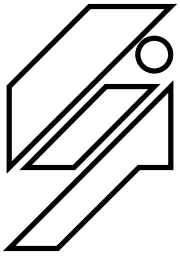
Is it possible to discriminate odors with common words ?

Regina Eberhardt, Helene Paugam-Moisy, Didier Puzenat, Jean-Pierre Royet



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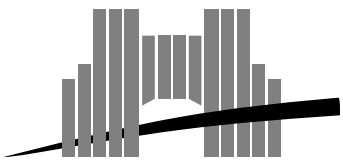

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Abstract

Several experiments have been performed in order to study the cognitive processes which are involved in odor recognition. The current report summarizes experimental protocol and analyzes collected data. The goal is to try to recognize odors from *descriptors* which are selected by subjects from a list. Different groups have to choose in several descriptor lists, some with *profound* descriptors and some with a few *surface* descriptors. *Profound* descriptors are supposed to involved more cognition than *surface* descriptors. Subjects also have to name the odors. Recorded data are first analyzed, and then learned by an incremental neural classifier. The problem is hard to be learned. It seems very difficult to discriminate the different odors from the sets of descriptors. A variant of the learning algorithm, less sensitive to difficult examples, is proposed. The pertinence of *surface* descriptors is discussed.

Keywords: Olfaction, Recognition, Neural Networks, Classification

Résumé

Des expériences ont été réalisées pour étudier les processus cognitifs impliqués dans la reconnaissance des odeurs. Ce rapport résume le protocole expérimental et étudie les données collectées. Le but est d'essayer de discriminer des odeurs à partir de descripteurs qui sont choisis par les sujets dans une liste. Plusieurs groupes travaillent avec différentes listes de descripteurs, ces descripteurs pouvant être *de surface* ou *profonds*. Les descripteurs *profonds* sont supposés être imliqués dans des traitememts plus cognitifs que les descripteurs *de surface*. Les sujets doivent également nommer les odeurs. Les données recueillies sont d'abord analysées, puis apprises par un classifieur neuronal incrémental. Le problème est difficile à apprendre. Il semble très délicat de discriminer les odeurs à partir des jeux de descripteurs. Une variante de l'algorithme d'apprentissage, moins sensible aux exemples difficiles, est proposée. La pertinence des descripteurs *de surface* est discutée.

Mots-clés: Olfaction, reconnaissance, réseaux neuronaux, classification

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Is it possible to discriminate odors with common words ?

Spade-work on data from experiments about olfaction perception, using an incremental neural classifier

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1 Introduction

It can be assumed that odor memorization takes place in both perceptive and associative memories [3]. This experiments are part of a project devoted to the study of perception and cognitive processes involved in olfactory memory. The current report summarizes experimental protocol and analyzes collected data. This study enables easier future works by doing spade-work on data.

2 Experimental protocol

Several odors have been presented to 174 subjects. Subjects have been divided into 5 groups: 3 groups of approximately 40 persons and 2 others of 24 persons.
In each group, all subjects judge all the 30 odors [1] shown in table 1. Each experiment consists of two parts: first the odor is described, and second the odor is named. The experimental protocols of these phases are related with more details below.

1. Lilac	11. Perspiration	21. Smoked salmon
2. Mint	12. Citronella	22. Lavender
3. Mushroom	13. Thyme	23. Nail varnish
4. Pepper *	14. Orange	24. Anise
5. Camphor	15. Chocolate *	25. Banana
6. Passion fruit	16. Ether	26. Tar
7. Rose	17. Peach	27. Cinnamon *
8. Herb	18. Strawberry	28. Vervain
9. Caramel	19. Pine *	29. Bitter almonds
10. Clove	20. Vinegar *	30. Lemon

Table 1: Names of the 30 odors (* marks the odors for which less than 10 examples have been correctly named in GP1)

2.1 First part, describing odors

In the first part of the experiment, subjects have to select from a descriptor list those which are suitable for the odor. For each group, lists of different descriptors are presented to the subjects. The number of descriptors in groups is given in table 2. The subjects choose as many descriptors as they like, in the fixed delay they have at their disposal. Descriptors of both groups GP1 and GP2 are said to be *profound* since they are supposed to involve more cognition than *surface* descriptors of the third group GS. Descriptors of the fourth group GSP are descriptors of both groups GP1 and GS. The subjects of the fifth group do calculation (such as additions, substractions and multiplications) during the first part of the experiment, instead of choosing descriptors.

