

# Soft Computing Models in Online Real Estate

Jozo Dujmović<sup>1</sup>, Guy De Tré<sup>2</sup>, Navchetan Singh<sup>1</sup>, Daniel Tomasevich<sup>1</sup>,  
and Ryoichi Yokoojji<sup>1</sup>

<sup>1</sup>Department of Computer Science, San Francisco State University, San Francisco, CA, USA  
jozo@sfsu.edu

<sup>2</sup>Dept. of Telecommunications and Information Processing, Ghent University, Ghent, Belgium  
Guy.DeTre@telin.ugent.be

**Abstract.** In this paper we present a decision support system that uses soft computing models for evaluation, selection and pricing of homes. The system (called LSPhome) is based on the Logic Scoring of Preference (LSP) evaluation method and implemented in the context of online real estate. The goal of this system is to use weighted compensative logic models that can precisely express user needs, and help both buyers and sellers of homes. The design of such a system creates specific logic and computational challenges. Soft computing logic problems include the use of verbalized importance scales for derivation of andness, penalty-controlled missingness-tolerant logic aggregation, detailed and verbalized presentation of evaluation results, and development of optimum pricing models. Computational problems include fast and parallel collection of heterogeneous information from the Internet, and development of user interface for fast and simple creation of customized soft computing decision criteria by nonprofessional decision makers.

**Keywords:** Evaluation, selection, real estate, missing data, verbalization.

## 1 Introduction

Real estate is an area that includes a spectrum of soft computing decision problems. In this paper we present a survey of the most important soft computing models that are used in online real estate (ORE). The first such a problem is the development of criteria for evaluation and selection of homes. The home evaluation criteria are based on weighted compensative logic functions that can model adjustable degrees of simultaneity and replaceability, mandatory, sufficient, and optional requirements, as well as adjustable degrees of importance of various home attributes. The aggregation of home quality and home affordability is also a soft computing logic problem. Similarly, the problem of optimum home pricing can also be solved using soft computing models. In ORE we frequently encounter problems of decision making with incomplete (missing) inputs, and the need to expand aggregation models with missingness-tolerant aggregators. Finally, the users of ORE decision models are not decision experts, but nonprofessionals who need simple verbalized approach to specifying soft computing decision models. These seemingly heterogeneous problems are closely related in the

context of ORE. Thus, the goal of this paper is to show all fundamental components of the soft computing decision infrastructure in ORE.

In the USA the real estate market data and procedures are governed by the National Association of Realtors [11]. Full information about homes on sale and other marketed properties can be found in the Multiple Listing Service (MLS) [14]. ORE web sites (e.g. [13],[16]) use MLS data and provide application programming interfaces (API) that can be used to access data about available homes and their characteristics. These data can be used as inputs for evaluation and selection process based on soft computing criteria.

The paper is organized in three main sections. Section 2 describes soft computing models for home evaluation in the context of buying and selling a home. Section 3 surveys the penalty-controlled missingness-tolerant aggregation, and the verbalization problems. Section 4 presents experimental results generated by the LSPhome system.

## 2 LSP criterion Function for Home Evaluation

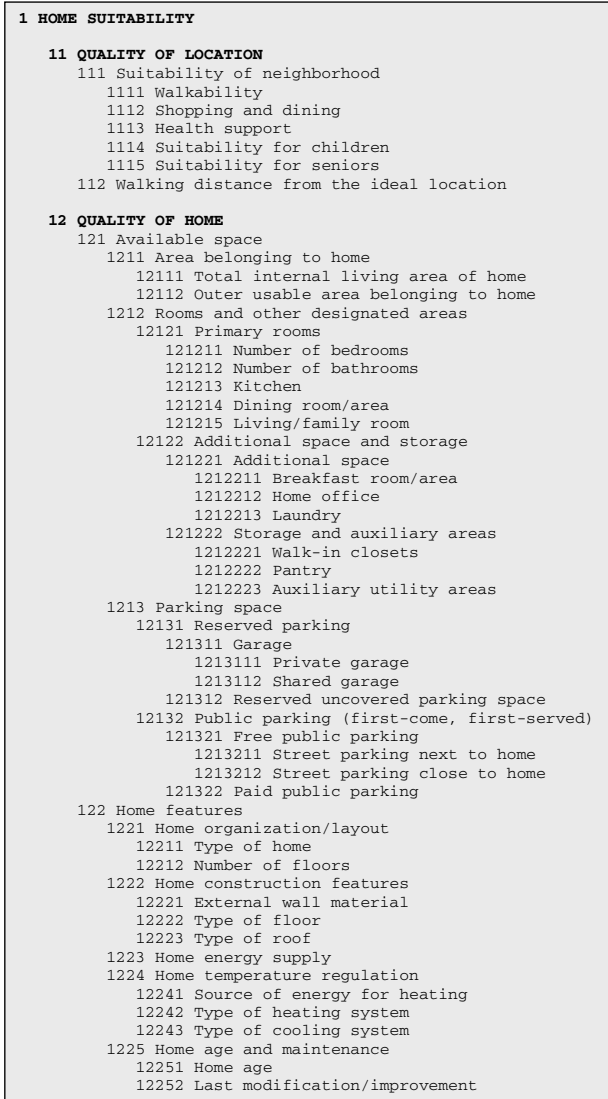
The LSP method [5] provides soft computing evaluation criteria built in three basic steps. The first step develops a list of attributes  $a_1, \dots, a_n$ ,  $a_i \in R$ ,  $i = 1, \dots, n$  that characterize relevant properties of evaluated homes. The second step is to provide requirements for each attribute in the form of elementary criteria functions  $g_i : R \rightarrow I$ ,  $I = [0, 1]$ ; they assign degrees of satisfaction to attribute values  $x_i = g_i(a_i)$ ,  $i = 1, \dots, n$ . The third step generates an overall degree of satisfaction (overall suitability) as an aggregate of attributes' degrees of satisfaction:  $S = L(x_1, \dots, x_n)$ . The mapping  $L : I^n \rightarrow I$  is based on weighted compensative logic functions [1],[10],[3],[12] that are implemented as specific forms of means [9], [2].

