Astron. Astrophys. Suppl. Ser. **116,** 395-402 (1996)

Classification of planetary nebulae by cluster analysis and artificial neural networks

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Received July 24; accepted September 18, 1995

Abstract. — According to the chemical composition, a sample of 192 Planetary Nebulae of different types has been re-classified, and 41 others have been classified for the first time, by means of two methods not employed so far in this field: hierarchical cluster analysis and supervised artificial neural network. The cluster analysis reveals itself as a good first guess for grouping Planetary Nebulae, while an artificial neural network provides reliable automated classification of this kind of objects.

Key words: planetary nebulae: general — methods: miscellaneous

1. Introduction

In the seventies, Planetary Nebulae (PN) were classified according to their chemical, spatial, kinematical, and morphological properties into four types, namely, Types I, II, III, and IV (for details on the classification see Peimbert 1978; Peimbert & Serrano 1980; Peimbert & Torres-Peimbert 1983; Peimbert 1990).

These nebulae are interesting tracers of the chemical evolution of the Galaxy and other galaxies. The analysis of the chemical properties of PN is important because it determines the abundances in the progenitor star, as well as the individual enrichment by the progenitor's nucleosynthesis, which, in turn, depends on the star's mass. According to Peimbert's classification, most nebulae are probably of Type II, having abundances $He/H < 0.125$, $\log (N/O) < -0.3$, distance to the galactic plane $|z| < 1$ kpc, and peculiar radial velocity $|v| < 60$ km/s.

New efforts were made in the eighties to classify PN, and Type II has been subsequently divided into two subtypes, named IIa and IIb, according to their nitrogen relative to hydrogen abundance ratio (see Faúndez-Abans & Maciel 1987a). The PN which belong to the population of the galactic bulge were classified as Type V objects (see Maciel 1989 for details). Also, an interesting classification of PN into three types has been presented by Amnuel et al. (1989), based on the values of the planetary and progenitor's masses; this has been altered recently to four types, by Amnuel (1993).

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The separation of PN in groups has been useful in the study of the presence of radial and vertical abundance gradients in the Galaxy. A detailed study of radial gradients from Type II PN was carried out by Faúndez-Abans & Maciel (1986, 1987b), who found clear oxygen gradients, besides other heavy elements quoted in those works, and a diagnostics of vertical gradient was made by Faúndez-Abans & Maciel (1988 and references quoted therein). Recently, Maciel & Köppen (1994) have made new determinations of abundance gradients of O, Ne, S, and Ar, elements which should not be manufactured by the progenitor.

In this work, we have used a homogeneous and up-to-date PN abundance data set, to first subdivide them, according to their chemical composition, by means of a cluster analysis and then, with these results in hand, to train an artificial neural network (ANN from now on) for classification of more objects.

2. Procedure

2.1. *The data*

The data for our classification test have been extracted from the homogeneous compilation of abundances for galactic PN given by Köppen et al. (1991), Chiappini (1993), and Maciel & Chiappini (1994, and references quoted in their Table 1), where Type V PN are excluded. This compilation gathers abundance fractions of He, O, N, S, C, Ne, Ar, and Cl relative to H. Nonetheless, as several PN lack information on C, Ne, and Cl, these chemical elements have not been included in our present analysis. We have thus worked with 233 objects. We have first considered only PN with a complete set of He/H, O/H, and N/H ratios, and then S/H and Ar/H data, when available (see Sect. 3). Thirdly, we have included in the cluster analysis objects lacking information on He abundance.

2.2. *The cluster analysis*

The techniques of cluster and discriminant analysis are suitable for identifying and organizing those PN parameters of interest to arrange these objects in groups (these techniques are fully discussed in Anderberg 1973; Tatsuoka 1971; Johnson & Wichern 1986).

The basics of the cluster analysis is to choose a measure of distance between the various families of parameters, from now on referred to as observations, and use it to decide whether an object belongs to a certain family. In this one-dimensional context, the method proceeds as follows: a) one sorts the observations in ascending order and treats each observation as a group with one member, b) one examines all pairs of adjacent groups to find those two which are closest, the distance between them being the distance to their nearest member, c) step "b" is repeated at will or until there is only one group. This simple method is capable of identifying the largest groups in a sequence of parameters (see Kendall & Stuart 1968; Anderberg 1973; Marriolt 1974).