Group name	GP1	GP2	GS	GSP
Number of Descriptors	16	16	3	19

Table 2: Number of descriptors in groups

For each odor, each time a subject chooses a descriptor, two informations are recorded:

- a value of intensity, for this descriptor,

- the response time, i.e. the elapsed time since the odor has been presented.

For both informations, if there are repeated modifications of one descriptor, only the last one is taken into account. Intensity ranges in [0.0, 1.0] and response time ranges in [0.0, 20.0]. A set of 3, 16, or 19 values for one odor will now be referred to as an example for the odor. The number of input values depends on the nature of the descriptors, according to the group (cf. table 2).

2.2 Second part, naming odors

Without having been told the name of the odor in the first part, subjects must name the odor with a common word of their own choice. Denomination time is recorded. Chosen name is labeled afterwards by an expert with either *no answer*, *wrong*, *right*, or *close to the correct answer*. Due to the difficulty of naming an odor, we assume that answers close to the correct one are correct, because in general it is very difficult to name a given odor. This leads to three different categories: *no answer*, *wrong*, and *correct* (**n**, **w** and **c**, respectively). The meaning of this classification is not straightforward, because a wrong denomination does not necessarily mean that the odor is not recognized. The semantic reference can be specific to the subject. Table 3 gives the number of examples available for each group.

Group	subjects	c	%	w	%	n	%	all
GP1	41	579	47	484	40	167	13	1230
GP2	24	342	48	234	33	143	19	719
GS	42	564	45	337	27	359	28	1260
CAL	24	320	42	169	26	231	32	720

Table 3: Number of examples available, according to the group

A number of examples between 719 and 1260, for one group, does not seem to be very small, but these examples are distributed among the 30 odors. Hence for some odors there are about 24 examples (one for each subject). Assuming there is a difference between values of the chosen descriptors depending on the correctness of the denomination, the number of examples for one odor is reduced. For example, in group GP1, there are only 579 correct denominations available, that is, only about 19 examples per odor. It is further necessary to distribute examples among a learning set and a test set. Despite a chosen proportion of 80 and 20 percent for the learning and test sets, respectively, there are odors that have less than 10 examples (still for group GP1) which correspond to a correct answer. These odors are marked with * in table 1. Finally, the numbers of answers for the 3 categories vary for the different odors.

3 Data analysis in group GP1

Data for group GP1 will now be further examined. The 16 descriptors to choose from the GP1 list are presented to the subject on the monitor screen as indicated in table 4.

3.1 Study of values for one odor

Generally only about 3 descriptors from the 16 proposed are chosen by a subject for one odor. All other descriptors equal zero. It is doubtful whether this zero value, which results

1. Woody (Boisée)	9. Acid (Acide)
2. Corporal (Corporelle)	10. Bitter (Amère)
3. Spicy (Epicée)	11. Salty (Salée)
4. Floral (Florale)	12. Sweet (Sucrée)
5. Fruity (Fruitée)	13. Heady (Entétante)
6. Smoked (Fumée)	14. Fresh (Fraiche)
7. Herbaceous (Herbacée)	15. Greasy (Graisseuse)
8. Medicinal (Médicinale)	16. Irritating (Irritante)