### 2.1 Attribute Tree

The home evaluation attribute tree based on data that can be retrieved from the Internet is shown in Fig. 1. The attributes are grouped in two main groups: the quality of home location, and the quality of the home. The quality of home location is based on an analysis of points of interest that are available from Google. The attributes that affect the home quality come from ORE web sites.

### 2.2 Elementary Criteria

The number of home evaluation attributes in the attribute tree in Fig 1. is 36. For each of these attributes we provide an attribute criterion function that reflects the requirements of a specific user. Some of attribute criteria are specific for each user and others can be shared by all users. Two such examples are shown in Fig. 2. The criterion #112 uses data obtained from the LSPhome user interface shown in Fig.3.



**Fig. 1.** The home evaluation attribute tree

The presented interface provides a limited capability for homebuyers to specify their requirements. This is necessary to avoid too much detail that would discourage the majority of general population users. In all cases the users are expected to specify the ideal location of their desired home and the maximum allowable distance  $D_{\max}$  from the ideal location. The evaluation of homes using the attribute criterion #112 (Fig. 2) is based on the relative distance  $100D/D_{\max}$ . The presented attribute criterion shows a relatively high tolerance for all distances except those close to  $D_{\max}$ . By selecting  $D_{\max}$  (see Fig. 3) the users can customize the attribute criterion function.

112		Walking distance from the ideal location
Value	%	The ideal location is a user-specified location selected as a point that completely satisfies all user requirements. The distance can be expressed as (1) walking, (2) car, (3) public transport, or (4) bicycle distance. We use the normalized relative walking distance $x = 100D/D_{max}$ , where $D$ = walking distance between an evaluated home and the ideal location (miles or km) $D_{max}$ = The maximum acceptable walking distance from the ideal location (miles or km). <i>D<sub>max</sub> must be selected by each user</i>
0	100	
40	86	
70	70	
90	50.6	
100	0	
12222		Type of floor
Value	%	The type or material of the walking surface of the primary living areas of the home. The main options are: ST = stone HW = hardwood SW = softwood L = laminate floor V = vinyl/linoleum P = parquet SL = slate T = tile (ceramic) C = carpet Evaluation method: 1 = ST/SL/T, 2 = V, 3 = SW/C, 4 = L, 5 = HW, 6 = P
1	35	
2	50	
3	70	
4	75	
5	85	
6	100	

Fig. 2. Sample elementary criteria

### Desired house properties

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**Preferred (ideal) location**

Zip code (USA)

Street Name

House number

Maximum distance from the ideal location (select only homes that are closer than this distance)  Miles

Maximum acceptable price \$  Thousand

House area in square feet (min acceptable value and maximum/sufficient value) Min  Max

Necessary number of bedrooms (min acceptable value and maximum/sufficient value) Min  Max

Necessary number of bathrooms (min acceptable value and maximum/sufficient value) Min  Max

Importance of house location

Importance of house quality

Importance of low price (compared to the importance of house quality+location)

Data missingness penalty  %

Fig. 3. LSPhome interface for specifying user requirements

Other user supplied elementary criteria are the available area, the number of bedrooms and the number of bathrooms. All of them are specified in the range from the minimum acceptable value  $a_{min}$  to the maximum (sufficient) value  $a_{max}$ . The simplest form of such elementary criteria is the following:  $x = g(a) = \min[1, (a/a_{max})]$ .

An alternative more flexible version can be obtained by assigning the minimum default suitability  $x_{\min}$  to the minimum acceptable value  $a_{\min}$  as follows:

$$x = g(a) = \begin{cases} 0, & a < a_{\min} \\ \min(1, (a - a_{\min} + x_{\min}(a_{\max} - a)) / (a_{\max} - a_{\min})), & a \geq a_{\min} \end{cases}$$

To simplify the use of LSPhome, only the essential user requirements are customizable. All user-shareable and less specific elementary criteria are not customizable and one such example is the criterion #12222 shown in Fig.2. That criterion is a fixed scoring system that reflects an average standpoint acceptable for the majority of users. E.g., if the ORE web site provides a home with hardwood floor, then, for all homebuyers, the corresponding floor satisfaction degree is 85%. The use of fixed elementary criteria significantly reduces the number of necessary user inputs and simplifies the communication with users.