In this work we have used a more sophisticated algorithm, namely, the Wards's hierarchical cluster method (Ward & Hook 1963; Ward 1963; Wishart 1969). This technique proceeds as follows: a) one starts with n groups, each group consisting of one observation, i.e., a planetary; b) at each step the number of groups is reduced by one, through merging those two groups whose combination gives the least possible increase in distance "w", defined as follows:

$$w = \sum_{i=1}^{g} \sum_{j=1}^{n_i} (x_{ij} - \bar{x}_i)^2;$$

the sample of n observations has then been divided into g groups, the ith group containing n_i observations with mean $\bar{x}$, x_{ij} being the jth observation in the i group; c) one might continue this hierarchical process for a total of $n-1$ mergers, when there would be only one group – which would encompass all the planetaries – (Ward 1963; Ward & Hook 1963). In any real-life problem, the clusters so produced must, nevertheless, satisfy the criteria of compactness and isolation, that is, the groups must be well isolated from each other and, at the same time, the distance between the members of each group must be minimal. In other words, one seeks a partition that maximizes the between-class variance as well as minimizes the intra-class variance. This criterion, or dissimilarity, may be expressed as follows:

$$V(P_1) - V(P_2) = V(g) - V(g_a) - V(g_b)$$

where V stands for variance, P_1 and P_2 are the previous and present partitions, respectively, where any original groups (classes) g_a and g_b have been agglomerated into a group g.

This technique has been applied to a sub-sample of 159 well-known PN using the PROC.-CLUSTER-S.A.S. package facilities with the IBM 9221 computer of the Universidad de Santiago de Chile (USACH). This subsampling is to be regarded as having been done with no previous knowledge of any subdivisions whatsoever.

The reader may refer to Murtagh & Heck (1987, pp 77-83) for references of works employing cluster analysis in Astronomy up to that year.

2.3. *The artificial neural network*

The ANN interests physicists, astronomers, engineers, computer and cognitive scientists, neuro-physiologists, biologists, and philosophers. The ANN can be characterized as computational tools with such properties as the ability to learn, generalize, and organize (classify) data, and of which operation is based on parallel processing (see Feldman & Ballard 1982; McClelland & Rumelhart 1986; Rumelhart & McClelland 1986; Rumelhart et al. 1986; Josin 1988; Hertz et al. 1991; Kröse & van der Smagt 1993, among others).

In Astronomy, the use of ANN increased recently in a significant manner, where most efforts have been centered on morphological classification of galaxies (Naim 1994; Adams & Wooley 1994; Lahav et al. 1995), automated star/galaxy discrimination (Odewahn & Nielsen 1994), spectral classification of galaxies (Sodré & Cuevas 1994), stellar spectral classification (Storrie-Lombardi et al. 1994), and predictions of solar activity (Calvo et al. 1995), among others.

There are many learning methods for ANNs by now. The main categorization of these methods is by the learning process: it may be supervised or unsupervised. In the first case, the ANN is trained by providing it with both input and matching output patterns; these patterns are provided either by an external teacher (an expert in the particular problem, for instance) or by the system which contains the ANN (self-supervised). The second process, or self-organization, the ANN is autonomous in the sense that in this paradigm the system itself discovers statistically meaningful features of the input sample, thus developing its own representation of the input population.

In this work we have used the supervised learning package by Ripley (1994a, b), which consists in a feed-forward, back-propagation, algorithm with three free parameters: the weight decay, the hidden layer node number, and the number of subsidiary lines specifying the connection of one of the units to a second range ones in our adopted topologies (see Ripley 1992, 1993, 1994a, and 1994b for details). These parameters have been determined and cross-validated as described in item 3. The calculations have been performed with a Sun SPARCstation2 of the LNA.

3. The results

The cluster analysis produced a total of 6 groups, identified as follows: two groups correspond to Type I, and the other four to Types IIa, IIb, III, and IV, respectively. The subdivision of Type I PN is discussed in detail by Faúndez-Abans et al. (1995) and Ormeño et al. (1996). In this work we ignore this separation for the sake of comparison with the previous classification. The results are displayed in Table 1, where the different columns show: 1) the common name, 2) the galactic coordinates designation ("PN G", after Acker et al. 1992), 3) the previous classification made by other authors (Faúndez-Abans & Maciel 1986; 1988; de Freitas-Pacheco et al. 1991 and references quoted therein, Chiappini 1993; Maciel & Chiappini 1994, "O"), 4) the classification by the cluster analysis ("CA"), 5) the classification by the ANN, and 6) our adopted type of PN ("A").

