Review on Neural Networks in Building Type Analysis

Nicola Maiellaro
Institute for Housing and Social Infrastructures, National Research Council
strada Crocifisso 2/B, 70125 Bari, Italy
Phone: +39-80-5481265, Fax: +39-80-5482533
email: maiellaro@ba.cnr.it

ABSTRACT: Classical statistical methods may be sensitive to assumptions about the populations of the group being classified. The use of neural networks as classifiers appears to be a valuable resource for decision making, relieving the decision-maker from the task of selecting an appropriate analysis method. Contrasting results between backpropagation and other networks applied to the specific field of typological classification of buildings, presented at EUFIT '98, require deeper investigation. This paper introduces some considerations about the traditional building type analysis, specifically related to building type variants; then a comparison between different neural networks is illustrated.

KEYWORDS: building type analysis, neural networks, classification

INTRODUCTION

Design for residential use has to cope with the problem of acting upon the existing building stock. As part of this tendency, recovering residential buildings in historic centres is an especially problematic frame of work, mainly because of the difficulty of adapting old building structures - inherited from dwelling patterns that are now obsolete - which are no longer compatible with current housing needs.
Recently, the most interesting examples of urban rehabilitation have received a major contribution from typological analysis as a means to determine site transformability both in terms of urban fabrics and of separate constituent elements; this approach allows continuous interaction between the town planning level and the design of the building structure. The really difficult problem is to understand the type’s adaptability to users' changing requirements, and the most engaging task is to translate the historical-typological reading into operative terms and to be able to use the reading in the design phase.
In particular, the neural networks described in this paper have been used as an aid in the classification of the architectural units of an old centre by types - a classification that is regarded as a fundamental preliminary instrument for the definition of guidelines to be used in project-making in the study context.

TRADITIONAL BUILDING TYPE ANALYSIS

In the example discussed here, the typological study is essentially intended to define architectural types by classes, based on the characteristics of the buildings’ structures, dimensions and distributions and on the relational systems observable between typological traits and degrees of transformability of the type with respect to different levels of functional and environmental requirements. In order to define a classification of building types, it is necessary:
- to define sets of descriptors of the building organisms and of how they relates to the urban fabric;
- to state criteria and rules enabling them to be ascribed to the different typological classes.

For the case study, information on the plan and elevation characters of the buildings was acquired and descriptors were defined concerning - in line with the previously described objectives - some features such as structures, dimensions, prospects and distribution of the building organisms, as well as some variables describing their relationship with the urban fabric. It should be noted that the work of ascribing a building to the appropriate class could be done by the expert by means of an interpretation approach essentially based on observation, hence on qualitative reasoning obviously subject to error; moreover, plans could not be found for all buildings, and buildings suffer remarkable changes.
In the case study, serial buildings in the old centre have been articulated into four classes of basic types and different diachronic variants. The variants are essentially determined by the difference in the location of the architectural organisms inside the urban fabric and defined in the light of problems relating to design rehabilitation work.

The building types, as in the Refurbishment Plan of the old centre for the Municipality of Capurso[1] (Figure 1), are:

- Basic type A
  1 cell; basement and mezzanine floor, one-faced, 1 main face axis, mono-family building, residential use of mezzanine floor
  - Variant A1 - levels: underground, basement and first floor; vertical layout of dwelling; non-residential use of ground floor and first floor.
  - Variant A2 - levels: underground (sometimes), ground, first, second (sometimes); external staircase.
- Basic type B
  2 cells; layout parallel to the main face axis; horizontal layout of dwelling; one-faced; 2 main face axis; one external staircase serving more storeys; multi-family; non-residential use of ground floor.
  - Variant B1 - layout normal to the main face axis; 1 main face axis
  - Variant B2 - cells>2; 2-3 main face axis; non-regular layout
- Basic type C
  cells>3; multi-storey; main face axis =>2; one staircase serving two dwellings each storey; multi-family building; residential use of ground floor
  - Variant C1 - one staircase serving one dwelling each storey
- Basic type D
  one internal staircase serving more storeys; multi-storey, main face axes>2, horizontal layout of dwelling, families: 1-2; non-residential use of ground floor

