Investigation of Bagging Ensembles of Genetic Neural Networks and Fuzzy Systems for Real Estate Appraisal

Olgierd Kempa[1], Tadeusz Lasota[1], Zbigniew Telec[2], and Bogdan Trawiński[2]

[1] Wrocław University of Environmental and Life Sciences,
Dept. of Spatial Management ul. Norwida 25/27, 50-375 Wrocław, Poland
[2] Wrocław University of Technology, Institute of Informatics,
Wybrzeże Wyspiańskiego 27, 50-370 Wrocław, Poland
olgierd_kempa@vp.pl, tadeusz.lasota@wp.pl,
{zbigniew.telec,bogdan.trawinski}@pwr.wroc.pl

Abstract. Artificial neural networks are often used to generate real appraisal models utilized in automated valuation systems. Neural networks are widely recognized as weak learners therefore are often used to create ensemble models which provide better prediction accuracy. In the paper the investigation of bagging ensembles combining genetic neural networks as well as genetic fuzzy systems is presented. The study was conducted with a newly developed system in Matlab to generate and test hybrid and multiple models of computational intelligence using different resampling methods. The results of experiments showed that genetic neural network and fuzzy systems ensembles outperformed a pairwise comparison method used by the experts to estimate the values of residential premises over majority of datasets.

Keywords: ensemble models, genetic neural networks, bagging, out-of-bag, property valuation.

1 Introduction

The application of soft computing techniques to assist with real estate appraisals has been intensively studied for last two decades. The main focus has been directed towards neural networks [16], [22], [26], [29], less researchers have been involved in the application of fuzzy systems [1], [11]. So far, we have investigated several approaches to construct predictive models to assist with real estate appraisal encompassing evolutionary fuzzy systems, neural networks, decision trees, and statistical algorithms using MATLAB, KEEL, RapidMiner, and WEKA data mining systems [13], [17], [19]. Quite recently, we have built and tested models employing evolving fuzzy systems eTS [21] and FLEXFIS [23] which treated cadastral data on property sales/purchase transactions as a data stream which in turn could reflect the changes of real estate market in the course of time. We studied also bagging ensemble models created applying such computational intelligence techniques as fuzzy systems, neural networks, support vector machines, regression trees, and statistical regression [14], [18], [20]. The results showed that all ensembles outperformed single base models but one based on support vector machines.

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Bagging ensembles, which besides boosting belong to the most popular multi-model techniques have been focused attention of many researchers for last fifteen years. Bagging, which stands for bootstrap aggregating, devised by Breiman [3] is one of the most intuitive and simplest ensemble algorithms providing a good performance. Diversity of learners is obtained by using bootstrapped replicas of the training data. That is, different training data subsets are randomly drawn with replacement from the original training set. So obtained training data subsets, called also bags, are used then to train different classification or regression models. Finally, individual learners are combined through an algebraic expression, such as minimum, maximum, sum, mean, product, median, etc. [27]. Theoretical analyses and experimental results proved benefits of bagging especially in terms of stability improvement and variance reduction of learners for both classification and regression problems [4], [9], [10].

This collection of methods combines the output of the machine learning systems, in literature called "weak learners" in due to its performance [28], from the group of learners in order to get smaller prediction errors (in regression) or lower error rates (in classification). The individual estimator must provide different patterns of generalization, thus the diversity plays a crucial role in the training process. Otherwise, the ensemble, called also committee, would end up having the same predictor and provide as good accuracy as the single one. It was proved that the ensemble performs better when each individual machine learning system is accurate and makes error on the different instances at the same time.

The goal of the study presented in this paper was twofold. Firstly, we would like to investigate the usefulness of genetic neural networks and genetic fuzzy systems to create ensemble models providing better performance than their single base models. Secondly, we aimed to compared soft computing ensemble methods with a property valuating method employed by professional appraisers in reality. The algorithms were applied to real-world regression problem of predicting the prices of residential premises based on historical data of sales/purchase transactions obtained from a cadastral system. The investigation was conducted with a newly developed system in Matlab to generate and test hybrid and multiple models of computational intelligence using different resampling methods. The experiments allowed also for the comparison of different approaches to create bagging ensembles with commonly used 10-fold cross validation as well as with models providing the estimation of the resubstitution error.