The maximum likelihood discriminant rule, applied to the five groups, shows the following coincidence percentages between the previous and the cluster division: 74% for Type I, 79.5% and 87.5% for Types IIa and IIb, respectively, 50% for Type III and 100% for Type IV. The poor result for Type III is explained by the non-inclusion of the peculiar radial velocity data (which, following Peimbert's works, is an important criterion of classification for Type III PN); the abundance parameters constitute a more homogeneous and free from large errors set.

In order to ascertain the ANN's learning ability, part of the coincident objects was used as a training set for the Ripley's ANN computer program. These nebulae have been chosen randomly among those with previously well-established PN type because of their previous well-established PN type; they represent roughly 81% of the whole sample. The training and test samples were composed by 126 and 63 independent nebulae, respectively (2/3 and 1/3 of the 81% sample above). The topologies employed were: 5 input units (He, O, N, S, and Ar abundance ratios), 5 output units, and tentatively six different widths for the hidden layer, namely, 3, 5, 10, 20, 25, and 30 units. More than 20 hidden layer units did not improve significantly the errors, so we adopted the 5:20:5 topology to start with. In this topology, each unit of the hidden layer has five input connections, and each unit of the output layer has twenty input connections.

After having classified nebulae with these known five ratios, we classified those with missing Ar and then those missing both Ar and S ratios, employing 4:20:5 and 3:20:5 topologies, respectively.

The ANN was re-trained each time the number of objects increased due to the decrease in the number of

Table 1. The planetary nebulae sample

Name	PN G	O	CA	ANN	A
A 21(YM-29)	205.1+14.2	I	I	I	I
BD+30.3639	064.7+05.5	IIb	IIb	—	IIb
BoBn-1	108.4−76.1	IV	IV	IV	IV
Cn 1-5	002.2−09.4	—	—	IIa	IIa
Cn 2-1	356.2−04.4	IIa	IIa	IIa	IIa
Cn 3-1	038.2+12.0	III	III	—	III
DdDm-1	061.9+41.3	IV	IV	IV	IV
Fg 1	290.5+07.9	IIb	—	IIb	IIb
H 1-17	358.3+03.3	—	—	IIa	IIa
H 1-18	357.6+02.6	I	I	I	I
H 1-20	358.9+03.2	—	—	III–IV	III
H 1-23	357.6+01.7	I	I	I	I
H 1-27	005.0+04.4	—	—	III–IV	III
H 1-29	355.2−02.5	—	—	IIb	IIb
H 1-31	355.1−02.9	—	—	IIa–III	III
H 1-35	355.7−03.5	—	—	III	III
H 1-51	356.7−06.4	—	IIb	—	IIb
H 1-54	002.1−04.2	III	IV	III	III
H 1-58	005.1−03.0	—	—	III	III
H 1-59	003.8−04.3	I	IIa	I	I
H 1-66	007.0−06.0	—	—	IIa	IIa
H 2-18	006.3+04.4	I	I	I	I
H 2-46	000.8−07.6	—	—	IIb	IIb
H 4-1	049.3+88.1	IV	IV	IV	IV
Hb 04	003.1+02.9	I	I	IIa	IIa
Hb 05	359.3−00.9	I	I	I	I
Hb 06	007.2+01.8	I	I	I	I
Hb 12	111.8−02.8	IIb	III	IIb	IIb
He 2-005	264.4−12.7	III	IIb	III–IV	III
He 2-007	264.1−08.1	III	IIb	III	III
He 2-009	258.1−00.3	III	III	III–IV	III
He 2-015	261.6+03.0	I	I	I	I
He 2-021	275.3−04.7	IIb	III	III	IIb
He 2-037	274.6+03.5	IIa	—	IIa	IIa
He 2-047	285.6−02.7	—	—	IIa–III	IIa:
He 2-048	282.9+03.8	IIb	—	IIb	IIb
He 2-051	288.8−05.2	I	—	I	I
He 2-055	286.3+02.8	IIb	—	IIb	IIb
He 2-071	296.4−06.9	—	—	III	III
He 2-086	300.7−02.0	I	I	I	I
He 2-099	309.0−04.2	IIb	—	IIb	IIb
He 2-108	316.1+08.4	III	—	IIb–III	III
He 2-111	315.0−00.3	I	I	I	I
He 2-112	319.2+06.8	I	I	I	I
He 2-115	321.3+02.8	IIb	IIb	IIb	IIb
He 2-117	320.9+02.0	I	IIb	I–IIa	IIa
He 2-118	327.5+13.3	—	—	IIa	IIa
He 2-119	317.1−05.7	I	—	I	I
He 2-123	323.9+02.4	IIa	I	I	I
He 2-131	315.1−13.0	III	III	—	III
He 2-140	327.1−01.8	—	—	IIa	IIa
He 2-141	325.4−04.0	IIa	—	IIa	IIa
He 2-149	329.4−02.7	—	—	III–IV	III
He 2-153	330.6−02.1	I	I	I	I
He 2-157	331.0−02.7	IIa	—	IIa	IIa
He 2-158	327.8−06.1	IIb	IIa	IIb–III	IIb
He 2-164	332.0−03.3	I	IIb	IIb	IIb
He 2-170	332.3−04.2	—	—	IIa–IIb	IIa:
He 2-175	345.6+06.7	—	—	I	I

