-validation provides 10 error estimates. For clusters containing a larger number of observations, for example >5,000, the 10-fold cross-validation experiment was repeated 3 times, and for clusters with a smaller number of observations, it was repeated 10 times. In each new experiment the data set was randomized again. This process produced either 30 or 100 unbiased, reliable, and realistic error estimates. This approach also ensures that data subsets used to train the models are completely independent from data subsets used to test the models. The number of folds, 10, and the number of experiments, i.e., 3 or 10, have been shown to be sufficient to achieve stabilization of cumulative average error measures.

The error estimates were averaged across all folds and runs, which ensured that the training samples used to build the models were fully independent of the test samples. The statistical significance among the performance of the seven models

Exhibit 6 | Feature Means and Standard Deviations for Four Clusters in Scenario 4

	Observations	*Sale price ($)*	*Location ($)*	*Square footage on floors*	*Year built*	*Number of baths*	*Fireplace*	*Land size*	*Garage size*
Cluster 1	3,188	318,399	300,506	2,510	1992	4.4	0.95	0.41	1.9
		80,241	65,476	584	23	1.1	0.22	0.78	0.4
Cluster 2	3,673	184,779	193,931	1,739	1979	3.3	0.76	0.25	1.4
		31,614	27,023	393	30	1.0	0.43	0.29	0.7
Cluster 3	4,705	118,794	124,129	1,276	1964	2.1	0.39	0.27	0.9
		30,174	18,216	315	24	1.1	0.49	0.50	0.8
Cluster 4	4,787	74,512	74,641	1,140	1947	1.5	0.15	0.18	0.6
		30,656	17,905	324	28	0.9	0.34	0.16	0.8

Exhibit 7 | Feature Means and Standard Deviations for Five Clusters in Scenario 5

	Observations	*Sale price* ($)	*Location* ($)	*Square footage on floors*	*Age*	*Number of baths*	*Fireplace*	*Land size*	*Garage size*
Cluster 1	147	521,429	420,498	3,846	8.5	5.9	0.99	0.76	1.99
		67,254	85,149	611	9.7	0.4	0.08	1.10	0.17
Cluster 2	2,262	314,741	312,844	2,466	6.6	4.5	0.96	0.38	1.92
		72,485	36,972	490	9.9	1.0	0.19	0.67	0.31
Cluster 3	655	231,630	205,002	2,190	84.0	3.1	0.75	0.33	0.98
		77,417	57,029	681	19.0	1.3	0.43	0.82	0.87
Cluster 4	3,556	194,546	181,295	1,830	5.9	3.7	0.70	0.27	1.56
		52,175	38,367	432	8.2	0.8	0.46	0.49	0.63
Cluster 5	9,746	108,804	103,395	1,211	53.3	1.8	0.32	0.23	0.81
		43,115	39,491	322	24.2	1.0	0.47	0.35	0.85

was measured by a paired two-tailed *t*-test at $\alpha = 0.05$ (Witten and Frank, 2005) to see if the error measures across the models within each scenario were significantly different from the MRA models, which were the reference points.

Results from Computer Simulations

The simulation results showed that nontraditional regression methods such as additive regression, M5P trees, and SVM-SMO consistently outperformed MRA and MBR in most simulation scenarios. However, in scenarios 1 and 5, NN also performed very well, yielding significantly lower error estimates than MRA (Exhibits 8 and 12). In scenario 1, MBR outperformed MRA (Exhibit 8). It appears that the AI-based methods tend to perform better for heterogeneous data sets containing properties with mixed features and the nontraditional regression methods produce better results for more homogeneous clusters of properties.

Analysis of each of the five simulation scenarios and clusters allows one to gain more insight into the performance of the models. In scenario 1 (Exhibit 8), which includes all properties with very mixed features, additive regression, M5P trees, NNs, RBFNN, and MBR significantly outperform MRA across most error measures. However, there is no significant difference between the performance of MRA and SVM-SMO.

In scenario 2, additive regression and M5P tree outperform MRA across all five error measures (Exhibit 9). However, there is no significant difference between NN, and SVM-SMO compared to MRA. The performance of both RBFNN and MBR is significantly worse than that of MRA. One can also see that the models created on all samples using an additional attribute ‘‘location’’ generate significantly lower error estimates (Exhibit 9) than those in scenario 1 (Exhibit 8).

Exhibit 10 shows the simulation results for scenario 3 for all three clusters. Again, all models are compared to MRA, which is the baseline. One can see that SVM-SMO, additive regression, and M5P tree models stand out and yield significantly better results than MRA and the remaining methods across all error measures for all three scenarios. For cluster 1, which contains recently built and more affluent properties, the error estimates are low relative to the mean *Sale price* for this cluster ($269,388). The same error measures for clusters 2 and 3, which still contain a very mixed set of older and low-end properties (Exhibit 5), are much higher.