2 Methods Used and Experimental Setup

The investigation was conducted with our new experimental system implemented in Matlab environment using Neural Network, Fuzzy Logic, Global Optimization, and Statistics toolboxes [7], [12]. The system was designed to carry out research into machine learning algorithms using various resampling methods and constructing and evaluating ensemble models for regression problems. The main modules of the system are: data management, experiment design, experiment execution, and result analysis and visualization. At the first stage of development particular emphasis was placed on evolutionary neural networks and fuzzy systems. Partitioning methods implemented so far comprise repeated holdout, repeated cross-validation and multiple bootstrap where percentage of base dataset instances drawn to training sets can be determined by a user while defining a data project. It is planned to extend our experimental system to include random subspaces and other diversity creation methods based on techniques of feature selection.

2.1 Expert's Valuation Method

In order to compare evolutionary machine learning algorithms with techniques applied to property valuation we asked professional appraisers to evaluate premises using historical data of sales/purchase transactions obtained from a cadastral system. In this section the pairwise comparison method used by the experts to estimate the values of premises comprised in our dataset is described. The experts simulated professional appraisers' work in the way it is done in reality.

First of all the whole area of the city was divided into 6 quality zones: 1 - the central one, 2 - near-medium, 3 - eastern-medium, and 4 – western-medium zones, and finally 5 - south-western-distant and 6 - north-eastern-distant zones. Next, the premises located in each zone were classified into 243 groups determined by 5 following quantitative features selected as the main price drivers: *Area, Year, Storeys, Rooms,* and *Centre.* Domains of each feature were split into three brackets as follows.

Area denotes the usable area of premises and comprises small flats up to 40 m^2, medium flats in the bracket 40 to 60 m^2, and big flats above 60 m^2.

Year (*Age*) means the year of a building construction and consists of old buildings constructed before 1945, medium age ones built in the period 1945 to 1960, and new buildings constructed between 1960 and 1996, the buildings falling into individual ranges are treated as in bad, medium, and good physical condition respectively.

Storeys are intended for the height of a building and are composed of low houses up to three storeys, multi-family houses from 4 to 5 storeys, and tower blocks above 5 storeys.

Rooms are designated for the number of rooms in a flat including a kitchen. The data contain small flats up to 2 rooms, medium flats in the bracket 3 to 4, and big flats above 4 rooms.

Centre stands for the distance from the city centre and includes buildings located near the centre i.e. up to 1.5 km, in a medium distance from the centre - in the brackets 1.5 to 5 km, and far from the centre - above 5 km.

Then the prices of premises were updated according to the trends of the value changes over 11 years. Starting from the beginning of 1998 the prices were updated for the last day of subsequent years. The trends were modelled by polynomials of degree three. The chart illustrating the change trend of average transactional prices per square metre is given in Fig. 1.

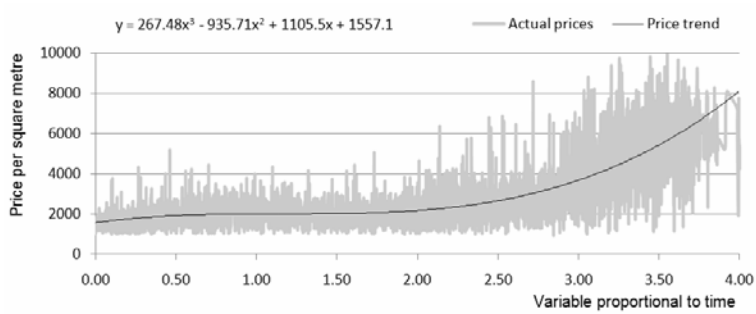

Fig. 1. Change trend of average transactional prices per square metre over time

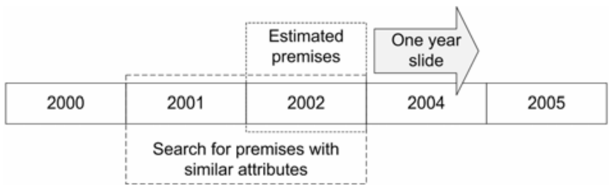

Fig. 2. Time windows used in the pairwise comparison method of experts' estimation

Premises estimation procedure employed a two-year time window to take transaction data of similar premises into consideration (Fig. 2).

1. Take next premises to estimate.
2. Check the completeness of values of all five features and note a transaction date.
3. Select all premises sold earlier than the one being appraised, within current and one preceding year and assigned to the same group.
4. If there are at least three such premises calculate the average price taking the prices updated for the last day of a given transaction year.
5. Return this average as the estimated value of the premises.
6. Repeat steps 1 to 5 for all premises to be appraised.
7. For all premises not satisfying the condition determined in step 4 extend the quality zones by merging 1 & 2, 3 & 4, and 5 & 6 zones. Moreover, extend the time window to include current and two preceding years.
8. Repeat steps 1 to 5 for all remaining premises.