Table 1. continued

Name	PN G	O	CA	ANN	A
He 2-406	008.6−07.0	—	—	I	I
Hu 1-1	119.6−06.7	IIa	IIa	IIa	IIa
Hu 1-2	086.5−08.8	I	I	I	I
Hu 2-1	051.4+09.6	III	III	III	III
IC 0351	159.0−15.1	IIb	IIb	IIb	IIb
IC 0418	215.2−24.2	IIb	IIb	IIb	IIb
IC 1297	358.3−21.6	IIa	IIa	IIa	IIa
IC 1747	130.2+01.3	IIa	IIa	IIa	IIa
IC 2003	161.2−14.8	IIa	IIa	IIa	IIa
IC 2149	166.1+10.4	IIa	IIa	IIa	IIa
IC 2165	221.3−12.3	IIa	IIa	IIa	IIa
IC 2448	285.7−14.9	IIa	—	IIa	IIa
IC 2501	281.0−05.6	IIa	IIa	IIa	IIa
IC 2621	291.6−04.8	IIa	IIa	IIa	IIa
IC 3568	123.6+34.5	IIb	IIb	IIb	IIb
IC 4406	319.6+15.7	I	I	I	I
IC 4593	025.3+40.8	III	IIa	III	III
IC 4634	000.3+12.2	III	III	III	III
IC 4673	003.5−02.4	I	IIa	I	I
IC 4732	010.7−06.4	III	III	III	III
IC 4776	002.0−13.4	IIb	IIb	IIb	IIb
IC 4846	027.6−09.6	III	III	III	III
IC 4997	058.3−10.9	III	—	III	III
IC 5117	089.8−05.1	IIa	IIb	IIa	IIa
IC 5217	100.6−05.4	IIa	IIa	IIa	IIa
J 320	190.3−17.7	IIb	IIb	IIb	IIb
J 900	194.2+02.5	IIb	IIb	IIb	IIb
K 3-61	096.3+02.3	I	I	I	I
K 3-67	165.5−06.5	III	IIb	IIa	IIa
M 1-01	130.3−11.7	IIb	III	IIb	IIb
M 1-04	147.4−02.3	IIb	I	IIb	IIb
M 1-05	184.0−02.1	IIb	IIb	IIb	IIb
M 1-06	211.2−03.5	—	—	III	III
M 1-08	210.3+01.9	I	—	IIa	IIa
M 1-12	235.3−03.9	—	—	IV	IV
M 1-13	232.4−01.8	I	IIa	I	I
M 1-17	228.8+05.3	I	I	IIa	IIa
M 1-22	007.5+07.4	—	—	I	I
M 1-25	004.9+04.9	IIa	IIa	IIa	IIa
M 1-26	358.9−00.7	III	III	III	III
M 1-30	355.9−04.2	—	—	IIa	IIa
M 1-34	357.9−05.1	IIa	IIa	I	I
M 1-35	003.9−02.3	I	I	I	I
M 1-40	008.3−01.1	I	I	I	I
M 1-42	002.7−04.8	I	I	I	I
M 1-50	014.6−04.3	IIb	IIb	IIb	IIb
M 1-51	020.9−01.1	I	IIa	IIa	IIa
M 1-54	016.0−04.3	IIa	IIa	I	I
M 1-56	016.1−04.7	—	—	IIa–III	III
M 1-57	022.1−02.4	IIa	I	IIa–III	IIa
M 1-60	019.7−04.5	—	—	IIa	IIa
M 1-61	019.4−05.3	—	—	IIb	IIb
M 1-72	054.4−02.5	—	—	III	III
M 1-74	052.2−04.0	IIa	IIa	IIa	IIa
M 1-75	068.8−00.0	I	I	I	I
M 1-78	093.5+01.4	III	III	III	III
M 1-80	107.7−02.2	IIa	IIa	IIa	IIa
M 2-02	147.8+04.1	IIb	—	IIb	IIb
M 2-06	353.3+06.3	III	III	III	III