Exhibit 11 presents the results for scenario 4. Again, additive regression and M5P tree models perform significantly better than the remaining models across four clusters, yielding lower error estimates than the remaining models, and SVM-SMO performs significantly better than MRA in two of the four clusters. Occasionally, RBFNN also does well. One can see that, in particular, the models more accurately estimate the sale prices of properties belonging to clusters 1 and 2, which contain more expensive and newer properties (MAPE = 9.5%, Exhibit 15). For example,

Exhibit 8 | Error Measures for Seven Models Used in Scenario 1

	MRA	NN	RBFNN	SVM-SMO	MBR 10[a]	Additive Regression	M5P Tree
MAE ($)	29,564	28,692*	28,606*	29,470	26,485*	25,607*	25,949*
RMSE ($)	39,288	38,235	38,641*	39,439	36,985*	35,281*	35,802*
RAE (%)	38.9	37.8	37.7*	38.8	34.9*	33.7*	34.2*
RRSE (%)	39.8	38.8	39.2*	40.0	37.5*	35.8*	36.3*
R^2	0.85	0.86**	0.85**	0.85	0.86*	0.86**	0.86**

Notes: All 16,366 records and 16 input variables, without *Location*.

[a] The MBR uses 10 nearest neighbors.

*Significantly lower than MRA at $\alpha = .05$.

**Significantly higher than MRA at $\alpha = .05$.

Exhibit 9 | Error Measures for Seven Models used in Scenario 2

	MRA	NN	RBFNN	SVM-SMO Regression	MBR 10	Additive Regression	M5P Tree
MAE ($)	23,148	22,706	24,278**	22,690	22,915	19,956*	20,567*
RMSE ($)	31,472	30,755	32,949**	31,651	33,729**	28,139*	28,614*
RAE (%)	30.5	29.9	32.0**	30.2	30.9	26.3*	27.1*
RRSE (%)	31.9	31.2	33.4**	32.3	34.2**	28.5*	29.0*
R^2	0.90	0.92**	0.88*	0.90	0.88*	0.92**	0.92**

Notes: All 16,366 records and 16 input variables, with *Location*.

[a] The MBR uses 10 nearest neighbors.

*Significantly lower than MRA at $\alpha = .05$.

**Significantly higher than MRA at $\alpha = .05$.

Exhibit 10 | Error Measures for Seven Models Used in Scenario 3

				SVM-SMO		Additive	
	MRA	NN	RBFNN	Regression	MBR 10	Regression	M5P Tree
Panel A: Cluster 1							
MAE ($)	27,368	31,824**	27,640**	26,626*	29,671**	25,374*	26,685*
RMSE ($)	36,235	43,010**	37,317**	36,022	43,950**	34,719*	35,996*
RAE (%)	36.9	42.8**	37.3	35.9*	40.0**	34.2*	36.0*
RRSE (%)	38.4	45.4**	39.5**	38.1	46.5**	36.7*	38.1*
R^2	0.85	0.83*	0.85	0.86**	0.79*	0.86**	0.85
Panel B: Cluster 2							
MAE ($)	20,833	24,824**	22,832**	20,449*	24,190**	19,875*	20,045*
RMSE ($)	28,460	34,389**	30,777**	28,137*	33,951**	27,155*	27,255*
RAE (%)	47.0	55.8**	51.5**	46.1*	54.6**	44.9*	45.6*
RRSE (%)	48.1	58.0**	52.0**	47.6*	57.4**	45.9*	46.1*
R^2	0.77	0.72*	0.72*	0.77**	0.69*	0.79**	0.79**
Panel C: Cluster 3							
MAE ($)	17,133	19,419**	18,848**	16,928*	18,462**	16,303*	16,295*
RMSE ($)	23,152	26,589**	25,386**	23,080	26,125**	22,002*	22,035*
RAE (%)	46.5	52.7**	51.1**	45.9*	50.1**	44.2*	44.2*
RRSE (%)	49.2	56.4**	53.9**	49.0	55.5**	46.8*	46.8*
R^2	0.76	0.72*	0.71*	0.76	0.71*	0.77**	0.77**

Notes:

*Significantly lower than MRA at $\alpha = .05$.