### 2.3 Logic Aggregation Structure

Aggregation of all attribute suitability degrees yields the overall suitability of the evaluated home. The aggregation is based on the superposition of several basic aggregators that are implemented using the generalized conjunction/disjunction function (GCD) [4]. The soft computing *suitability aggregation structure* (SAS), in the form of a “shade diagram,” [5] is shown in Figs. 4 and 5. The suitability aggregation structure uses a spectrum of weighted compensative logic functions. In the case of GCD we use the system of 17 distinct degrees of orness  $\omega = 0, 1/16, \dots, 1$ , (or andness  $\alpha = 1 - \omega$ ) symbolically denoted C, C++, C+, C+-, CA, C-, C--, A, D--, D-, D+, DA, D+-, D+, D++, D, described in [3]. The aggregators starting with letter C denote various forms of conjunction (pure and hard or soft partial) and aggregators starting with letter D denote various forms of disjunction (pure and hard or soft partial) [4]. The hard partial conjunction function is a model of mandatory requirements ( $f_c(x_1, \dots, x_k) = 0, x_i = 0, i \in \{1, \dots, k\}, k > 1$ ) and the hard partial disjunction is a model of sufficient requirements ( $f_d(x_1, \dots, x_k) = 1, x_i = 1, i \in \{1, \dots, k\}, k > 1$ ). Soft versions provide a positive output if a single input is positive. The aggregator A denotes the neutrality (the arithmetic mean). E.g., to evaluate the suitability of neighborhood (#111) we first identify the locations of all relevant points of interest for evaluation of walkability, shopping and dining, health support, and suitability for children and seniors, and then we aggregate these suitability degrees using a weighted soft partial conjunction C- (andness  $\alpha = 5/8$ ), with the highest relative importance (weight) assigned to walkability and to suitability for children. Such weights reflect the fact that most homebuyers are young families. In Figs. 4 and 5 “+” in the first column denotes mandatory attributes and “-“ denotes optional attributes.

The SAS shown in Fig. 4 includes a user-supplied final aggregator  $F$  of location suitability and home quality. The user is requested to specify in verbal form the overall importance of location suitability and house quality (Fig. 3) and the parameters of the resulting GCD aggregator are then computed as shown in Section 3 and [7]. The resulting overall suitability scores for  $N$  competitive homes are  $S_i, i = 1, \dots, N$ .

- 1111 Walkability		25	111 Suitability of neighbourhood		60	11 Quality of location		W <sub>L</sub>
- 1112 Shopping and dining		20						
- 1113 Health support		15						
- 1114 Suitability for children		25						
- 1115 Suitability for seniors		15						
+ 112 Distance from ideal location		40						
+ 1211 Total internal living area of home		Mandatory		1211 Area belonging to home		50	CA Available 60 Space	121 Type of rooms/ area
- 12112 Outer usable area belonging to home		-20 , 15						
+ 121211 Number of bedrooms		30	12121 Primary rooms			Mandatory -40 , 20	1212 Type of rooms/ area	30
+ 121212 Number of bathrooms		25				Optional		
+ 121213 Kitchen		20						
+ 121214 Dining room/area		15						
+ 121215 Living/family room		10						
- 1212211 Breakfast room/area		30	12122 Additional space and storage		55	12122 Additional space and storage		C-
- 1212212 Home office		50						
- 1212213 Laundry		20						
- 1212221 Walk-in closets		40	121222 Storage and auxiliary areas		45	121222 Storage and auxiliary areas		C--
- 1212222 Pantry		30						
- 1212223 Auxiliary utility areas		30						
- 121311 Private garage		Sufficient	12131 Garage		80	12131 Reserved parking		DA
- 1213112 Shared garage		-0 , +70						
- 121312 Reserved uncovered parking space					20			
- 1213211 Street parking next to home		Sufficient	121321 Free Public Parking			12132 Public parking		Sufficient -20 , 40 Optional
- 1213212 Street parking close to home		-0 , +70						
- 121322 Paid public parking								
+ 12211 Type of home		Mandatory	1221 Home organization/layout		25			C++
- 12212 Number of floors		-20 , 15						
- 12221 External wall material		15	1222 Home construction features		15			
- 12222 Type of floor		60						
- 12223 Type of roof		25						
- 1223 Home energy supply					15			
- 12241 Source of energy for heating		40	1224 Home temperature regulation		25			
- 12242 Type of heating system		40						
- 12243 Type of cooling system		20						
- 12251 Home age		Sufficient	1225 Home age and maintenance		20			
- 12252 Last modification/improvement		-20 , 40						

Fig. 4. The home criterion suitability aggregation structure (SAS)