Table 1. continued

Name	PN G	O	CA	ANN	A
M 2-09	010.8+18.0	III	IV	III	III
M 2-10	354.2+04.3	IIa	IIa	IIa–III	IIa
M 2-11	356.9+04.5	—	—	IIb	IIb
M 2-13	011.1+11.5	—	—	IIa–III	IIa:
M 2-18	357.4−03.5	—	—	IIb	IIb
M 2-23	002.2−02.7	III	IIb	III	III
M 2-29	004.0−03.0	—	—	III–IV	IV
M 2-30	003.7−04.6	—	—	III	III
M 2-42	008.2−04.8	—	—	IIa–III	III
M 2-46	024.8−02.7	—	—	IIa	IIa
M 2-50	097.6−02.4	III	III	III	III
M 3-01	242.6−11.6	III	—	III	III
M 3-02	240.3−07.6	I	IIa	III	III
M 3-03	221.7+05.3	I	—	I	I
M 3-04	241.0+02.3	IIa	—	IIa	IIa
M 3-05	245.4+01.6	I	—	IIa	IIa
M 3-06	253.9+05.7	IIb	IIb	IIb	IIb
M 3-10	358.2+03.6	—	—	IIa	IIa
M 3-14	355.4−02.4	I	I	I	I
M 3-15	006.8+04.1	IIa	IIa	IIa	IIa
M 3-21	355.1−06.9	—	—	IIa	IIa
M 3-29	004.0−11.1	III	IIb	IIa	IIa
M 3-38	356.9+04.4	—	—	IIa–III	III
M 4-3	357.2+07.4	III	IIb	III	III
Me 1-1	052.5−02.9	I	I	I	I
Me 2-1	342.1+27.5	III	IIb	III	III
Me 2-2	100.0−08.7	I	IIa	I	I
Mz 2	329.3−02.8	I	I	I	I
Mz 3	331.7−01.0	I	I	I	I
NGC 0650-51	130.9−10.5	I	I	I	I
NGC 1535	206.4−40.5	IIb	IIb	IIb	IIb
NGC 2022	196.6−10.9	IIb	IIb	IIb	IIb
NGC 2242	170.3+15.8	III	—	III–IV	III
NGC 2346	215.6+03.6	I	IIa	IIa	IIa
NGC 2371-72	189.1+19.8	IIa	III	IIa	IIa
NGC 2392	197.8+17.3	IIa	IIa	IIa	IIa
NGC 2438	231.8+04.1	IIa	IIa	IIa	IIa
NGC 2440	234.8+02.4	I	I	I	I
NGC 2452	243.3−01.0	I	I	I	I
NGC 2610	239.6+13.9	III	—	III	III
NGC 2792	265.7+04.1	IIa	—	I	I
NGC 2818	261.9+08.5	I	IIa	I	I
NGC 2867	278.1−05.9	IIa	IIa	IIa	IIa
NGC 2899	277.1−03.8	I	—	I	I
NGC 3132	272.1+12.3	I	—	IIa	IIa
NGC 3195	296.6−20.0	IIa	—	IIa	IIa
NGC 3211	286.3−04.8	IIb	IIb	IIb	IIb
NGC 3242	261.0+32.0	IIb	IIb	IIb	IIb
NGC 3587	148.4+57.0	IIa	—	IIa	IIa
NGC 3918	294.6+04.7	IIa	IIa	IIa	IIa
NGC 4361	294.1+43.6	III	III	III	III
NGC 5189	307.2−03.4	I	I	I	I
NGC 5307	312.3+10.5	IIb	III	IIb	IIb
NGC 5315	309.1−04.3	I	I	I	I
NGC 5873	331.3+16.8	III	—	III	III
NGC 5882	327.8+10.0	IIa	IIa	IIa	IIa
NGC 5979	322.5−05.2	III	—	IIb	IIb
NGC 6153	341.8+05.4	I	I	I	I
NGC 6210	043.1+37.7	IIb	IIb	IIb	IIb