**Significantly higher than MRA at $\alpha = .05$.

Exhibit 11 | Error Measures for Seven Models Used in Scenario 4

	MRA	NN	RBFNN	SVM-SMO Regression	MBR 10	Additive Regression	M5P Tree
Panel A: Cluster 1							
MAE ($)	31,579	33,259	29,887*	31,373*	32,196	29,187*	29,284*
RMSE ($)	40,871	44,075	39,069*	41,004	46,529**	38,966*	38,970*
RAE (%)	50.7	53.3	47.9*	50.3*	51.6	46.8*	47.0*
RRSE (%)	50.9	54.8	48.7	51.1	57.9**	48.5	48.5
R^2	0.74	0.64	0.76**	0.74	0.67*	0.76**	0.76**
Panel B: Cluster 2							
MAE ($)	17,832	18,828**	18,039	17,757	18,510	16,448*	16,978*
RMSE ($)	23,003	24,897**	23,173	22,967	24,979**	21,709*	22,280*
RAE (%)	69.1	72.9**	69.9	68.8	71.6	63.7*	65.8*
RRSE (%)	72.9	78.9**	73.4	72.8	79.1**	68.8*	70.6*
R^2	0.48	0.48	0.46	0.48	0.42*	0.53**	0.50**
Panel C: Cluster 3							
MAE ($)	16,583	18,879**	16,696	16,341*	17,822**	15,969*	16,033*
RMSE ($)	22,652	24,869**	22,786	22,659	24,670**	21,820*	21,906*
RAE (%)	70.9	80.8**	71.4	69.9*	76.3**	68.3*	68.6*
RRSE (%)	75.1	82.5**	75.5	75.1	81.8**	72.3*	72.6*
R^2	0.44	0.45	0.42	0.44	0.38*	0.48**	0.48**

Exhibit 11 | (continued)

Error Measures for Seven Models Used in Scenario 4

	MRA	NN	RBFNN	SVM-SMO Regression	MBR 10	Additive Regression	M5P Tree
Panel D: Cluster 4							
MAE ($)	16,545	19,073**	16,738**	16,392*	18,535**	16,282*	16,344*
RMSE ($)	21,176	24,564**	21,403**	21,026*	24,646**	20,854*	20,937*
RAE (%)	66.9	77.1**	67.8**	66.3*	75.0**	65.8*	66.1*
RRSE (%)	69.1	80.1**	69.8**	68.6*	80.4**	68.0*	68.3*
R^2	0.52	0.48*	0.52*	0.53**	0.41*	0.53**	0.53**

Notes:

*Significantly lower than MRA at $\alpha = .05$.

**Significantly higher than MRA at $\alpha = .05$.

the average age of properties belonging to cluster 1 is 17 years (average *Year built* = 1992) and the mean *Sale price* is $318,399. However, the same methods generate larger prediction errors for low-end properties built in the last 45–60 years grouped in clusters 3 and 4, with the mean *Sale price* of about $119,000 and $74,500, respectively. For example, for cluster 3 the MAPE is 16.9% (Exhibit 15).

Five clusters were created in scenario 5 based on the home sale price, location, age, and the floor size. Again, additive regression and M5P tree models stand out. Also, NN models do well for three out of five clusters (Exhibit 12). As in the previous scenarios with clusters, the models perform much better for clusters 1, 2, and 4, which contain the properties with the average home age of about seven years. For the three clusters, MAPE amounts to 7.0%, 10.2%, and 9.7%, respectively (Exhibit 15). However, none of the models predicts sufficiently well for clusters 3 and 5, which contain older properties, i.e., 84 and 53 years old on average, respectively. These two clusters also contain more mixed properties in terms of sale prices. See the mean *Sale price* and standard deviation in Exhibit 7.

Nontraditional regression-based methods such as additive regression, M5P trees, and occasionally SVM-SMO, are very appealing as they perform consistently better than other methods in all five simulation scenarios. The superior performance of SVM-SMO against MRA and AI-based methods observed in this study is consistent with those found in other fields (Viaene, Derrig, Baesens, and Dedene, 2002; Cui and Curry, 2005). AI-based methods (NNs, RBFNN, and MBR) tend to work better for less homogeneous and possibly overlapping clusters representing lower end neighborhoods. Another advantage of the regression-based methods is that they are easier to interpret than the black-box AI methods. For example, in M5P trees, knowledge is encoded in the regression parameters (Exhibits 13 and 14) and if-then rules (Exhibit 16), while in NN and RBFNN knowledge is represented in numerical connections between neurons, called weights, which are difficult to interpret.

The structure and parameters of the pruned M5P tree created for cluster 1 are presented as an example. This cluster contains properties located in more affluent neighborhoods and more recently built properties. The average property sale price and age are about $318,000 and 17 years, respectively. The M5P tree, along with additive regression, consistently outperformed other models in all five simulation scenarios. One can see that the tree is easy to interpret and shows the three significant variables *Floor*, *Basement* (square footage on the floors and basement), and *Location* (the average property sale price in the neighborhood). The branches and split values partition the tree into five segments represented by five linear models. Depending on the input values for the three variables, one of the five models is selected to calculate the predicted property sale price. For example, if the *Floor* (the square footage on the floors) is greater than 2,681 sq. ft., the linear model 5 (LM5) is selected to estimate the property sale price (right top branch of the tree). Similarly, if *Floor* ≤ 2,681 sq. ft., *Basement* ≤ 961 sq. ft., *Floor* ≤ 2,037 sq. ft., and *Location* ≤ $264,663, the linear model 1 (LM1) is