Table 4: Descriptors for group GP1

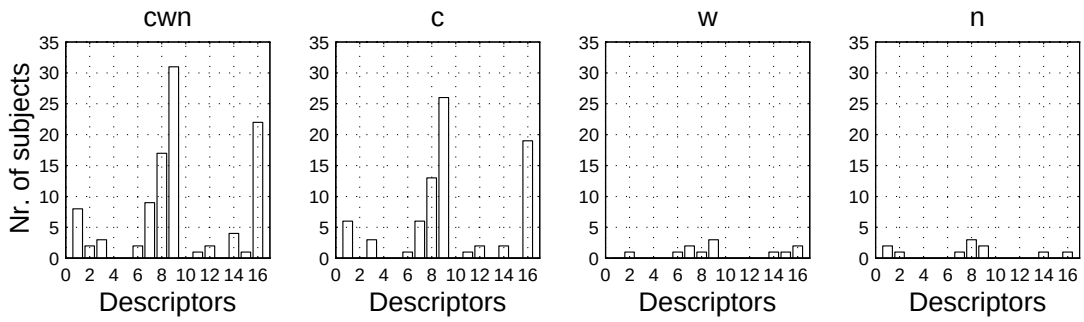

Figure 1: Frequencies of descriptors selected for orange, by the subjects of GP1, as a function of the denomination correctness (*correct*, *wrong*, or *no answer*)

when a subject does not choose a descriptor at all, can be taken as an active choice of the value zero. The odor of an orange is correctly named by a rather large number of persons and is therefore retained as an example. The total number of subjects which have selected each descriptor is shown in figure 1.

3.2 Intensity

For each descriptor, two values are recorded: intensity and response time. Some selected examples of the given values of intensity for the orange odor are shown in figure 2 with correct denomination responses. It is clear that some examples can be totally different (examples 1 and 2), and that others can be very similar (examples 3 and 4). Figure 3 represents intensity, for orange odor, with incorrect denomination responses (w = wrong, n = no answer).

3.3 Response time

Figure 4 shows response time for some other orange examples. As for intensity, some examples are totally different (examples 1 and 2) and others are similar (examples 3 and 4). Comparing these examples with those from figure 2, it is difficult to say if these examples are more distinct than the other ones. Regarding more examples for one odor,

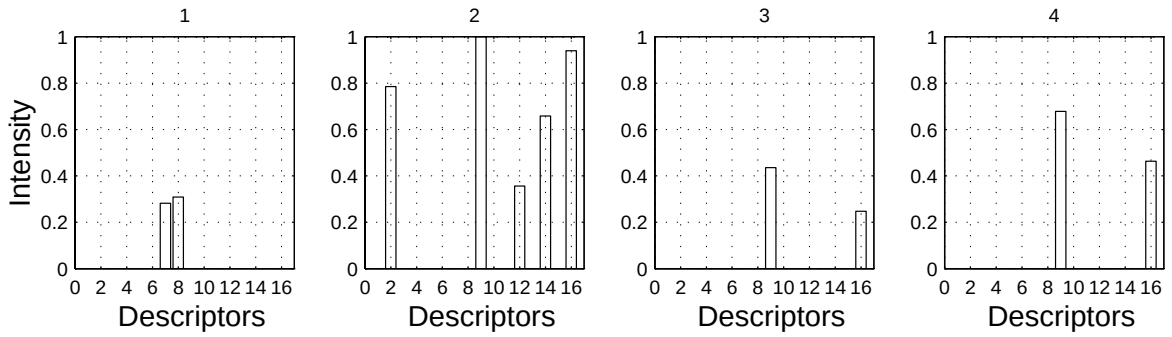

Figure 2: Four examples of individual responses of intensity, for orange odor, as a function of 16 descriptors, with correct denomination responses

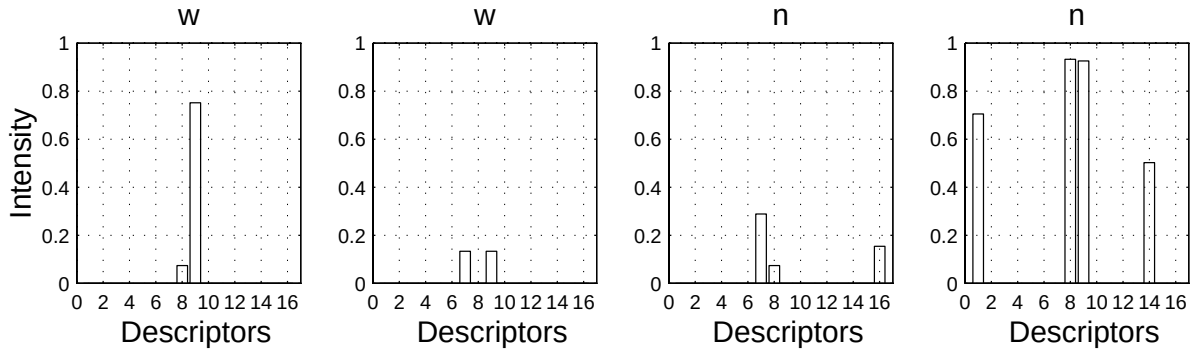

Figure 3: Four examples of individual responses of intensity, for orange odor, as a function of 16 descriptors, with incorrect denomination responses

the response time of a descriptor seems to be random and not specific to each descriptor.