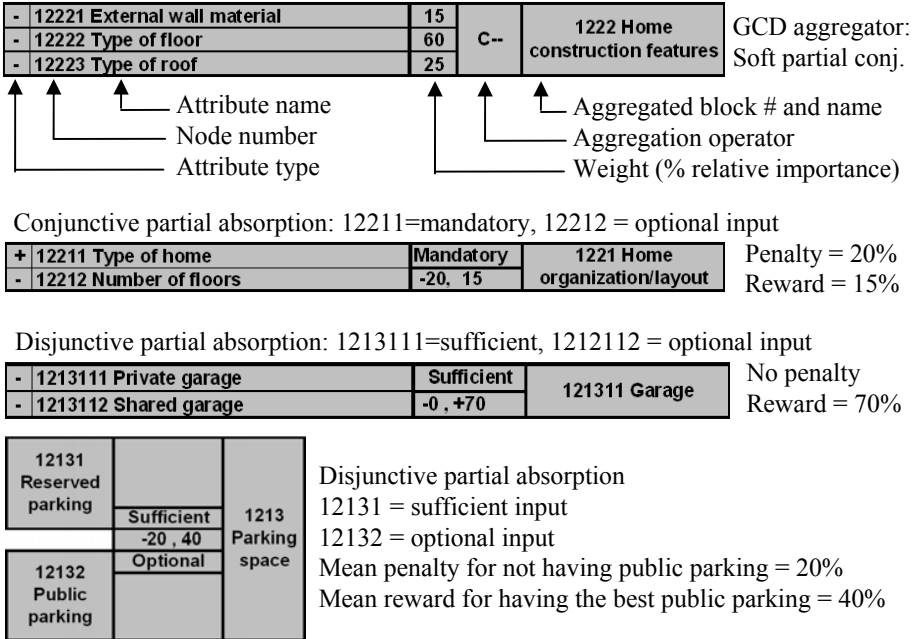


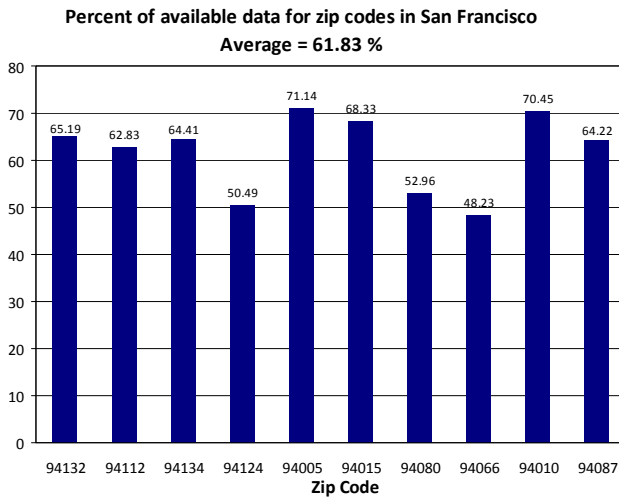
Fig. 5. Explanation of fields in the shade diagram

We also express the soft computing logic relationships by using the conjunctive partial absorption aggregators that aggregate mandatory and optional inputs and the disjunctive partial absorption aggregators that aggregate sufficient and optional inputs [3],[5]. In both cases the properties of these aggregators are determined using the desired level of penalty (decrease of output in the case of unsatisfied optional input) and reward (increase of output in the case of perfectly satisfied optional input). E.g., in the case of parking space (#1213) it is sufficient to have a reserved parking place and the availability of public parking is optional with the mean penalty of -20% and the mean reward of +40%. An obvious advantage of shade diagrams is their rectangular form: similarly to Nassi-Shneiderman structured flow charts, a new shade diagram can be inserted in each rectangular space, making easily readable aggregation structures. Shading of diagrams facilitates the perception of grouping of inputs.

If home costs are  $C_1, \dots, C_N$  then logic aggregation also includes a hard partial conjunction ( $\bar{\Delta}$ ) for aggregating the overall home quality  $Q_i = S_i / \max(S_1, \dots, S_N) \in [0, 1]$  and the home affordability  $A_i = \min(C_1, \dots, C_N) / C_i \in [0, 1]$  yielding (in the case of equal weights) the overall home values  $V_i = Q_i \bar{\Delta} A_i, i = 1, \dots, N$ . In the case of home sale this model can be used to find the *maximum price of our home*  $C_i^*$ , so that (even with that price) the home is still the most attractive in a selected area (attains the maximum value  $V_i = Q_i \bar{\Delta} \min(C_1, \dots, C_N) / C_i^* \geq Q_j \bar{\Delta} \min(C_1, \dots, C_N) / C_j, \forall j \neq i$ ).

### 3 Missingness-Tolerant Aggregation and Verbalization

The LSP criterion function consists of attribute criteria and the suitability aggregation structure and assumes the availability of all  $n$  input attribute values. In reality, however, the ORE web sites regularly offer incomplete data about available homes. For example, our experiments with homes available through ORE API in San Francisco show on the average the availability in the range from 50% to 70% of input attributes, as illustrated in Fig. 6. For each of ten zip codes we averaged the availability of attributes for all marketed homes providing reliable insight into the missingness problem. The home attribute data come from various sources: home owner/seller, county records, and broker listing feeds, and some of them are frequently incomplete. So, we have two options: to abandon the idea of home evaluation and selection using ORE data, or to use techniques for penalty-controlled missingness-tolerant aggregation. We use the method presented in [8] where the user can select the degree of penalty  $P \in [0,1]$  (or  $P \in [0,100\%]$ ) for missing data, as shown in Fig. 3. Then nonnegative inputs  $x_i \geq 0$  correspond to known attributes, and negative inputs denote unknown attributes defined as  $x_i = P - 1$ . So,  $x_i = 0$  denotes either no satisfaction of the corresponding elementary criterion or the maximum penalty assigned to an unknown attribute. In the case of negative suitability we have  $0 \leq P < 1$ ,  $-1 \leq x_i < 0$  and the zero penalty yields  $x_i = -1$ . Our missingness-tolerant aggregation structure maps  $[-1,1]^n \rightarrow [0,1]$ ; for details, see [8].



**Fig. 6.** ORE data availability for ten zip codes in San Francisco

The aggregation of suitability degrees is related to the perception of the importance of inputs. For example, if a homebuyer requires a high degree of simultaneity of the home quality and the home location quality, that requirement necessarily yields a



perception that both the home quality and the location quality are (for that specific homebuyer) very important. Thus, a high andness is a consequence of high overall importance of inputs. Similar situation also holds in the case of high orness. However, while the concepts of andness and orness are familiar to professional decision-makers, the concept of overall importance is familiar to everybody. This fact can be used to derive the andness/orness and other parameters of partial conjunction and partial disjunction from the verbalized perception of the overall importance of inputs. This idea was introduced in [7] and implemented in the LSPhome interface shown in Fig. 3 where users can select verbalized degrees of importance of home location, home quality, and home price. Using the method presented in [7] the selected degrees of importance of home location and home quality are used to derive the andness and weights for the final suitability aggregation block ( $W_L, W_H, F$ , Fig. 4). Then, the mean importance of location and home quality and the importance of price are used to derive the andness and the weights of the aggregator that aggregates the overall suitability and the overall affordability and provides the overall home value.