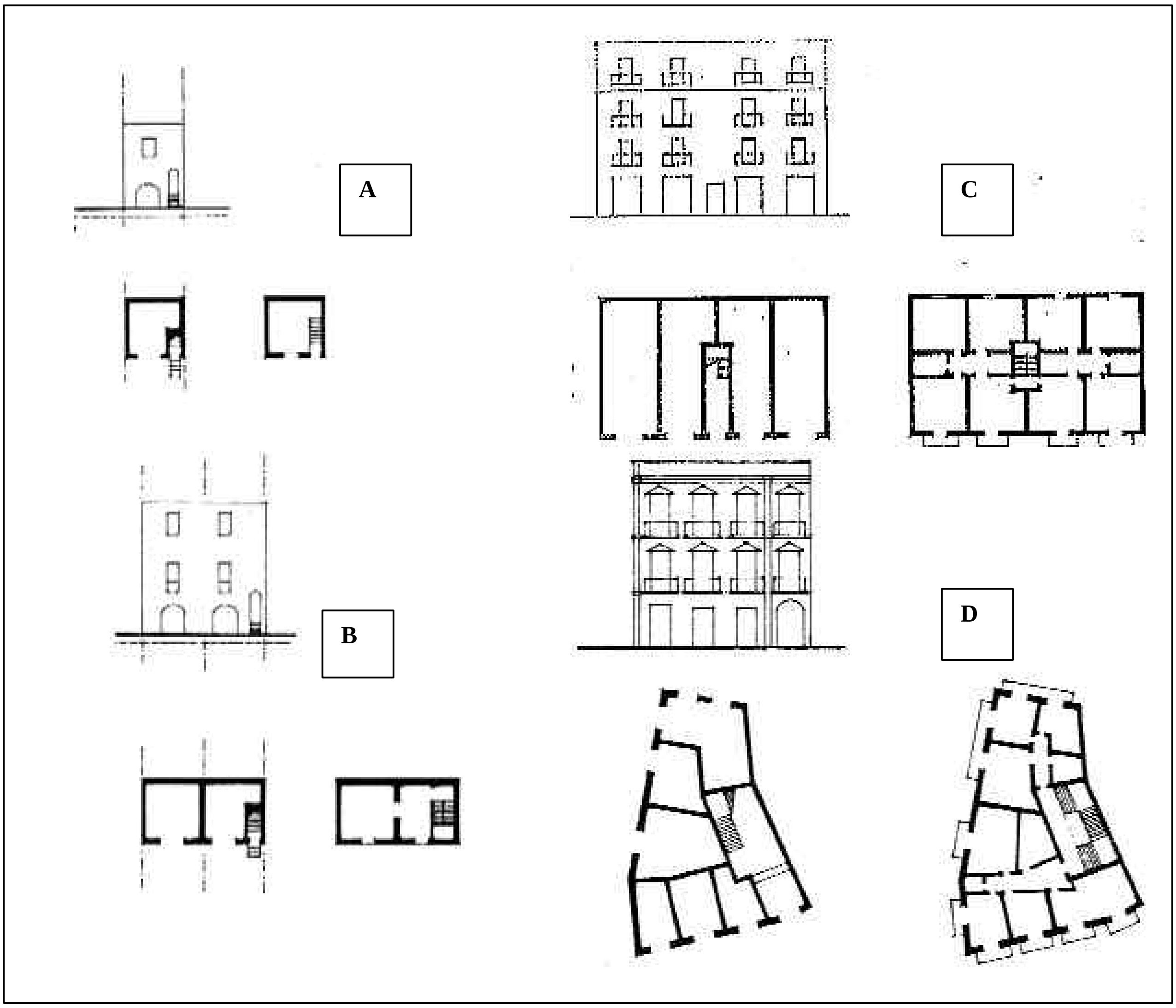

Figure 1: Basic types of buildings in the old centre of Capurso.