3.4 Mean intensity

Computing mean intensity gives a global information of all examples for one odor. This brings us to the question either to calculate the mean over all values or to calculate the mean of non-zero values. Both results can be seen in figures 5 and 6. It is not clear that calculating the mean of all examples for one odor is valuable. Indeed, examples from one odor are very distinct in their chosen descriptors and their intensity.

3.5 Normalization of the responses of the subjects

It is obvious that some subjects are used to give greater values than others. Handling with a small number of subjects, it must be considered whether values can be taken directly or if a normalization process is required. An easy normalization process consists in ordering intensity or time values. According to this resulting order, the highest descriptor intensities are set to fixed values (e.g. 0.8 for the first one, 0.6 for the second one, and so on). On the one hand, this reduces differences between subjects. On the other hand, this normalization induces a loss of information, since the difference between two nearly

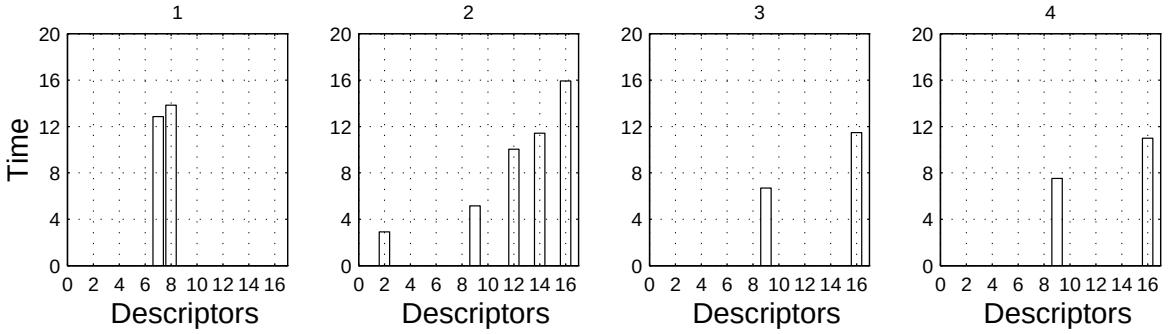

Figure 4: Odor orange: response time for the 4 examples of figure 2

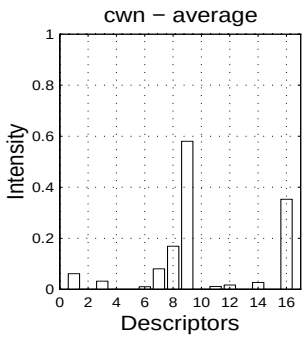

Figure 5: Mean of all intensity responses, for orange odor

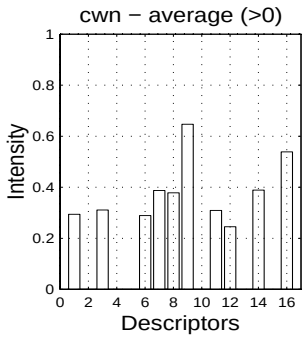

Figure 6: Mean of intensity responses greater than 0, for orange odor

similar values is magnified. This would be the case for example 1 of figure 2.
Another drawback can appear when comparing two examples of the same odor provided by two different subjects. Assume that the subjects have chosen two common descriptors, with nearly similar values for these two descriptors. The ordering process can lead to an inversion for these descriptors, from one of the examples to the other. Hence the normalization induces a great disparity which was not present in initial data. In this case, the normalization would emphasize the difference and not the actual similarity.

3.6 Comparison of the data of different odors

Comparing examples of different odors, it appears that a lot of examples are similar. These examples are not only equal in chosen descriptors, but also in selected intensities.