If the user wants a simultaneous satisfaction of  $k$  inputs and has the perception that their levels of overall importance (selected from the verbalized importance scale with  $L+1$  levels) are  $S_1, \dots, S_k$ ,  $S_i \in \{0, \dots, L\}$ ,  $i = 1, \dots, k$ ,  $k > 1$ , then, according to [7], the corresponding andness is interpreted as the mean relative overall importance:  $\alpha = (S_1 + \dots + S_k) / kL$ . Indeed, the perception of importance and the value of andness increase simultaneously and the above model is based on the linear relationship between the andness and the mean overall importance. The verbalized overall importance scale can also be used to derive the degrees of relative importance of inputs. Among three linear models proposed in [7] for computing weights  $W_1, \dots, W_k$ , the simplest is the proportional scaling model  $W_i = S_i / (S_1 + \dots + S_k)$ ,  $i = 1, \dots, k$ .

## 4 Experimental Results

Using the LSP methodology presented in previous sections we developed a web application called LSPhome that helps users to find the most suitable home according to their specific criteria. Traditional ORE web sites offer searches of available real estate inventory in the style of the traditional SQL SELECT-FROM-WHERE statement. The user is only allowed to specify a few crisp conditions in the WHERE clause. Such conditions are used as a filter, i.e. as a strictly binary selector that rejects all homes that do not satisfy any of the filtering conditions selected by the user. In a typical case the ORE web sites offer the filter conditions from the following list: (1) home type, (2) price range, (3) minimum number of bedrooms, (4) minimum number of bathrooms, (5) square feet range, (6) lot size range, (7) home age range, (8) time on market, (9) keywords used to select desired features (e.g. pool, patio), and (10) desired location/neighborhood. The filtering method considers all selected filtering conditions as the binary mandatory requirements. For example, if the home type is specified as condo/apartment, then all single family and multi family homes will be rejected. Obviously, the filtering process is useful, but it is not the home evaluation.

The home filtering is merely the partitioning of inventory in two basic groups: homes that are not acceptable and homes that might be acceptable. At this time the customers of ORE web sites do not have the possibility to determine the degree of acceptability (suitability) according to their specific needs. Evaluation and ranking of potentially suitable homes is left to the user and it is done intuitively. Of course, the number of attributes is too big for easy intuitive evaluation, and the process of home selection is usually stressful and time consuming.

The primary advantages of the soft computing approach and the LSP method with respect to the traditional filtering process are the evaluation and ranking of homes according to user needs, the reduction of search/decision time, and the justification of proposed decisions; that increases the confidence and improves the experience of homebuyer (and/or home seller). Of course, the central problem is how to define the user needs. The number of home attributes that we used (36) is a typical value and it is difficult to reduce it without losing the credibility of evaluation results. On the other hand, it is not reasonable to ask an average homebuyer to specify 36 elementary criteria (or fuzzy set membership functions) followed by an advanced aggregation structure. Thus, we proposed a hybrid approach: the user specifies 9 crucial requirements using the LSPhome interface shown in Fig. 3 and the remaining parts of the LSP criterion are prefabricated (fixed, reflecting average general requirements). In this way we combine the simplicity of specification of requirements and the breadth of covering relevant attributes. In particular, a significant advantage of our method is the integration of the home quality and the location quality attributes, with the possibility to conveniently adjust the relative importance of home quality versus the location quality. The location quality analysis is based on data about all points of interest provided by Google using techniques developed in [6] and [15].

#### LSPhome has found the following houses for you:

Rank	Score [%]	Price	Value	Address
1	76.94	890000	100.00	<a href="#">1746 20th Ave, San Francisco, CA 94122</a>
2	71.41	850000	98.58	<a href="#">1675 26th Ave, San Francisco, CA 94122</a>
3	71.01	860000	97.73	<a href="#">1621 31st Ave, San Francisco, CA 94122</a>
4	67.80	827000	97.38	<a href="#">1242 12th Ave, San Francisco, CA 94122</a>
5	29.20	649999	72.08	<a href="#">1350 41st Ave, San Francisco, CA 94122</a>
6	36.01	900000	68.03	<a href="#">1699 19th Ave, San Francisco, CA 94122</a>
7	35.33	900000	67.38	<a href="#">1683 27th Ave, San Francisco, CA 94122</a>
8	31.31	900000	63.44	<a href="#">1526 45th Ave, San Francisco, CA 94122</a>
9	26.49	780000	62.68	<a href="#">1879 48th Ave, San Francisco, CA 94122</a>
10	23.47	800000	58.25	<a href="#">1207 30th Ave, San Francisco, CA 94122</a>

[Show all competitive systems.](#) [Show all evaluation results](#)