2.2 Genetic Neural Networks and Genetic Fuzzy Systems

In our experiments we employed two basic evolutionary approaches to real-world regression problem of predicting the prices of residential premises based on historical data of sales/purchase transactions obtained from a cadastral system, namely genetic neural networks (GNN) and genetic fuzzy systems (GFS). In both techniques we used the same the input and output variables as did the experts in their pairwise comparison method described above, namely five inputs: *Area, Year, Storeys, Rooms, Centre*, and *Price* as the target variable. The parameters of the architecture of GNN and GFS as well as genetic algorithms are listed in Table 1.

Table 1. Parameters of GNN and GFS used in experiments

GNN	GFS
Network type: feedforward backpropagation	Type of fuzzy system: Mamdani
No. of input variables: 5	No. of input variables: 5
No. of neurons in input layer: 5	No. of input membership functions (mf): 3
No. of hidden layers: 1	No. of output mf: 3
No. of neurons in hidden layer: 5	Type of mf: triangular and trapezoidal
	No. of rules: 15
	Mf parameter variability intervals: ±40%
Chromosome: weights of neuron connections	Chromosome: rules and mf
Chromosome coding: real-valued	Chromosome coding: real-valued
Population size: 150	Population size: 50
Creation function: uniform	Creation function: uniform
Selection function: tournament	Selection function: tournament
Tournament size: 4	Tournament size: 4
Elite count: 2	Elite count: 2
Crossover fraction: 0.8	Crossover fraction: 0.8
Crossover function: two point	Crossover function: two point
Mutation function: Gaussian	Mutation function: custom
No. of generations: 300	No. of generations: 100

Our GNN approach consisted in the evolution of connection weights with a predefined architecture of feedforward network with backpropagation comprising five neurons in an input layer and also five neurons in one hidden layer. Our preliminary tests showed that we can use such a small number of neurons in one hidden layer without the loss of prediction accuracy.

A whole set of weights in a chromosome was represented by real numbers. Similar solutions are described in [15], [30]. In turn, in GFS approach for each input and output variable three triangular and trapezoidal membership functions were automatically determined by the symmetric division of the individual attribute domains. The evolutionary optimization process combined both learning the rule base and tuning the membership functions using real-coded chromosomes. Similar designs are described in [5], [6], [17].

2.3 Dataset Used in Experiments

Real-world dataset used in experiments was drawn from a rough dataset containing above 50 000 records referring to residential premises transactions accomplished in one Polish big city with the population of 640 000 within eleven years from 1998 to 2008. In this period most transactions were made with non-market prices when the council was selling flats to their current tenants on preferential terms. First of all, transactional records referring to residential premises sold at market prices were selected. Then the dataset was confined to sales transaction data of apartments built before 1997 and where the land was leased on terms of perpetual usufruct. Hence, the final dataset counted 5303 records and comprised all premises which values could be estimated by the experts.

Due to the fact that the prices of premises change substantially in the course of time, the whole 11-year dataset cannot be used to create data-driven models. Therefore it was split into subsets covering individual years, and we might assume that within one year the prices of premises with similar attributes were roughly comparable. The sizes of one-year data subsets are given in Table 1.

Table 2. Number of instances in one-year datasets

1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008
269	477	329	463	530	653	546	580	677	575	204

2.4 Subsampling and Other Methods Used for Comparison

A series of machine learning experiments was conducted over one-year datasets as base original datasets separately to obtain three bagging ensembles, models providing the resubstitution errors, and 10-fold cross-validation models. Moreover, the property valuation experts built their models using the pairwise comparison method. As a result following models were created and evaluated.

BaseBase – models learned and tested using the same original base dataset, no resampling was used, their performance MSE(BaseBase) refers to the so called resubstitution error or apparent error. The resubstitution errors are overly optimistic because the same samples are used to build and to test the models. They were used to calculate correcting components in the 0.632 bootstrap method.

BagBase – models learned using bags, i.e. bootstrap replicates and tested with the original base datasets, it represents a classic bagging ensemble devised by Breiman. The overall performance of the model MSE(BagBase) equals the average of all MSE values obtained with test set for individual component models. The prediction errors are underestimated since the learning and test sets overlap.