[1] Project Team: A. Cucciolla, R. Ferrari, F. Guerra

These building types are quite different from the previous classification operated for the same centre, as reported in Maiellaro (1998), due the presence of a different team. Aggregating experts' knowledge to define descriptors better would be further investigated, as in Mak, Bui and Blanning (1996).
As possible, the descriptors refer to building photos and plans; the descriptors elicitated were:
1. Cells
2. External faces overlooking road
3. Main front with respect to the road axis (-1=contiguous; 0=no value; 1=opposit)
4. Staircase typology
5. Fronts with respect to road axis (1=trasversal; 2=parallel)
6. Number of external faces overlooking courtyards
7. Set-up of dwelling (1=horizontal 2=vertical)
8. Internal courtyard
9. Underground floor
10. Basement floor
11. Mezzanine floor
12. 1^{st} floor
13. 2^{nd} floor
14. Number of main face axes
15. External staircases
16. Internal staircases
17. Non-residential use of building levels
18. Families in building

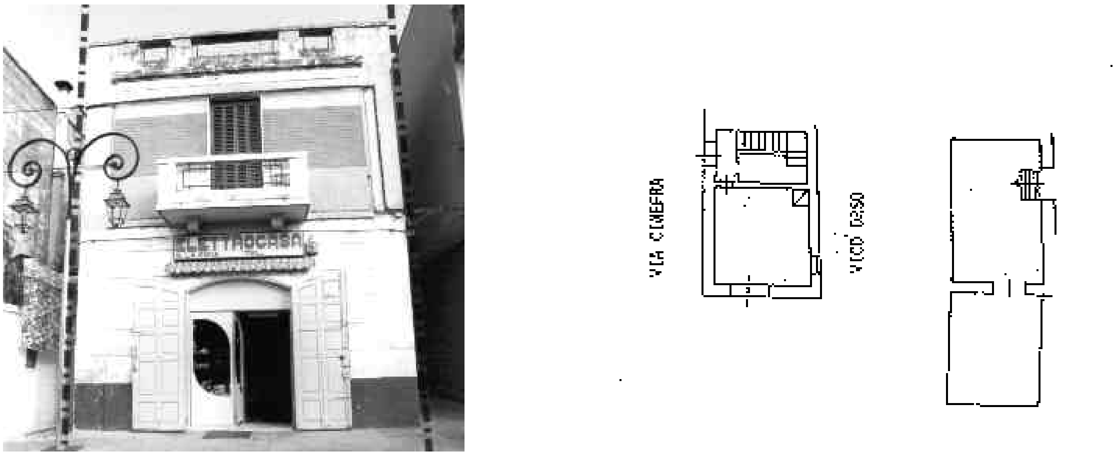

Figure 2: Parcel #88 - Photo and plan.

NEURAL NETWORK APPROACH

The classification problem is one of assigning an object into categories, based on a set of independent variables. A classification technique, that has the potential of adapting itself to general conditions, utilises a neural network to learn the relationships implied by the data while making no assumptions about the distributions of the data. Moreover, neural nets are found to perform best under conditions of high noise and low sample size (as in our case study).
The training of the neural network was performed using data related to 113 cadastral parcels, randomly chosen among 162 patterns for which plans were available and thus a complete description was possible. As it is in reality, the distribution among different types was heterogeneous. In this paper, the classification problem is solved using four methods as developed in the package NeuroShell 2®:
- each layer connected only to the previous layer (3 layer standard nets);
- recurrent networks with dampened feedback (Jordan-Elman nets);
- multiple hidden slabs with different activation functions (Ward nets[2]);

[2] A regular three-layer Backpropagation network with two slabs in the hidden layer. Use a different activation function for each slab in the hidden layer to detect different features in the data.

- each layer connected to every previous layer (jump connections nets).

Other assumption are:

- use the hyperbolic tangent as scale function[3];
- use the logistic function as activation function[4];
- use momentum for weight updates;
- save the network every time it reaches a new minimum average error for the training set;
- using a trained neural network, set to 1 the highest output (others to 0), each output being a category.