3.6.1 Similarity

A great similarity among example 1 of figure 7 and both examples 3 and 4 of figure 2 (page 6) can be recognized. The same descriptors have been chosen, and intensities are also very similar. Values for banana lie between the two examples for orange. For one of these examples it is difficult to determine the correct odor. Other examples of figure 7 show that there are also similarities between several odors : orange, strawberry, and peach. In this case odors are different kinds of fruits. This kind of similarity exists also

between odors which do not belong to the same categories. Figure 8 illustrates examples of mint and caramel odors.

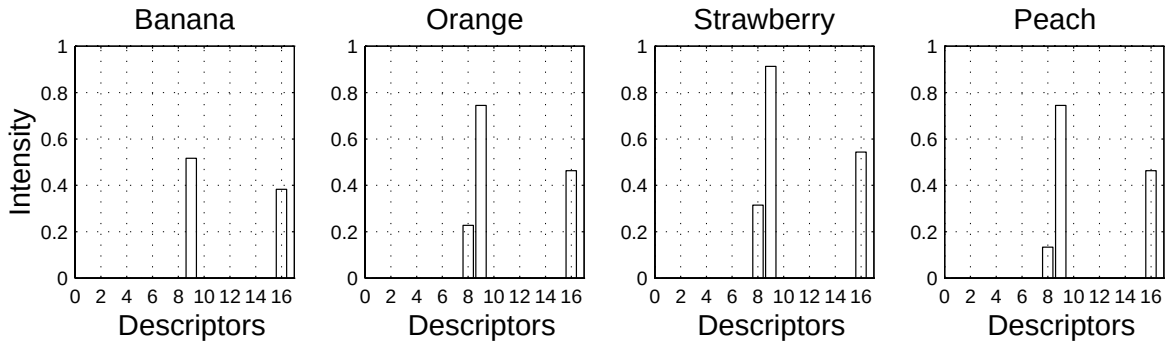

Figure 7: Similar examples, for different fruit odors

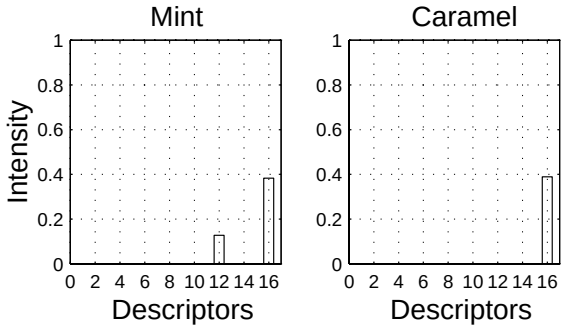

Figure 8: Similar examples, for Mint and Caramel

3.6.2 Distances between examples

Figure 9 (page 9) shows distances between recorded intensities, for several odors. A good measure of the similarity of two examples is the distance which is calculated as follows:

$$dist = \sqrt{\sum_i (u_i - v_i)^2} \qquad where\ U = (u_i)\ and\ V = (v_i)\ are\ examples \tag{1}$$

The title of each sub-plot indicates the name of the odor and its number according to table 1. Each circle mark in a sub-plot corresponds to one example of one odor. For this example, the minimal distance to all other examples is marked. The x-axis represents the number of the odor to which this closest example belongs. The y-axis is for the value of this minimal distance. If different examples of a same odor were very similar among themselves and very distinct from other odors, their marks would all be in the row of this odor. Experimental results are not so simple. Only for some of the odors, most of their closest examples belong to the same odor (e.g. odor 16, ether). For most of the odors, their closest examples are distributed among many different odors. There are odors for which there is not even one example with its closest example belonging to the same odor.

From these odors, there are some for which closest examples are distributed among all the other odors (e.g. odor 25, banana) and others for which they are accumulated in a few odors (e.g. odor 30, lemon). These figures enhance the inherent difficulties for separating the different classes (odors) from each others. Considering this amount of similarity and overlapping between examples, it is doubtful that a better distance measure could be found.