Exhibit 12 | Error Measures for Seven Models Used in Scenario 5

	MRA	NN	RBFNN	SVM-SMO Regression	MBR 10	Additive Regression	M5P Tree
Panel A: Cluster 1							
MAE ($)	37,627	37,888	38,285**	38,711**	41,479**	37,008*	36,967*
RMSE ($)	46,557	48,761**	47,865**	46,574	56,306**	45,529*	45,459*
RAE (%)	75.5	75.8	76.8**	77.8**	82.6**	74.2*	74.2*
RRSE (%)	70.9	73.9**	72.9**	70.8	84.1**	69.3*	69.2*
R^2	0.52	0.46*	0.49*	0.52	0.46*	0.53**	0.53**
Panel B: Cluster 2							
MAE ($)	31,444	30,806*	32,101**	31,672**	33,563**	31,417*	31,426
RMSE ($)	40,419	39,809*	41,352**	40,575**	43,793**	40,343*	40,362*
RAE (%)	53.8	52.7*	54.9**	54.2**	57.4**	53.7*	53.7*
RRSE (%)	55.8	55.0*	57.1**	56.0**	60.5**	55.7*	55.7*
R^2	0.69	0.71**	0.67*	0.69	0.64*	0.69**	0.69**
Panel C: Cluster 3							
MAE ($)	36,896	37,204	37,920**	38,661**	40,807**	36,598	36,591
RMSE ($)	44,828	46,143**	46,586**	44,828	53,827**	44,313*	44,239*
RAE (%)	76.1	76.2	78.1**	80.0**	82.0**	75.5	75.5
RRSE (%)	72.1	73.3	74.9**	72.2	82.7**	71.2*	71.1*
R^2	0.49	0.48	0.46*	0.49	0.40*	0.50**	0.50**

Exhibit 12 | (continued)

Error Measures for Seven Models Used in Scenario 5

	MRA	NN	RBFNN	SVM-SMO Regression	MBR 10	Additive Regression	M5P Tree
Panel D: Cluster 4							
MAE ($)	19,309	17,989*	21,977**	20,249**	20,840**	18,336*	18,351*
RMSE ($)	26,464	24,965*	30,269**	27,107**	30,257**	25,699*	25,708*
RAE (%)	47.9	44.7*	54.6**	50.3**	51.7**	45.5*	45.6*
RRSE (%)	50.8	48.0*	58.1**	52.1**	58.1**	49.4*	49.4*
R^2	0.74	0.77**	0.66*	0.74*	0.67*	0.76**	0.76**
Panel E: Cluster 5							
MAE ($)	17,199	16,808*	20,667*	17,339**	19,101**	16,791*	16,780*
RMSE ($)	22,817	22,168*	26,991**	22,876**	25,286**	22,114*	22,158*
RAE (%)	50.1	48.9*	60.2**	50.5**	55.6**	48.9*	48.8*
RRSE (%)	52.9	51.4*	62.6**	53.1**	58.7**	51.3*	51.4*
R^2	0.72	0.74**	0.61*	0.72*	0.66*	0.74**	0.74**

Notes:

*Significantly lower than MRA at $\alpha = .05$.

**Significantly higher than MRA at $\alpha = .05$.

Exhibit 13 | Parameter Estimates for the Five Smoothed Linear Regression Models

Attribute	LM1	LM2	LM3	LM4	LM5
Construction type = 2*	−576	−2,800	−9,693	−6,744	−2,281
Construction type = 3	−1,116	−11,963	−22,154	−7,211	22,507
Square footage of the basement	7.7	28.0	0.5	28.0	27.0
Square footage on the floors	21.6	75.6	54.3	77.1	83.5
Wall type = 2*	1,013	9,373	16,125	14,757	32,512
Wall type = 3	3,473	39,272	28,385	15,101	13,788
Basement type = 1 or 2*	3,763	41,756	32,549	1,304	21,217
Garage type = 1 or 3*	−12,162	24,268	−595	−1,061.7	−139.7
Garage type = 2	1,940	37,422	155	155	323
Garage type = 4 or 5	953	24,848	−560	−1,019	−229
Number of baths	461	3,451	8,839	4,331	7,195
Lot type	614	614	16,130	23,804	19,828
Garage size (number of cars)	258	258	141	192	—
Land size	4,931	−178	−2,974	−8,279	−70
Location mean price	0.204	0.102	0.2	0.36	0.286
Age	−135	2.3	333.1	−0.8	−319
Intercept	179,192	−10,894	9,715	−59,111	−89,709

Notes:

*The variable has nominal/ordinal values. The parameter values have been rounded. The parameter values for *Construction type* = 1, *Wall type* = 1, *Basement type* = 0, and *Garage type* = 0 are 0s.