After a first evaluation (table I), the input "courtyard" was deleted; the inputs "underground floor" and "mezzanine floor" were grouped because they presented the same value. Repeated examples were also deleted. Statistical[5] calculations show a better performance for recurrent networks.

1st set		3 layer standard net			recurrent networks			Ward nets			Jump connections net		
Types	#/type	.T.	%	r	.T.	%	r	.T.	%	r	.T.	%	R
A	27	14	52%	0,52	10	37%	0,51	19	70%	0,57	2	7%	0,25
A1	29	28	**97%**	0,64	29	**100%**	0,83	18	62%	0,73	29	**100%**	0,51
A2	12	7	58%	0,65	10	83%	0,67	6	50%	0,64	5	42%	0,48
B	15	5	33%	0,56	13	87%	0,77	7	47%	0,66	4	27%	0,50
B1	50	36	72%	0,72	50	**100%**	**0,92**	46	**92%**	0,75	34	68%	0,67
B2	6	2	33%	0,46	0	0%	0,00	2	33%	0,46	1	17%	0,21
C	2	1	50%	0,71	0	0%	0,00	1	50%	0,71	0	0%	0,00
C1	16	13	81%	0,67	12	75%	0,70	13	81%	0,68	13	81%	0,56
D	5	5	**100%**	0,74	1	20%	0,24	5	**100%**	0,70	1	20%	0,20
Total:	162	111	69%		125	**77%**		117	72%		89	55%	

Table I:. 1st set (training set: 113; patterns: 162; descriptors: 18), elaborated with different networks

2nd set		3 layer standard net			recurrent networks			ward nets			Jump connections net		
Types	#/type	.T.	%	r	.T.	%	r	.T.	%	r	.T.	%	R
A	25	17	68%	0,54	24	**96%**	0,51	20	80%	0,63	25	**100%**	0,69
A1	22	15	68%	0,71	18	82%	0,75	15	68%	0,64	14	64%	0,71
A2	12	5	42%	0,44	8	67%	0,89	4	33%	0,44	4	33%	0,56
B	16	10	63%	0,49	13	81%	0,75	10	63%	0,66	12	75%	0,60
B1	33	24	73%	0,67	29	88%	0,82	26	79%	0,74	24	73%	0,79
B2	6	3	50%	0,53	3	50%	0,70	3	50%	0,40	3	50%	0,60
C	2	1	50%	0,50	0	0%	0,00	1	50%	0,70	1	50%	0,70
C1	15	8	53%	0,70	12	80%	0,81	9	60%	0,64	9	60%	0,58
D	4	4	**100%**	0,57	4	**100%**	0,81	4	**100%**	0,62	3	75%	0,60
Total:	135	87	64%		111	**82%**		92	68%		95	70%	

Table II:. 2nd set (training set: 90; patterns: 135; descriptors: 16), elaborated with different networks

The 2nd set of patterns (reduced to 135) and descriptors (reduced to 16) shows an improvement with the recurrent network (table II). Recurrent networks are trained the same as standard backpropagation networks except that patterns must always be presented in the same order; random selection is not allowed. The only difference in the structure is that there is one extra slab in the input layer that is connected to the hidden layer just like the other input slab. This extra slab holds the contents of one of the layers as it existed when the previous pattern was trained. In this way the network sees previous knowledge it had about previous inputs. This extra slab is sometimes called the network's "long term" memory. The descriptors "underground and mezzanine floor" and "ground floor" were deleted due their low

[3] When variables are loaded into a neural network, they must be scaled from their numeric range into the numeric range that the neural network deals with efficiently.