BagOoB – models learned using bags, i.e. bootstrap replicates and tested with the out-of-bag datasets. The overall performance of the model was calculated as the average of all MSE values obtained with test set for individual component models. Due to the fact that training sets comprise on average 63.2 percent of all observations the prediction errors tend to be overestimated.

.632 – model represents the 0.632 bootstrap method correcting the out-of-bag prediction error using the weighted average of the BagOoB and BaseBase MSEs with the weights equal to 0.632 and 0.368 respectively [8].

10cv – ten-fold cross validation, the widely used form of cv for obtaining a reliable estimate of the prediction error. It is known that by growing the number of folds when using k-fold cv the bias can be reduced but at the same time the variance is increased.

Expert – a model based on pairwise comparison approach developed by professional property valuators, its performance was expressed in terms of mean squared error of predicted and actual prices of residential premises.

In the case of bagging method 50 bootstrap replicates (bags) were created on the basis of each base dataset with the number of instances equal to the cardinality of a given dataset. As performance functions the mean square error (MSE) was used and as aggregation functions averages were employed.

3 Results of Experiments

The performance of six models, i.e. *BaseBase*, *BagBase*, *BagOoB*, *.632*, *10cv*, and *Expert* created by GNN and GFS in terms of MSE was presented in Tables 3 and 4 and compared graphically in Figures 3 and 4 respectively. The analysis of the results is carried out separately for GNN and GFS because the experimental conditions did not allow a fair comparison. It can be easily seen that the performance of the experts' method fluctuates strongly achieving for some datasets, i.e. 1999, 2001, and 2008, excessively high MSE values. The differences between *BagBase* and *BagOoB* are apparent in favour of the former method. 10-fold cross validation which is often employed as a method of evaluating single base models reveals worse predictive accuracy than a classic bagging method with a whole original dataset as a test set, i.e. *BagBase*. .632 - the corrected bagging technique provides better results than 10cv for majority of datasets.

Table 3. Performance of models generated using genetic neural networks (GNN)

Dataset	BaseBase	BagBase	BagOoB	.632	10cv	Expert
1998	0.01039	0.01085	0.01274	0.01188	0.01237	0.01262
1999	0.00785	0.00863	0.00930	0.00876	0.00875	0.01335
2000	0.00679	0.00709	0.00787	0.00747	0.00829	0.01069
2001	0.00434	0.00461	0.00499	0.00475	0.00712	0.01759
2002	0.00524	0.00544	0.00610	0.00578	0.00579	0.00760
2003	0.00594	0.00630	0.00650	0.00629	0.00670	0.00753
2004	0.00904	0.01053	0.01094	0.01024	0.01159	0.01049
2005	0.00610	0.00651	0.00673	0.00650	0.00682	0.00936
2006	0.00889	0.00897	0.00954	0.00930	0.00915	0.00905
2007	0.00426	0.00429	0.00464	0.00450	0.00518	0.00659
2008	0.00550	0.00576	0.00668	0.00624	0.00670	0.01400

Table 4. Performance of models generated using genetic fuzzy systems (GFS)

GFS	BaseBase	BagBase	BagOoB	.632	10cv	Expert
1998	0.01003	0.01106	0.01380	0.01241	0.01517	0.01262
1999	0.00902	0.00980	0.01099	0.01027	0.01081	0.01335
2000	0.00662	0.00834	0.01072	0.00921	0.00861	0.01069
2001	0.00483	0.00552	0.00647	0.00587	0.00623	0.01759
2002	0.00537	0.00637	0.00710	0.00647	0.00654	0.00760
2003	0.00662	0.00741	0.00791	0.00743	0.00788	0.00753
2004	0.01170	0.01079	0.01207	0.01194	0.01087	0.01049
2005	0.00666	0.00725	0.00826	0.00767	0.00811	0.00936
2006	0.01108	0.01031	0.01162	0.01142	0.01092	0.00905
2007	0.00587	0.00519	0.00605	0.00598	0.00621	0.00659
2008	0.00709	0.00713	0.00948	0.00860	0.00939	0.01400

The Friedman test performed in respect of MSE values of all models built over eleven one-year datasets showed that there are significant differences between some models in the case both genetic neural networks and genetic fuzzy sets. Average ranks of individual models are shown in Table 5, where the lower rank value the better model. In Table 6 the results of nonparametric Wilcoxon signed-rank test to pairwise comparison of the model performance are presented. The zero hypothesis stated there were not significant differences in accuracy, in terms of MSE, between given pairs of models. In Table 6 + denotes that the model in the row performed significantly better than, – significantly worse than, and ≈ statistically equivalent to the one in the corresponding column, respectively. In turn, / (slashes) separate the results for GNN and GFS respectively. The significance level considered for the null hypothesis rejection was 5%. Main outcome is as follows: BaseBase models showed significantly better performance than any other model but one BagBase for GFS, BagBase models performed significantly better than any other model but one BaseBase which turned out to be statistically equivalent. These two observations conform with theoretical considerations. Expert models revealed significantly lower MSE than most of other models except BagOoB, .632, and 10cv for GFS.