Exhibit 14 | Example Computations for Linear Model 5 (LM5)

Attributes	LM5 Parameters	Example House Features	Comments	Partial Calculations
Construction type = 2	−2,281.0	2	1.5 story	−2,281
Basement size (sq. ft.)	27.0	900		24,300
Floor size (sq. ft.)	83.5	2,931		244,739
Wall type = 2	32,512.0	2	Brick	32,512
Basement type = 1	21,217.0	1	Partially finished	21,217
Garage type = 3	−139.7	3	Attached	−140
Baths	7,195.0	4		28,780
Lot type	19,828.0	1	≤0.25 acre	19,828
Land size (acre)	−70.0	0.16	Acre	−11
Age (years)	−319.0	44	Years	−14,036
Location	0.286	$410,000	Mean sale price in neighborhood	117,260
Intercept	−89,709			−89,709
Actual Sale Price	$399,950			
Predicted Sale Price	$382,458			
Residual	$17,492			

Notes: Variables: *Fireplace, Presence of central air,* and *Basement type* have been pruned. The rightmost column represents the partial calculations. For example, for the nominal variable *Construction type* = 2, the value of a regression coefficient is −2,281. Thus, the value of the coefficient is copied to the respective row in the rightmost column representing the contribution of this variable to the overall price. The regression coefficient 83.5 for the ratio variable *Floor size* is multiplied by 2,931 representing the square footage on the floors yielding 244,739 in the rightmost column. Finally, *Predicted sale price* represents the sum of the values shown in the rightmost column.

used. Exhibits 13 and 14 show the parameters of the five linear models and example calculations of the predicted price, respectively. The signs of the regression parameters for the five linear models help interpret the results. For example, the *Square footage of the basement*, *Square footage on the floors*, *Floor size*, *Basement type*, *Lot type*, and *Location* attributes have positive signs. This is a strength of the M5P method when compared with black-box AI methods such as NN-based methods. As expected, the M5P tree also discards relatively insignificant attributes such as *Presence of central air* and *Fireplace* as the vast majority of the properties in this cluster contain these two features. The algorithm does not generate the values for their parameters either.

Researchers use different performance measures across studies to compare the predictive effectiveness of the models used for automated mass appraisal. They

Exhibit 15 | MAPE and Percentages of Predictions within 5% through 25% of the Actual Sale Prices for the Best Models

Scenario	Cluster	Best Model	MAPE (%)	≤5%	≤10%	≤15%	≤20%	≤25%
2		Additive regression	18.0	25.9	48.2	64.4	74.9	81.9
3	1	Additive regression	10.3	35.5	62.2	80.5	89.6	94.5
4	1	Additive regression	9.5	36.1	65.5	82.3	90.5	94.9
4	2	Additive regression	9.5	38.9	66.0	82.4	90.1	94.1
4	3	Additive regression	16.9	26.7	50.1	67.5	78.4	85.1
5	1	M5P tree	7.0	38.2	78.8	93.1	97.2	99.3
5	2	Neural network	10.2	32.4	60.0	78.8	89.5	93.9
5	4	Neural network	9.7	36.7	64.3	82.1	90.9	95.3

are typically based on the mean or median of the predicted and actual sale prices. One of the commonly used error measures is MAPE. Also, lenders often set some threshold for model performance on the basis of which a model can be accepted or rejected. For example, Freddie Mac's criterion states that on the test data, at least half of the predicted sale prices should be within 10% of the actual prices (Fik, Ling, and Mulligan, 2003). The MAPE and percentages of predictions were calculated within 5%–25% of the actual sale prices for the best models (Exhibit 15). More than half of the models were very close or exceeded the Freddie Mac 50% threshold (Exhibit 15). In general, the models predict very well for the clusters of the properties built more recently and located in high-end neighborhoods. In addition, the best model in scenario 2 created on the entire data set consisting of 16,366 transactions was quite close to the Freddie Mac criterion and 48.2% of the predicted sale prices generated by this model were within 10% of the actual sale prices.