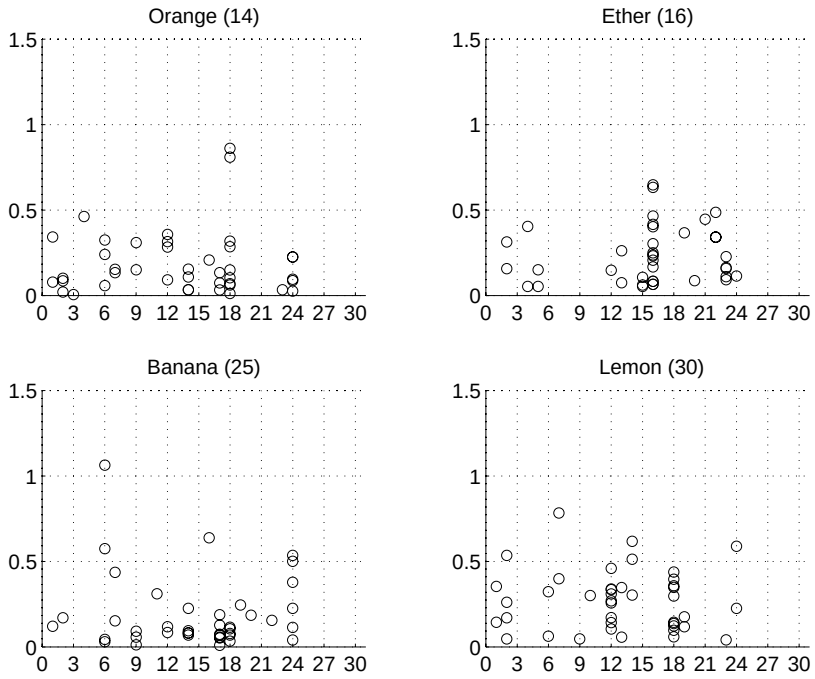

Figure 9: Distances between examples

3.7 Cross-correlation coefficients

As shown in figures 5 and 6, it is not clear that calculating the mean of all examples for one odor is valuable. Despite this fact, the cross-correlation coefficients over mean values have been computed for the 30 odors (see figure 10). For each odor, the mean value over all examples is calculated, regardless the category of denomination. The result is a k-dimensional vector of mean values for each odor, where k is the number of descriptors. Cross-correlation coefficients for these vectors are illustrated in figure 10 for the orange odor.

4 Results with an incremental neural network

The aim is to distinguish odors with the help of descriptors. For this, an incremental neural classifier in a supervised mode is used [2, 4]. It compares input vectors with all already existing prototypes. Distance of formula 1 is used as the measure of similarity.

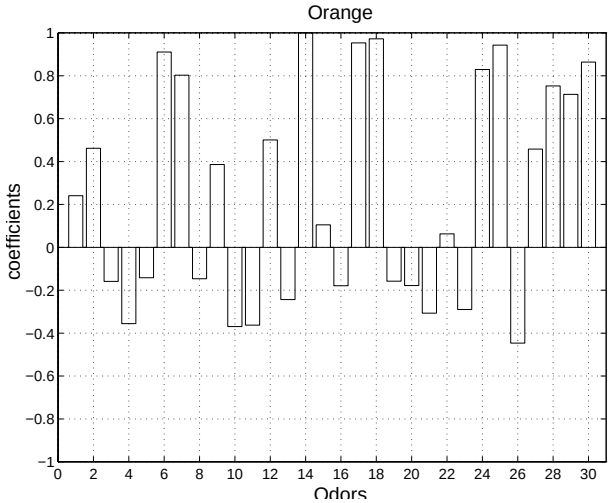

Figure 10: Cross-correlation coefficients of orange (odor 14) to all other odors

4.1 Algorithm of the classifier

Figure 11 presents an incremental neural network. In this report, we are using a more algorithmic point of view (figure 12).

4.1.1 Learning

When an input pattern X is presented to the classifier, the algorithm computes distance d_{P_j} between each prototype P_j and the input pattern.