Table 1. continued

Name	PN G	O	CA	ANN	A
NGC 6302	349.5+01.0	I	I	I	I
NGC 6309	009.6+14.8	IIa	IIa	IIa	IIa
NGC 6369	002.4+05.8	I	IIb	IIa–III	III
NGC 6439	011.0+05.8	IIa	IIb	IIa	IIa
NGC 6445	008.0+03.9	I	I	I	I
NGC 6537	010.1+00.7	I	—	I	I
NGC 6543	096.4+29.9	IIb	IIb	IIb	IIb
NGC 6563	358.5−07.3	IIa	IIb	IIa	IIa
NGC 6565	003.5−04.6	IIa	IIa	IIa	IIa
NGC 6567	011.7−00.6	IIb	III	IIb–III	III
NGC 6572	034.6+11.8	IIa	IIa	IIa	IIa
NGC 6578	010.8−01.8	IIa	IIb	IIa	IIa
NGC 6620	005.8−06.1	I	IIa	I	I
NGC 6629	009.4−05.0	IIb	IIb	IIb	IIb
NGC 6644	008.3−07.3	III	IIb	III	III
NGC 6720	063.1+13.9	IIa	IIa	IIa	IIa
NGC 6741	033.8−02.6	I	I	I	I
NGC 6751	029.2−05.9	I	I	I	I
NGC 6778	034.5−06.7	I	I	I	I
NGC 6781	041.8−02.9	I	I	I	I
NGC 6790	037.8−06.3	IIb	IIb	IIb	IIb
NGC 6803	046.4−04.1	I	I	I	I
NGC 6807	042.9−06.9	III	IIb	III	III
NGC 6818	025.8−17.9	IIa	IIb	IIa	IIa
NGC 6826	083.5+12.7	IIb	IIb	IIb	IIb
NGC 6833	082.5+11.3	III	IIb	III	III
NGC 6853	060.8−03.6	I	IIa	I	I
NGC 6879	057.2−08.9	IIb	IIb	IIb	IIb
NGC 6881	074.5+02.1	I	I	I	I
NGC 6884	082.1+07.0	IIb	IIb	IIb	IIb
NGC 6886	060.1−07.7	IIa	IIa	IIa	IIa
NGC 6891	054.1−12.1	IIb	IV	IIb	IIb
NGC 6894	069.4−02.6	IIa	—	IIa	IIa
NGC 6905	061.4−09.5	IIa	IIa	IIa	IIa
NGC 7008	093.4+05.4	I	—	I	I
NGC 7009	037.7−34.5	IIa	IIa	IIa	IIa
NGC 7026	089.0+00.3	IIa	IIa	IIa	IIa
NGC 7027	084.9−03.4	IIa	IIa	IIa	IIa
NGC 7293	036.1−57.1	I	—	I	I
NGC 7354	107.8+02.3	I	I	I	I
NGC 7662	106.5−17.6	IIb	IIb	IIb	IIb
PB 6	278.8+04.9	I	I	I	I
PC 14	336.2−06.9	IIa	—	IIa	IIa
Pe 1-01	285.4+01.5	—	—	IIa	IIa
Pe 1-17	024.3−03.3	I	IIa	I	I
Pe 1-18	027.3−02.1	IIa	I	IIa–III	IIa
Pe 2-14	013.0−04.3	—	—	IV	IV::
Ps-1(K 648)	065.0−27.3	IV	IV	IV	IV
Sn-1	013.3+32.7	III	IIb	III	III
SwSt-1	001.5−06.7	III	IIb	III	III
Tc-1	345.2−08.8	III	—	III	III
Th 2-A	306.4−00.6	IIa	—	IIa	IIa
Vd 1-1	344.2+04.7	—	—	IV	IV
Vy 1-2	053.3+24.0	III	IIb	III	III
Vy 2-1	007.0−06.8	—	—	IIb–III	III
Vy 2-2	045.4−02.7	III	III	III	III

parameters, being forced to recognize the new sample once again. This ensured the self-consistency of the classification. Even then, for 29 objects (Type III included) the ANN do not show the best agreement and display indecisions between IIa–III, IIb–III, and III–IV; for 6 objects it assigns similar probabilities for I-IIa and IIa–IIb. In this step we used the radial velocities compiled by Acker et al. (1992) to improve the results. We trained the ANN with 138 objects using He, O, N, and the radial velocity (topology 4:20:5), and again forced to recognize the whole sample (203 objects with velocities). The before precisely classified objects matched this last test; the 29 objects became 20, and the 6, 2. The errors we have obtained for both training and test stages are of 1% and 2% for the 5:20:5 and 4:20:5 topologies, respectively. For the topology 3:20:5, they are close to 2% and 7%, respectively. In spite of this error value, 3 seems to be the minimum number of input parameters for this ANN classifier to yield satisfactory results.

4. Discussion

In the beginning of this work, the assumption was made that the sample is homogeneous and there was no previous knowledge of any classification of the PN.

The cluster analysis has proved to be suitable as a first guess of classification, and the coincidence with the previous classification was 70.3%.