Conclusion

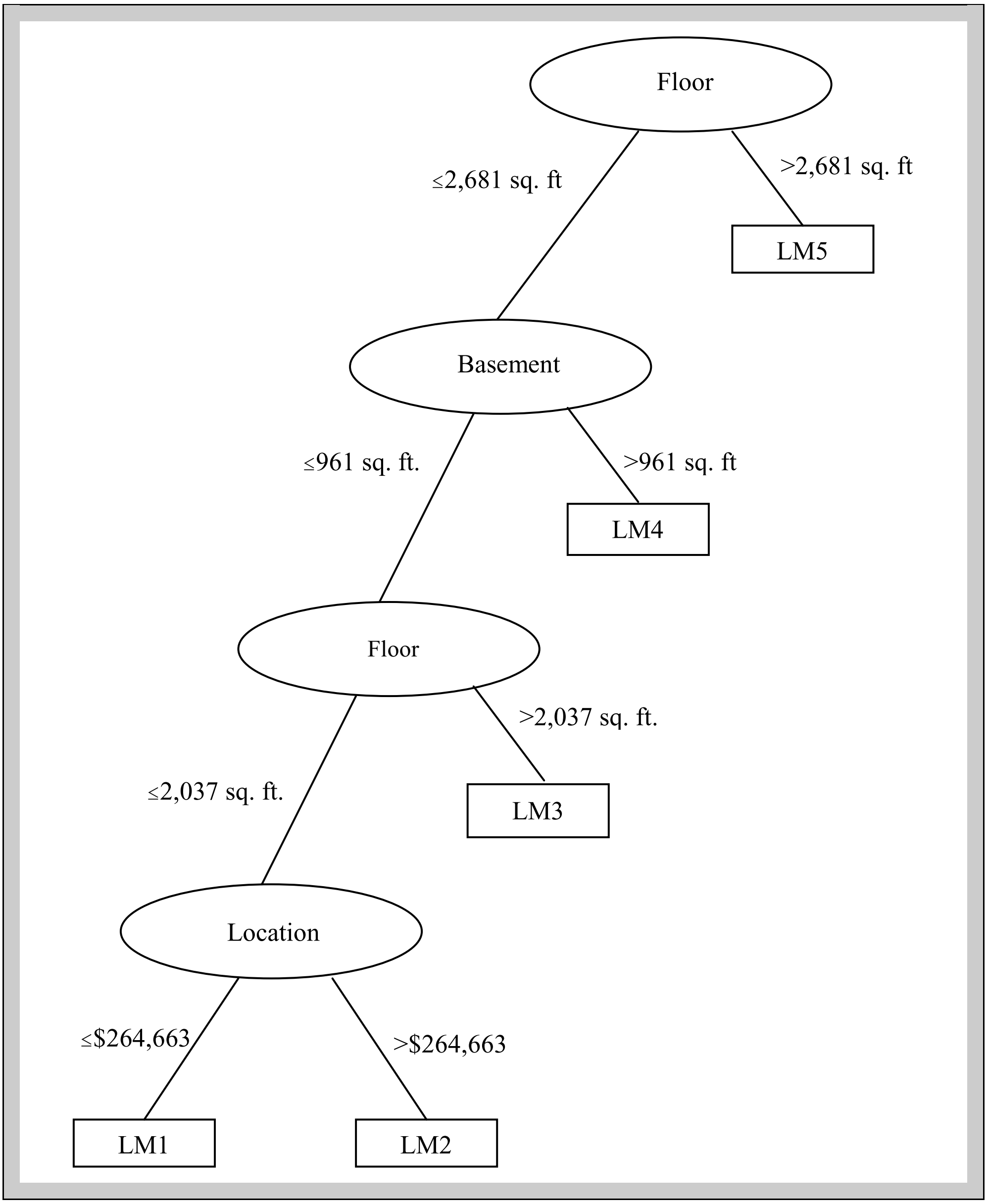
This paper describes the results of a comparative study that evaluates the predictive performance of seven models for residential property value assessment. The tested models include MRA, three non-traditional regression-based models, and three AI-based models. The study represents the most comprehensive comparative study on a large and very heterogeneous data sample. In addition to comparing NN, MRA, and MBR, a variation of NN is also introduced, i.e., RBFNN, and several methods relatively unknown to the mass assessment community, i.e., additive regression, M5P tree, and SVM-SMO.

The simulation results clearly show that the nontraditional regression models produce significantly better results than AI methods in various simulation scenarios, especially in scenarios with more homogeneous data sets. The performance of these nontraditional methods compares favorably with reported studies in terms of their MAPE and R^2 values, though meaningful comparison is difficult for the reasons given. AI-based methods perform better for clusters containing more heterogeneous data in some isolated simulation scenarios. None of the models perform well for low-end and older properties. They generate relatively large prediction errors in those cases. The relatively large prediction errors may be due to the fact that clusters with low-end and older properties are very mixed in terms of sale prices, though not necessarily in terms of property attribute values in the assessor's data set. Finally adding ''location'' has substantially improved the prediction capability of the models. In this study, location is defined as the mean sale price of the properties located in the same district within the same neighborhood. In addition, the data set also contains a group of about 260 properties with large or very large land sizes, ranging from 1 acre to 17.34 acres, which also could have led to large prediction errors. This fact and possibly the use of crisp K-means clustering may explain the relatively low R^2 values for several clusters in scenarios 4 and 5 (Exhibits 11 and 12). Moreover, the MAPE measures for some of these clusters are quite reasonable, exceeding the 50% threshold established by Freddie Mac (Exhibit 15).

There are several areas in which this study can be improved. First, the attributes examined were restricted to those currently used by tax assessors, which exclude variables that cannot be modeled by an MRA equation. But there could be other significant variables that AI models would be able to process. Examples include age and condition of kitchen and bathroom appliances/fixtures, views from the windows, brightness of the foyer, condition and color of the paint, and quality of decorative molding. The incorporation of this type of feature in AI-based methods needs to be further investigated. Second, refining the definition of location to represent the mean actual sale price of the properties within a tax assessment block of houses could further enhance the predictive capability of the models. It might be particularly helpful to introduce this more subtle and modified definition of location for low-end and older properties. For example, AI-based methods can be used to better select/define the comparables that are used to calculate the value of the location variable. The treatment of location in this paper is based on a common practice by realtors and uses existing data from the local assessment office. This definition of has been shown to improve the results of the estimation in this study.