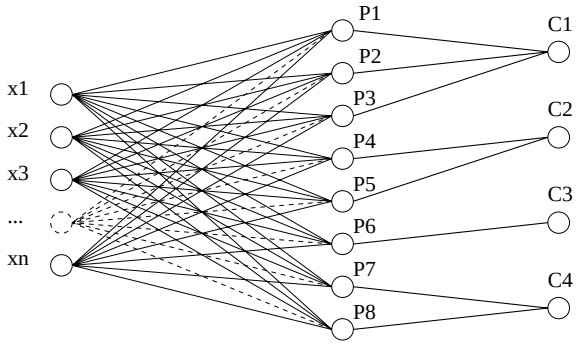

Figure 11: Architecture of the classifier

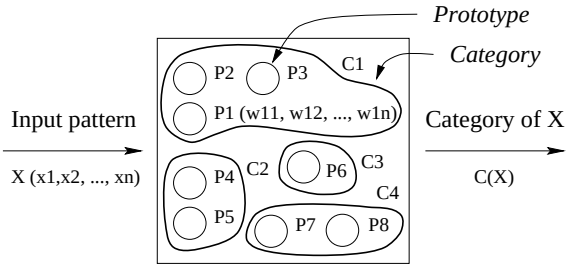

Figure 12: An algorithmic point of view

Step 1 The algorithm finds the best prototype P_{best}, that is the prototype with the shortest distance d_{best}. The prototype P_{second} (distance d_{second}) is the second best prototype from another category. Thus $C(P_{best}) \neq C(P_{second})$ where $C(P_j)$ is the category of P_j. In other words, P_{second} is the best prototype among prototypes that do not belong to $C(P_{best})$. P_{best} must be close enough to X and far enough from P_{second} (equations 2). If both conditions are not verified, P_{best} does not exist.

$$\begin{cases} d_{best} < \Theta_{influence} \\ d_{best} - d_{second} > \Theta_{confusion} \end{cases} \tag{2}$$

Step 2 The algorithm modifies or creates prototypes.

Presentation of a pattern X **with a label** $C(X)$

- If P_{best} exists **and** $C(P_{best}) = C(X)$:
  - X is recognized,
  - upgrade P_{best} to take X into account.
- Else :
  - X is not recognized,
  - Create P_{new} from X, with $C(P_{new}) = C(X)$.

4.1.2 Generalization

The generalization algorithm is almost the learning algorithm, but prototypes are not anymore tuned. Step 1 does not change. Step 2 becomes:

Presentation of a pattern X

- If P_{best} exists : X is recognized to belong to $C(P_{best})$.
- Else : X is not recognized.

4.2 Results with input data from group GP1

4.2.1 Results for the 30 odors

Table 5 shows classification results for all the odors of table 1.

Data columns The input vector of the classifier is a vector of either intensities or response times for the 16 descriptors (column 2). Assuming there is a difference between examples whether there are correct (c), or wrong (w), or not at all classified (n), available examples are divided into these 3 categories. The third column of the table indicates which categories are taken as input data. Depending on this choice, the number of available examples varies (LearnEx). During the learning phase, every example is treated similarly, regardless of the category, and the network creates as many prototypes as necessary. The number of prototypes created can be taken as a measure of generalization capabilities. A high number illustrates that, for most of the examples, a new prototype is created, and it is bad for generalization. As a matter of fact, a small number of prototypes, in relation to the number of examples, for each odor, has more chance to imply a good generalization ability.

Results columns The last 4 columns illustrate the classification results.

- *Right Cl.* is the number of test examples which are correctly classified. The next column gives the same result in percentage, depending on the number of available test examples.

- *Wrong Cl.* stands for a classification to another odor.
- *No Cl.* is the number of examples that could not be matched to any odor.

Nr.odors	value	category	LearnEx	**Nr.Proto**	Right Cl.	%	Wrong Cl.	No Cl.
30	intens	cwn	990	**814**	28	**12**	192	20
30	intens	c	463	**361**	19	**16**	92	5
30	intens	cn	596	**468**	26	**17**	109	15
30	time	cwn	990	**961**	3	**1**	56	181
30	time	c	463	**447**	5	**4**	14	97

Table 5: Classification results for all the 30 odors

Results with intensity Table 5 presents a number of prototypes very close to the number of learning examples. Generalization performance is rather bad. The best classification result is 17 %. It comes from examples with a correct denomination (c) or no denomination (n). Considering all available examples (cwn), only 12 % of the test set are correctly classified. The difference between these two results is small. Nevertheless, it shows that denomination correctness must be taken into account.