[4] The hidden layers produce outputs based on the sum of weighted values passed to them. So does the output layer. The way they produce their outputs is by applying an "activation" function to the sum of the weighted values. The activation function, maps this sum into the output value, which is then "fired" on to the next layer. The logistic function is: $f(x)=1/(1+\exp(-x))$

[5] The Linear Correlation Coefficient "r" is a statistical measure of the strength of the relationship between the actual vs the predicted outputs. It can range from -1 to +1. The closer r is to 1, the stronger the positive linear relationship, and the closer r is to -1 the stronger the negative linear relationship. When r is near 0 there is no linear relationship.

contribution (table IV). Some repeated examples were also deleted. The 3rd set of patterns (reduced to 127) and descriptors (reduced to 14) is now elaborated using different types of recurrent network (trained with rotation, since order is important):

- Input Layer Fed Back Into Input Layer
  The long term memory remembers the new input data and uses it when the next pattern is processed.
- Hidden Layer Fed Back Into Input Layer
  The long term memory remembers the hidden layer, which contains features detected in the raw data of previous patterns. This is the most powerful recurrent network.
- Output Layer Fed Back Into Input Layer
  Long term memory remembers outputs previously predicted.

A different combination of activation function and weight updated (Vanilla and "turboprop") produces similar results. The best performance is reached for the "Output Layer Fed Back Into Input Layer" (table III - 4th column):

- saving the network every time it reaches a new minimum average error for the test set;
- 14 neurons in the 1st and 2nd slab, 9 neurons in the 3rd and 4th slab (figure 3);
- activation function: Gaussian complement 1 - exp(-x^2) for the 2nd slab and logistic for the 3rd slab (output).

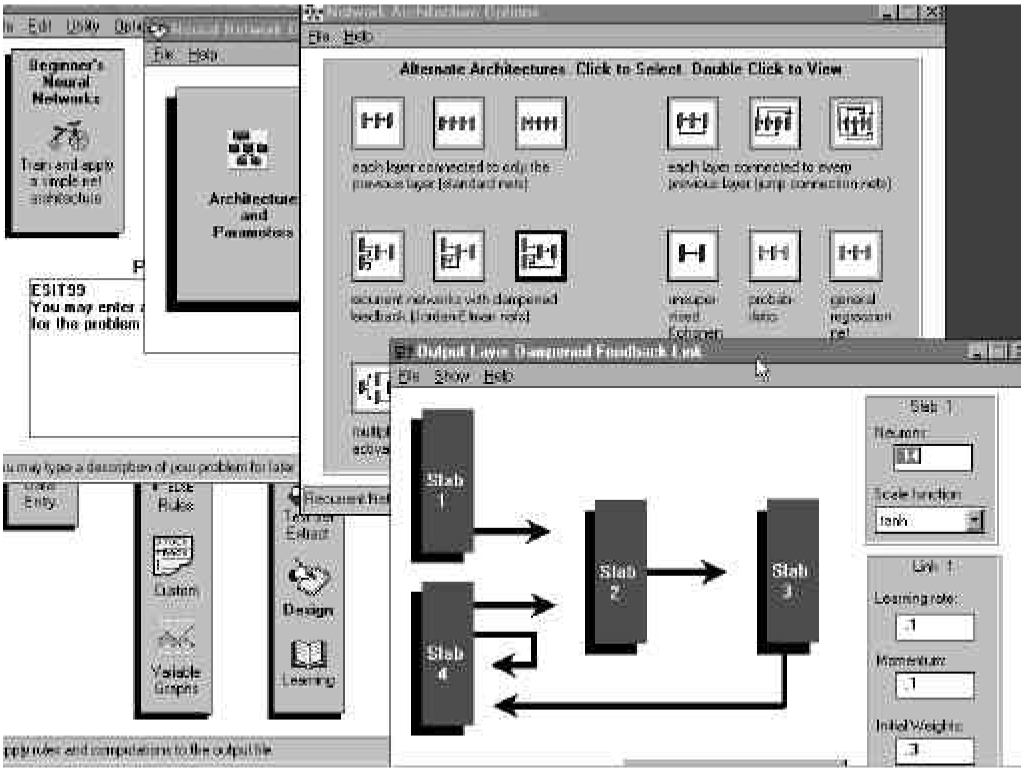

Figure 3: Architecture and parameters.