The neural network was trained with 2/3 of these coincident objects (topology 5:20:5) in the first run and forced to recognize the whole sample. Based on these results we have increased the number of training objects for the subsequent topologies. In the final ANN classification, 74.1% of the objects match the previous classification, and 13.2% the ANN "indecisions" (two most probable types) include the previous type. The inclusion of the radial velocity values did not improve significantly the performance of the ANN in the case of Type III objects; furthermore, the velocity parameter has a broad scatter which is reflected in the ANN error. We have adopted basically the classification given by the ANN. In four cases, when the He abundance is missing, we have adopted the classification of the cluster analysis.

The comparison between the results of the cluster analysis and the ANN's shows 64.5% of coincidence in their classification.

The ANN became an interesting tool of classification, principally because it can be trained to a degree that warrants satisfactorily reliable results without loss of generalization ability. In this work, 41 PN have been classified for the first time, and 13 PN had their types changed by the ANN.

Obviously, a few PN of the sample may suffer changes in classification in the future mainly because the abundance values may change due to electron temperature fluctuations (see Dinerstein et al. 1985; Peimbert et al. 1993).

But, in general, it is expected that the present classification remains.

With reference to the previous criteria of classification by other authors, the grouping of our sample does not agree strictly for each parameter criterion. For example, for Type I PN the He/H ratio spreads from 0.090 to 0.186 in our sample, where the first value is lower than the He/H cut-off criterion for the Type I PN ($\gtrsim 0.125$). Also, we have classified a few originally Type I objects as IIa, IIb, and III, which have a high He abundance value for this class if one follows strictly the criterion. Another example is Type III PN, where in our sample the radial velocity spreads from 5 to approximately 224 km/s. The abundance parameters of these objects in several cases are close to the IIa, IIb, and IV ones; anyway, the cluster analysis and the ANN can group partially this class using only abundance parameters. We expect that an ANN with more than five abundance parameters classifies the Type III better.

The four well-known Type IV PN BoBn–1, DdDm–1, H 4–1, and Ps–1, have been recognized correctly by the ANN, and four more ones have been added to the list, namely, M 1–12, M 2–29, Pe 2–14, and Vd 1–1. There is not, nonetheless, much information on these objects in the literature. M 1–12 has had its distance individually determined by Zhang & Kwok (1993) , a statistical one, of 6.42 kpc, given by van de Steene & Zijlstra (1994) and Zhang (1995); and 6.48 kpc for the final distance scale for the galactic bulge PN), and no radial velocity; M 2–29 shows a high radial velocity 114 $\pm$ 11 km/s, given by Schneider et al. (1983), and has been quoted as a galactic halo object by Peimbert (1991), of which distance runs from 9.31 kpc to 11.33 kpc (van de Steene & Zijlstra 1994) and Cahn et al. (1992), respectively; Zhang (1995) calculates a statistical distance of 9.31 kpc and a final distance for the galactic bulge PN of $\sim$ 9.98 kpc. Pe 2–14 has neither individual distance nor radial velocity determinations, just a statistical estimate of the distance ranging from 3.1 kpc to 6.07 kpc, as given by Maciel (1984) and Cahn & Kaler (1971); finally, Vd 1–1 has no distance determinations and its high radial velocity is -142.1 ± 3.5 km/s (Schneider et al. 1983). Further observational studies of these objects will be made in the near future.

Either the cluster analysis or the supervised ANN seems to be a suitable tool for the problem of PN classification. The results obtained in Table 1 show that the parameters used “tell classes apart” and can be restricted to about 3 for a minimum reliable classification. When 5 input parameters are used, the ANN classification error improves notoriously, no matter what guesses on the weight decay are given because different combinations of these two variables yield results that are statistically equivalent. We expect that the application of both tools to Amnuel's data would yield the same results or, at least, complement them.

For the sake of illustration, Figs. 1-3 show the coincident objects as classified by Amnuel and by us in diagrams of He against N for low (L), intermediate (In), and massive (M) planetaries, respectively. A few of Amnuel's anomalous PN have been included in these samples. It is noted that Peimbert's types are intermixed on this scenario, as can be seen from these figures. It is only in Fig. 2 that a clear correlation appears for Class In PN. On the other hand, a more careful look at Fig. 1 makes it apparent that IIa and IIb nebulae seem to exhibit rather definite trends, with negative and positive slopes, respectively (excluding the deviant IIa M1-30). Here we pose the following question: if the CN-cycle is important in all progenitor stars, and the ON-cycle plays a rôle in stars with $M \lesssim 3\ M_\odot$ (Amnuel 1993), why would low-mass PN distribute themselves as in Fig. 1? An enhancement of He would be expected due to the CN-cycle and the depletion of the initial O by the ON-cycle, being converted into secondary N; both processes should possibly cause the trend seen in Fig. 2.