A possible area of future research is to incorporate more formal methods of spatial analysis using externalities and spatial characteristics (Dubin, 1998; Pace, Barry, and Sirmans, 1998; Soibelman and Gonzalez, 2002; Kauko, 2003; Gonzalez, Soibelman, and Formoso, 2005). Recent studies of spatial analysis have shown clear improvement of assessment accuracy (Bourassa, Cantoni, and Hoesli, 2010). These results are consistent with the findings presented here based on a more intuitive and simple definition of location. Use of more formally defined and tested spatial analysis techniques, especially those that lead to better disaggregated submarkets, may further improve prediction results.

Exhibit 16 | Example of M5P Tree



It might be reasonable to introduce the age squared variable to magnify the effect of the house age, as well as try higher powers of age for building the models as was done in several other studies. This comparative study has demonstrated the potential value of nontraditional regression-based methods in mass assessment. Though the AI-based methods tested in this study did not produce competitive results, other AI-based methods need to be explored. For example, Guan, Zurada, and Levitan (2008) found that combining neural networks and fuzzy logic produced results comparable to MRA, but their findings suffer from limited generalizability because of their small data set (300 observations) and lack of diversity in property features (properties came from two modest neighborhoods.) Another area of further research is to implement feature reduction methods to increase the predictive capability and interpretability of the models. The fewer the features are in a model, like the M5P structure in Exhibit 16, the better understood the model is. Implementing fuzzy C-means clustering to find more homogeneous segments of properties is also useful, especially when examining less affluent neighborhoods and older properties. Employing a hybrid system might be a viable option as well, i.e., using several models simultaneously and averaging their predicted sale prices.

Thus, the findings in this study, with its large sample, variety of techniques, and rigorous performance comparisons, help improve understanding of the strengths and weaknesses of various mass assessment approaches.

References

Bagnoli, C. and H.C. Smith. The Theory of Fuzzy Logic and Its Application to Real Estate Valuation. *Journal of Real Estate Research*, 1998, 16:2, 169–200.

Bonissone, P.P. and W. Cheetham. Financial Applications of Fuzzy Case-Based Reasoning to Residential Property Valuation. Proceedings of Sixth International Conference on Fuzzy Systems (FUZZ-IEEE'97). Barcelona, Spain, 1997, 37–44.

Bors, A.G. Introduction of the Radial Basis Function (RBF) Networks. Online Symposium for Electronics Engineers, 2001, 1–7.

Boser, B., I. Guyon, and V. Vapnik. A Training Algorithm for Optimal Margin Classifiers. Proceedings of the Fifth Annual Workshop on Computational Learning Theory. Pittsburgh, Pennsylvania, 1992, 144–52.

Bourassa, S.C., E. Cantoni, and M. Hoesli. Predicting House Prices with Spatial Dependence: A Comparison of Alternative Methods. *Journal of Real Estate Resach*, 2010, 32:2, 139–59.

Byrne, P. Fuzzy Analysis: A Vague Way of Dealing with Uncertainty in Real Estate Analysis? *Journal of Property Valuation and Investment*, 1995, 13:3, 22–41.

Cui, D. and D. Curry. Prediction in Marketing Using the Support Vector Machine. *Marketing Science*, 2005, 24:4, 595–615.

Do, A.Q. and G. Grudnitski. A Neural Network Approach to Residential Property Appraisal. *The Real Estate Appraiser*, 1992, 58:3, 38–45.

Dubin, R. Spatial Autocorrelation: A Primer. *Journal of Housing Economics*, 1998, 7, 304–27.

Fik, T.J., D.C. Ling, and G.F. Mulligan. Modeling Spatial Variation in Housing Prices: A Variable Interaction Approach. *Real Estate Economics*, 2003, 31:4, 623–46.

Friedman, J., T. Hastie, and R. Tibshirani. Additive Logistic Regression: A Statistical View of Boosting (with discussion and rejoinder by the authors). *Annals of Statistics*, 2000, 29: 5, 337–407.

Gonzalez, A.J. and R. Laureano-Ortiz. A Case-Based Reasoning Approach to Real Estate Property Appraisal. *Expert Systems With Applications,* 1992, 4:2, 229–46.

Gonzalez, M.A.S. and C.T. Formoso. Mass Appraisal with Genetic Fuzzy Rule-Based Systems. *Property Management,* 2006, 24:1, 20–30.

Gonzalez, M.A.S., L. Soibelman, and C.T. Formoso. A New Approach to Spatial Analysis in CAMA. *Property Management,* 2005, 23:5, 312–27.

Guan, J. and A.S. Levitan. Artificial Neural Network Based Assessment of Residential Real Estate Property Prices: A Case Study. *Accounting Forum,* 1997, 20:3/4, 311–26.

Guan, J., J. Zurada, and A.S. Levitan. An Adaptive Neuro-Fuzzy Inference System Based Approach to Real Estate Property Assessment. *Journal of Real Estate Research,* 2008, 30: 4, 395–420.