Fig. 7. An example of typical LSPhome evaluation results

A typical example of the summarized home evaluation and selection results generated by the LSPhome system is shown in Fig. 7 (“score” denotes the overall suitability). The user looking for a home in the vicinity of the 19<sup>th</sup> Avenue in San Francisco is given the ranking of 10 homes selected by LSPhome. The first four homes satisfy more than 2/3 of user requirements and other have too low suitability scores. The overall value is computed as a hard partial conjunction of the normalized suitability and normalized affordability:  $V_i = W(\min(C_1, \dots, C_N) / C_i) \bar{\Delta} (1 - W)(S_i / \max(S_1, \dots, S_N)) \in [0, 1]$ ,  $i = 1, \dots, N$ . The weight  $W$  denotes the relative importance of affordability compared to the relative importance of home quality. It is computed from the importance of low price selected by the homebuyer using the LSPhome interface (Fig. 3). The results in Fig. 7 show the normalized relative value  $V_i^{(norm)} = 100V_i / \max(V_1, \dots, V_N)$ ,  $i = 1, \dots, N$ , so that the top ranking home is rated 100%. In our example the four leading homes differ for less than 3%, while others have significantly lower values. Consequently, in this case the user is expected to focus on the four best options, compare homes using the values and the suitability of attributes (Fig. 8 and Fig. 9) and expand the investigation using suitability maps or a detailed analysis of the quality of urban location.

Walkability	47.0	54.0	49.0	49.0	23.0	44.0	32.0	82.0	53.0	40.0
Shopping and dining	76.0	79.0	79.0	84.0	55.0	83.0	66.0	87.0	80.0	81.0
Health support	38.0	42.0	64.0	66.0	41.0	59.0	35.0	74.0	64.0	63.0
Suitability for children	64.0	34.0	56.0	59.0	36.0	65.0	38.0	89.0	56.0	69.0
Suitability for seniors	40.0	39.0	61.0	59.0	28.0	58.0	51.0	79.0	63.0	54.0
Walking distance from the ideal location	1.76	1.75	0.02	0.65	1.29	0.72	1.92	1.01	0.26	0.88
Total internal living area of home	1350.0	982.0	1700.0	1385.0	1152.0	2266.0	1647.0	1046.0	2190.0	1686.0
Outer usable area belonging to home	1650.0	2014.0	1700.0	1611.0	1500.0	206.0	474.0	1046.0	2190.0	1912.0
Number of bedrooms	2.0	2.0	3.0	2.0	2.0	5.0	4.0	3.0	4.0	2.0
Number of bathrooms	2.0	1.0	2.0	1.0	1.0	4.0	2.0	1.5	3.0	1.1
Kitchen	50.0	40.0	60.0	*****	0.0	0.0	40.0	*****	*****	*****
Dining room/area	0.0	1.0	0.0	*****	1.0	0.0	1.0	*****	*****	*****
Living/family room	1.0	0.0	1.0	*****	0.0	1.0	0.0	*****	*****	*****
Breakfast room/area	1.0	1.0	1.0	*****	0.0	0.0	0.0	*****	*****	*****
Home office	1.0	0.0	0.0	*****	0.0	0.0	1.0	*****	*****	*****
Laundry	70.0	70.0	100.0	*****	0.0	0.0	35.0	*****	*****	*****
Walk-in closets	1.0	0.0	1.0	*****	0.0	0.0	0.0	*****	*****	*****
Pantry	0.0	0.0	0.0	*****	0.0	0.0	0.0	*****	*****	*****
Auxiliary utility areas	0.0	0.0	0.0	*****	0.0	0.0	0.0	*****	*****	*****
Private garage	0.0	3.0	3.0	*****	3.0	3.0	3.0	3.0	*****	*****
Shared garage	0.0	0.0	0.0	*****	0.0	0.0	0.0	0.0	*****	*****
Reserved uncovered parking space	0.0	0.0	0.0	*****	0.0	0.0	0.0	0.0	*****	*****
Street parking next to home	1.0	0.0	0.0	*****	0.0	0.0	0.0	0.0	*****	*****
Street parking close to home	0.0	0.0	0.0	*****	0.0	0.0	0.0	0.0	*****	*****
Paid public parking	0.0	0.0	0.0	*****	0.0	0.0	0.0	0.0	*****	*****
Type of home	4.0	4.0	1.0	4.0	4.0	4.0	4.0	1.0	1.0	4.0
Number of floors	1.0	1.0	2.0	*****	*****	1.0	2.0	*****	*****	*****
External wall material	1.0	1.0	*****	*****	*****	2.0	1.0	*****	*****	*****
Type of floor	5.0	3.0	2.0	*****	1.0	5.0	1.0	*****	*****	*****
Type of roof	1.0	1.0	*****	*****	0.0	0.0	0.0	1.0	*****	*****
Home energy supply	0.0	1.0	1.0	1.0	1.0	0.0	0.0	1.0	1.0	1.0
Source of energy for heating	3.0	*****	*****	*****	*****	3.0	3.0	*****	*****	*****
Type of heating system	2.0	*****	*****	*****	*****	4.0	4.0	*****	*****	*****
Type of cooling system	0.0	0.0	*****	*****	0.0	0.0	0.0	0.0	*****	*****
Home age	97.0	109.0	12.0	77.0	90.0	84.0	65.0	108.0	12.0	81.0
Last modification/improvement	33.0	*****	*****	*****	*****	7.0	*****	5.0	*****	*****

Fig. 8. Attributes of ten competitive homes showing typical cases of missing data