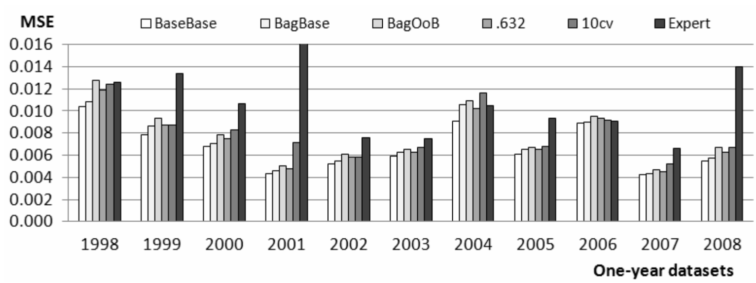

Fig. 3. Performance of models generated using genetic neural networks (GNN)

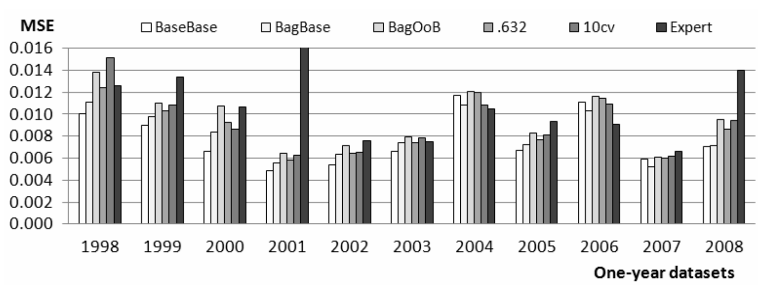

Fig. 4. Performance of models generated using genetic fuzzy systems (GFS)

Table 5. Average rank positions of models determined during Friedman test

	1st	2nd	3rd	4th	5th	6th
GNN	BaseBase (1.00)	BagBase (2.36)	.632 (3.00)	BagOoB (4.64)	10cv (4.64)	Expert (5.36)
GFS	BaseBase (1.64)	BagBase (1.91)	.632 (3.45)	10cv (4.09)	Expert (4.64)	BagOoB (5.27)

Table 6. Results of Wilcoxon tests for the performance of GNN/GFS models

	BaseBase	BagBase	BagOoB	.632	10cv	Expert
BaseBase		+ / ≈	+ / +	+ / +	+ / +	+ / +
BagBase	– / ≈		+ / +	+ / +	+ / +	+ / +
BagOoB	– / –	– / –		– / –	≈ / ≈	+ / ≈
.632	– / –	– / –	+ / +		+ / ≈	+ / ≈
10cv	– / –	– / –	≈ / ≈	– / ≈		+ / ≈
Expert	– / –	– / –	– / ≈	– / ≈	– / ≈	

4 Conclusions and Future Work

The experiments, aimed to compare the performance of bagging ensembles built using genetic neural networks and genetic fuzzy systems were conducted. Moreover, the predictive accuracy of a pairwise comparison method applied by professional appraisers in reality was compared with soft computing machine learning models for residential premises valuation. The investigation was carried out with our new experimental system implemented in Matlab designed to conduct research into machine learning algorithms using various resampling methods and constructing and evaluating ensemble models for regression problems.

The overall results of our investigation were as follows. The bagging ensembles created using genetic neural networks as well as genetic fuzzy systems revealed prediction accuracy not worse than the experts' method employed in reality. It confirms that automated valuation models can be successfully utilized to support appraisers' work. Moreover, the bagging ensembles outperformed single base models assessed using 10-fold cross validation.

Due to excessive times of generating ensemble models on the basis of both genetic neural networks and genetic fuzzy systems it is planned to explore resampling methods ensuring faster data processing such as random subspaces, subsampling, and techniques of determining the optimal sizes of multi-model solutions. This can lead to achieve both low prediction error and an appropriate balance between accuracy and complexity as shown in recent studies [2], [24], [25].

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