3rd set		Input Layer Fed Back Into Input Layer			Hidden Layer Fed Back Into Input Layer			Output Layer Fed Back Into Input Layer			Output Layer Fed Back Into Input Layer (best test set)		
Types	#/type	.T.	%	c	.T.	%	c	.T.	%	c	.T.	%	c
A	18	18	**100%**	0,91	18	**100%**	1,00	18	**100%**	1,00	18	**100%**	1,00
A1	22	20	**91%**	0,89	17	77%	0,77	22	**100%**	0,97	22	**100%**	0,97
A2	12	8	67%	0,75	12	**100%**	0,82	11	**92%**	0,95	9	75%	0,86
B	16	14	88%	0,86	12	75%	0,85	15	**94%**	0,93	15	**94%**	0,90
B1	33	31	**94%**	0,92	31	**94%**	0,92	33	**100%**	0,98	32	**97%**	0,96
B2	6	3	50%	0,53	3	50%	0,53	3	50%	0,70	3	50%	0,60
C	2	1	50%	0,70	1	50%	0,70	2	**100%**	1,00	1	50%	0,49
C1	14	9	64%	0,74	4	29%	0,27	4	29%	0,36	11	79%	0,73
D	4	4	**100%**	0,62	4	**100%**	0,59	4	**100%**	0,53	4	**100%**	0,60
Total:	127	108	85%		102	80%		112	88%		115	**91%**	

Table III:. 3rd set (training set: 85; patterns: 127; descriptors: 14), elaborated with different recurrent networks

TYPES	A		A1		A2		B		B1		B2		C		C1		D	
DESCRIPTORS	min	max	min	max	min	max	min	max	min	max	min	max	min	max	min	max	min	max
1 . Cells	1	1	1	1	1	2	1	3	1	2	2	3	4	4	1	4	3	4
2. External faces overlooking road	-1	0	-1	1	-1	1	-1	1	-1	1	-1	1	-1	1	-1	1	-1	1
3. Main front with respect to the road axis (-1=contiguous; 0=no value; 1=opposit)	1	1	1	1	1	2	1	2	1	2	1	2	1	1	1	2	1	2
4. Staircase typology	1	2	1	2	1	2	1	2	1	2	1	2	1	2	1	2	1	2
5. Fronts with respect to road axis (1=trasversal; 2=parallel)	1	2	1	3	1	2	1	3	1	3	1	3	2	3	1	3	2	3
6. Number of external faces overlooking courtyards	0	1	0	0	0	0	0	1	0	1	0	1	0	0	0	0	0	1
7. Set-up of dwelling (1=horizontal 2=vertical)	2	2	2	2	1	2	1	2	1	2	1	2	1	1	1	2	1	1
8. 1st floor	0	1	0	1	0	1	0	1	0	1	1	1	1	1	1	1	1	1
9. 2nd floor	0	0	0	1	0	1	0	1	0	1	0	1	0	1	0	1	0	1
10. Number of main face axes	1	1	1	3	1	1	1	2	1	2	1	3	3	3	1	3	2	3
11. External staircases	0	1	0	2	0	1	0	2	0	2	0	2	2	2	0	1	0	1
12. Internal staircases	1	2	1	3	1	3	1	3	1	2	1	1	1	1	1	2	1	2
13. Non-residential use of building levels	1	2	0	2	0	2	1	2	0	2	1	2	2	2	0	2	2	2
14. Families in building	1	1	1	1	1	2	1	2	1	2	1	2	2	2	1	2	2	2

Table IV:. Descriptors (minimum and maximum values for each category)

CONCLUSIONS

The use of neural networks as classifiers appears to be a valuable resource for decision making, relieving the decision-maker from the task of selecting a proper analysis method. Classical statistical methods may be sensitive to assumptions about the populations of the group being classified. The work described here aims at comparing the results of different neural networks in the specific field of typological classification of buildings.

The best result is obtained with a recurrent network with Output Layer Fed Back Into Input Layer (best test set). This results claims for further investigation, due to the fact that this type of Backpropagation network has been successfully used in predicting financial markets (recurrent networks can learn sequences, so they are excellent for time series data).

Only two building types (B2 and C) are predicted with uncertainty (50%), but this bad performance is probably due the low number of patterns (6 and 2).

Next steps will be to find further patterns for the types above mentioned, and to apply the trained network to other old centres.

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ACKNOLEDGMENTS

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