1213	Parking space	33.60	75.50	75.50	*****	75.50	75.50	75.50	*****	75.50	*****
12132	Public parking (first-come, first-served)	75.00	0.00	0.00	*****	0.00	0.00	0.00	*****	0.00	*****
122	Home features	43.37	30.30	62.74	63.18	32.64	53.16	48.79	61.72	30.48	62.15
1225	Home age and maintenance	22.92	9.17	90.00	35.83	25.00	49.26	45.83	32.50	42.49	90.00
1221	Home organization/layout	94.28	94.28	58.87	100.00	100.00	94.28	100.00	100.00	50.00	50.00
12131	Reserved parking	0.00	94.48	94.48	*****	94.48	94.48	94.48	*****	94.48	*****
121311	Garage	0.00	100.00	100.00	*****	100.00	100.00	100.00	*****	100.00	*****
1212	Type of rooms/area	0.00	0.00	0.00	58.35	0.00	0.00	0.00	61.02	87.53	100.00
1211	Area belonging to home	91.86	71.75	100.00	93.76	81.07	83.91	88.77	100.00	74.01	100.00
121321	Free public parking	75.00	0.00	0.00	*****	0.00	0.00	0.00	*****	0.00	*****
1224	Home temperature regulation	50.37	0.00	*****	*****	0.00	64.32	64.32	*****	0.00	*****
1222	Home construction features	77.23	68.46	50.00	*****	44.22	81.13	46.46	*****	70.00	*****
12121	Primary rooms	0.00	0.00	0.00	58.35	0.00	0.00	0.00	61.02	87.53	100.00
12122	Additional space and storage	58.34	2.64	29.83	*****	0.00	0.00	4.27	*****	*****	*****
121222	Storage and auxiliary areas	29.83	0.00	29.83	*****	0.00	0.00	0.00	*****	*****	*****
121221	Additional space	93.64	26.09	29.83	*****	0.00	0.00	42.16	*****	*****	*****
11	QUALITY OF LOCATION	65.60	60.69	72.02	71.94	46.80	70.65	53.58	69.67	86.08	72.84
111	Suitability of neighborhood	56.89	50.65	60.06	61.61	34.48	60.17	42.84	59.36	82.96	61.68
12252	Last modification/improvement	29.75	*****	*****	*****	*****	79.00	*****	*****	85.00	*****
12251	Home age	19.17	9.17	90.00	35.83	25.00	30.00	45.83	32.50	10.00	90.00
12243	Type of cooling system	0.00	0.00	*****	*****	0.00	0.00	0.00	*****	0.00	*****
12242	Type of heating system	60.00	*****	*****	*****	*****	100.00	100.00	*****	*****	*****
12241	Source of energy for heating	90.00	*****	*****	*****	*****	90.00	90.00	*****	*****	*****

Fig. 9. A fragment of evaluation results showing the missing attribute and subsystem data

A typical problem of missing data is visible in Fig. 8 (obtained using the “show all competitive systems” option in Fig. 7) and in Fig 9 (obtained using the “show all evaluation results” option in Fig. 7). Out of ten competitive homes only two homes have the complete attribute data. All other data are incomplete. Furthermore, the missing attribute data propagate through the aggregation tree and some subsystems (e.g. garage and reserved parking) have missing values shown in Fig. 9.

In order to deal with missing data evaluators must decide about the most suitable value of the missingness penalty parameter. The effects of missingness penalty are shown in Fig. 10. In all cases increasing the missingness penalty causes a decrease of the overall suitability. For the maximum penalty the overall suitability for missing nonmandatory attributes is positive, and for missing mandatory attributes it is zero.

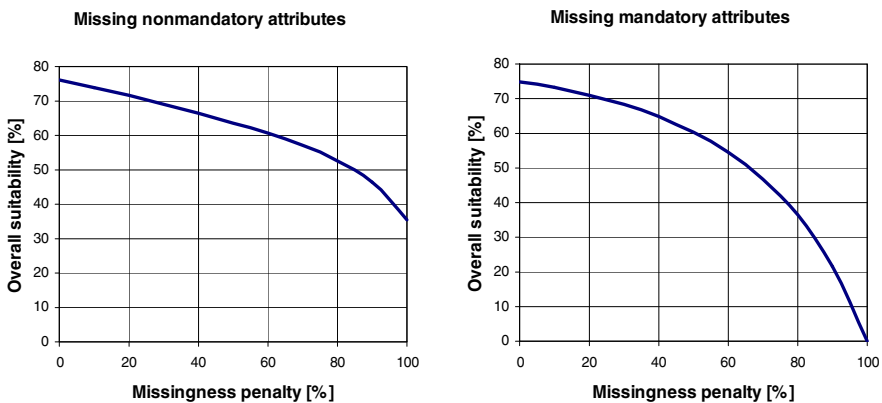


Fig. 10. Overall suitability as a function of missingness penalty

The selection of missingness penalty is based on the decision maker missingness tolerance level. Indeed, the missing data can be intentionally hidden because they are inconvenient, or they can be unknown to all data providers. In the case of suspected inconvenient data it is justifiable to apply the highest penalty. In the case where we have reasons to believe that the unknown attributes are satisfied (e.g. the house with missing parking data is in a residential district that is known to have free public parking space) we may select a lower penalty value. To decide about the most appropriate missingness penalty it is suitable to first plot and analyze the overall suitability curves similar to those shown in Fig. 10. The suitability functions in Fig. 10 are strictly concave and the penalty of 80% should be applied if we want to get the overall suitability that is approximately halfway between the extreme values.