Jang, J.S.R. ANFIS: Adaptive-Network-Based Fuzzy Inference System. *IEEE Transactions on Systems, Man, and Cybernetics,* 1993, 23:3, 665–85.

Kauko, T. Residential Property Value and Locational Externalities. *Journal of Property Investment and Finance,* 2003, 21:3, 250–70.

Krol, D., T. Lasota, W. Nalepa, and B. Trawinski. Fuzzy System Model to Assist with Real Estate Appraisals. *Lecture Notes in Computer Science,* 2007, 4570, 260–69.

Larsen, J.E. and M.O. Peterson. Correcting for Errors in Statistical Appraisal Equations. *The Real Estate Appraiser and Analyst,* 1988, 54:3, 45–49.

Limsombunchai, V., C. Gan, and M. Lee. House Price Prediction: Hedonic Price Model Vs. Artificial Neural Network. *American Journal of Applied Sciences,* 2004, 1:3, 193–201.

Mark, J. and M. Goldberg. Multiple Regression Analysis and Mass Assessment: A Review of the Issues. *Appraisal Journal,* 1988, 56:1, 89–109.

McCluskey, W. and S. Anand. The Application of Intelligent Hybrid Techniques for the Mass Appraisal of Residential Properties. *Journal of Property Investment and Finance,* 1999, 17:3, 218–38.

McGreal, S., A. Adair, D. McBurney, and D. Patterson. Neural Networks: The Prediction of Residential Values. *Journal of Property Valuation and Investment,* 1998, 16, 57–70.

Newsome, B.A. and J. Zietz. Adjusting Comparable Sales Using Multiple Regression Analysis—the Need for Segmentation. *The Appraisal Journal,* 1992, 60:1, 129–33.

Nguyen, N. and A. Cripps. Predicting Housing Value: A Comparison of Multiple Regression Analysis and Artificial Neural Networks. *Journal of Real Estate Research,* 2002, 22:3, 313–36.

Osuna, E., R. Freund, and F. Girosi. An Improved Training Algorithm for Support Vector Machines. Proceedings of the 1997 IEEE Workshop on Neural Networks for Signal Processing. Amelia Island, Florida, 1997, 276–85.

Pace, R., R. Barry, and C. Sirmans. Spatial Statistics and Real Estate. *The Journal of Real Estate Finance and Economics,* 1998, 17:1, 5–13.

Park, J. and J.W. Sandberg. Universal Approximation Using Radial Basis Functions Network. *Neural Computation,* 1991, 3, 246–57.

Peterson, S. and A.B. Flanagan. Neural Network Hedonic Pricing Models in Mass Real Estate Appraisal. *Journal of Real Estate Research,* 2009, 31:2, 147–64.

Platt, J.C. Fast Training of Support Vector Machines using Sequential Minimal Optimization. In: B. Scholkopf, C. Burges, and A. Smola (eds.), *Advances in Kernel Methods: Support Vector Machines.* Cambridge, MA: MIT Press, 1998.

Poggio, T. and F. Girosi. Networks for Approximation and Learning. *Proceedings of IEEE,* 1990, 78:9, 1481–97.

Quinlan, J.R. Learning with Continuous Classes. Proceedings of the 5th Australian Joint Conference on Artificial Intelligence. Singapore, 1992, 343–48.

Rossini, P. Artificial Neural Networks Versus Multiple Regression in the Valuation of Residential Property. *Australian Land Economics Review,* 1997, 3:1, 1–12.

Soibelman, L. and M.A.S. Gonzalez. A Knowledge Discovery in Databases Framework for Property Valuation. *Journal of Property Tax Assessment and Administration*, 2002, 7:2, 77–104.

Taffese, W.Z. Case-Based Reasoning and Neural Networks for Real Estate Valuation. Proceedings of the 25th Conference on Proceedings of the 25th IASTED International Multi-Conference: Artificial Intelligence and Applications. Innsbruck, Austria, 2007, 84–9.

Vapnik, V.N. *Statistical Learning Theory*. New York: Wiley, 1998.

Viaene, S., R.A. Derrig, B. Baesens, and G. Dedene. A Comparison of State-of-the-Art Classification Techniques for Expert Automobile Insurance Claim Fraud Detection. *Journal of Risk Insurance,* 2002, 63:3, 373–421.

Wang, Y. and I. Witten. Inducing Model Trees for Continuous Classes. Proceedings of Poster Papers. Ninth European Conference on Machine Learning. Prague, Czech Republic, 1997, 128–37.

Witten, I.H. and E. Frank. *Data Mining: Practical Machine Learning Tools and Techniques*. San Francisco: Morgan Kaufmann, 2005.

Worzala, E., M. Lenk, and A. Silva. An Exploration of Neural Networks and Its Application to Real Estate Valuation. *Journal of Real Estate Research*, 1995, 10, 185–202.

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