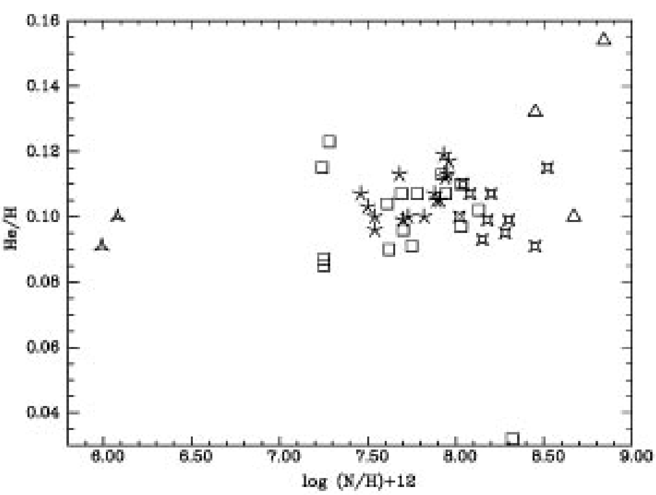

Fig. 1. Distribution of low-mass PN (L). The symbols represent Peimbert's types I (△), IIa (open cross), IIb (squeletal pentagon), III (□), and IV (squeletal triangles)

We finally stress that the number of useful parameters in PN is restricted because of the lack of complete abundance data for all the PN known to present date. In a future work, we intend to employ an unsupervised ANN architecture, which is not very complex due to the low number of input parameters, as shown by the present work, and add the morphology as another input parameter.

Acknowledgements. This work was partially supported by CNPq (Brazil). One of us, M. I. O. A., thanks Claudio Silva for some help and comments on the cluster analysis and the Departamento de Física of the USACH (Chile) for partial support. We thank Laerte Sodré for kindly supplying the ANN program, for his help and advice on the use of the neural network,

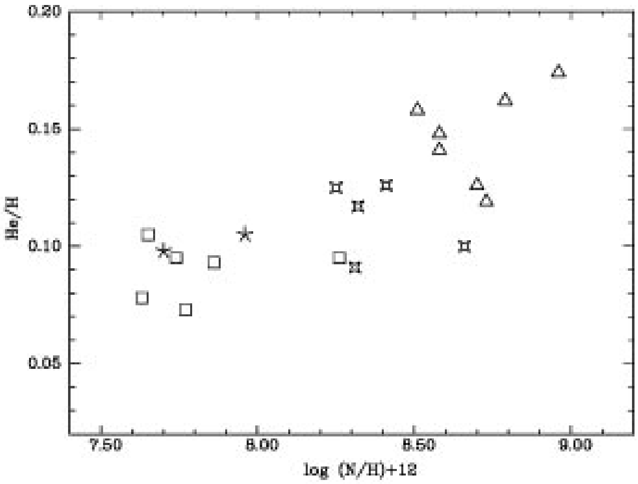

Fig. 2. The same as Fig. 1 for intermediate-mass planetaries (In)

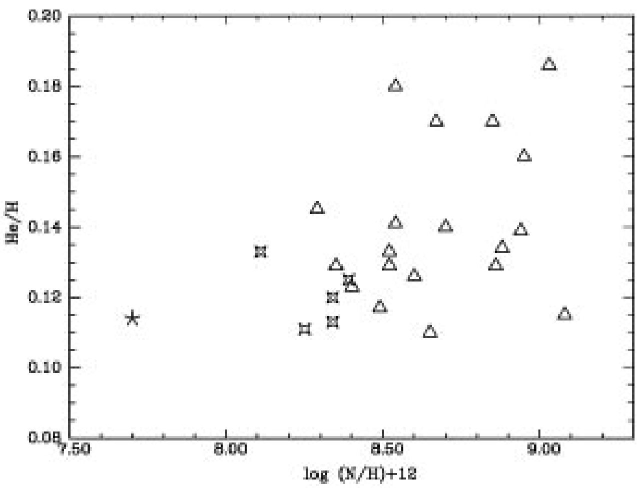

Fig. 3. The same as Fig. 1 for massive nebulae (M)

and reading of the manuscript. The neural network program is available via anonymous ftp from markov.stats.ox.ac.uk.

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