The evaluation results (Fig. 7) offer the possibility for detailed investigation of the suitability of home location and its neighborhood. The evaluation tools [6], [15] (also available at [www.seas.com](http://www.seas.com)) provide suitability maps, which are geographic maps with an overlay showing the distribution of suitability degrees. Fig. 11 shows the suitability map for walkability (possibility to access selected points of interest by walking) where the suitability degrees are presented as numeric values on top of a Google map with selected points of interest. We define walkability as a conjunctive partial absorption of a set of mandatory points of interest and a set of optional points of interest. For the best home proposed in Fig. 7, the walkability is 53%. The potential homebuyer can also investigate the suitability of selected neighborhood for business, children, entertainment, shopping, etc., or make his/her own suitability map.

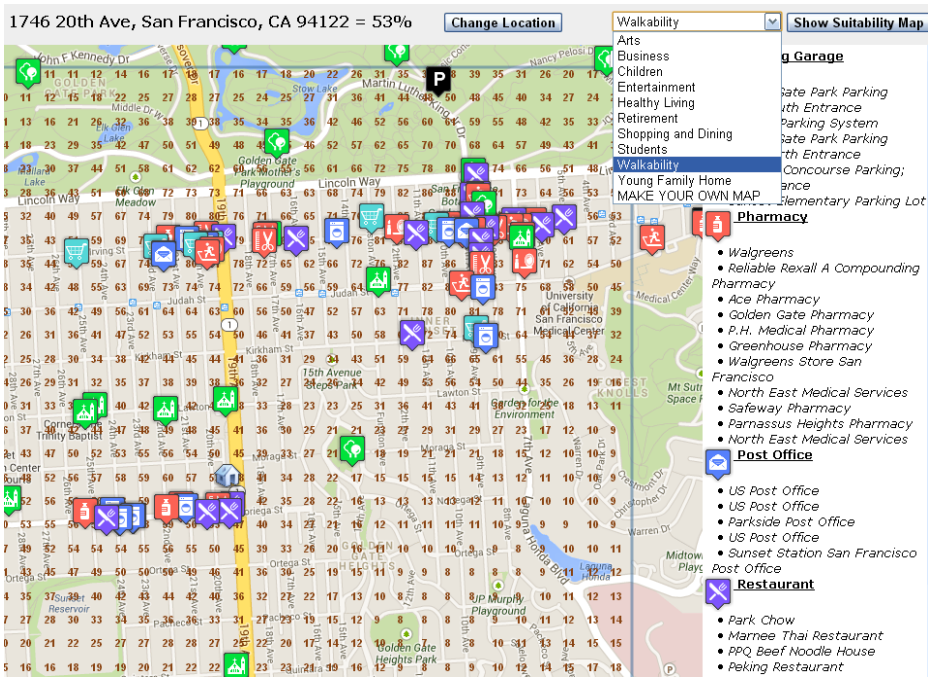


Fig. 11. Suitability map on top of a Google map in the vicinity of the selected home

Suitability maps based on points of interest provided by Google give useful information about the suitability of neighborhood, but they do not include physical, environmental, and safety aspects of the neighborhood. Such information can be collected from other sources (e.g. government) and used for additional analysis of the suitability of location. Fig. 12 shows a sample of such an analysis (based on the analyzer of the quality of urban locations developed in [15] and activated as an option in Fig. 7). The quality of urban locations is analyzed using suitability maps based on 11 diverse attributes presented in Fig. 12. In the given point of the best home reported by LSPHome the quality of location is 64%. This value can be compared with the presented distribution of the location quality in the whole city (the best values around 70% and the mean value of 55.41%). Thus, the neighborhood of the selected home is notably above the city average and not too far from the best locations in the city.

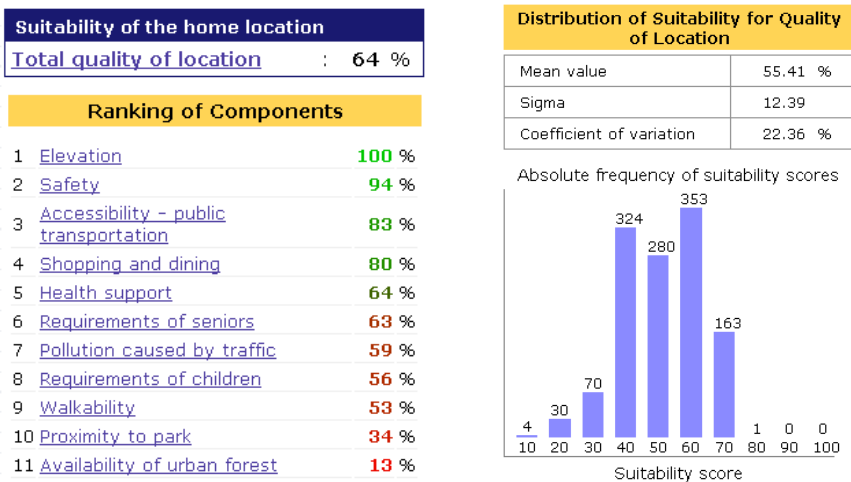


Fig. 12. Quality of urban locations based on 11 diverse attributes

## 5 Conclusions

Evaluation and selection of homes is essentially a soft computing logic problem. ORE web sites offer data that enable the use of customized compensative logic criteria for fast ranking of available homes. This paper shows a way such criteria can be designed using the LSP method, and implemented in a software tool available over the Internet. Specific problems related to online buying and selling of homes include the missingness-tolerant aggregation and the use of the verbalized concept of overall importance to derive the andness/orness and weights of partial conjunction and partial disjunction aggregators. Soft computing decision methods are a way to significantly improve both the efficiency and the customer experience in online real estate.

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