Results with response time The two bottom lines of table 5 are obtained with response times. The classifier refuses to give an answer for many examples. With a correct classification of around 4 % it is evident that response time is less significant than intensity for discriminating odors.

4.2.2 Results with 25 odors only

There are odors with less than 10 examples with a correct denomination. These odors, marked (*) in table 1, are omitted in further tests. Table 6 illustrates results for the reduced number of 25 odors. Classification is a bit better. Best result comes from examples with a correct denomination (20 %).

Nr.odors	value	category	LearnEx	**Nr.Proto**	Right Cl.	%	Wrong Cl.	No Cl.
25	intens	cwn	825	**655**	27	**14**	160	13
25	intens	c	440	**342**	22	**20**	83	4
25	intens	cn	521	**402**	25	**19**	98	8

Table 6: Classification results for 25 odors

4.2.3 Classification according to answer correctness

In previous experiments, all examples are treated similar regardless of their category (c, w, n). It can be argued that the chosen descriptors, or their intensities, are very

different depending on their category. In this case, taking examples of all categories is difficult. Examples are therefore differently marked, according to their denomination category. A further vector element is added. The new input is 0 if the denomination is wrong or none (w, n), and 1 if labeling is correct (c). Results are presented in table 7. The correct classification of 16 % or 20 % does not bring a meaningful improvement.

Nr.odors	value	category	LearnEx	**Nr.Proto**	Right Cl.	%	Wrong Cl.	No Cl.
25	intens	cwn	825	**649**	32	**16**	157	11
25	intens	cw	440 ?	**342**	22	**20**	83	4

Table 7: Classification results according to denomination correctness

4.2.4 Classification according to denomination quickness

We can assume that a *good* choice of descriptors has an influence on the needed time to denominate odors. A quick decision for a name of an odor could be a result of a *correct* choice of descriptors. To examine this possibility an additional vector element for the denomination time is used. One of the obtained results is shown in table 8. This further input element has no great influence on the number of correctly classified test samples (16 %).

Nr.odors	value	category	LearnEx	**Nr.Proto**	Right Cl.	%	Wrong Cl.	No Cl.
25	intens	cwn	825	**670**	32	**16**	165	3

Table 8: Classification results according to denomination time

4.2.5 A new learning algorithm

As mentioned in section 3.6, there are a lot of very similar examples which belong to different odors. It is the case for example 1 of figure 7 (banana) and examples 3 and 4 of figure 3 (orange). The classifier creates news prototypes to cope with the conflict. However, so many prototypes lead to poor generalization capacities. To hold back prototype creations, the learning algorithm of the neural network is changed so that each input example is only compared to the prototypes of his own odor. Comparing tables 9 and 6, the reduction of the number of prototypes is clear (from 342 to 62 for correct denominations). The classification results attained are better but still low. Best result is 28 %. Comparing with table 6, 9 examples miss-classified are now correctly classified (the number of examples not classified is the same). We can assume that the new algorithm has filtered difficult examples.

4.2.6 Tests with normalized data

In section 3.1, the problem of a probably necessary normalization is mentioned. We have tested the influence of this normalization process. After ordering the intensity values,

Nr.odors	value	category	LearnEx	**Nr.Proto**	Right	%	Wrong	NoClas
25	intens	cwn	825	**68**	40	**20**	156	4
25	intens	c	440	**62**	31	**28**	74	4
25	intens	cn	521	**68**	31	**24**	100	0

Table 9: Classification results when an example is only compared to prototypes of its odor

for each example, we have set the three greatest, non-zero, values to respectively 0.8, 0.6 and 0.4. Table 10 illustrates the classification performance on such normalized data. As learning examples are again compared with all prototypes (initial learning algorithm), a large number of prototypes are created. Compared to experiments represented in table 6, the correct classification is clearly decreased. Best classification result is only 16 %. This shows that this normalization increases differences between examples and results in worst performance.

Nr.odors	value	category	LearnEx	**Nr.Proto**	Right	%	Wrong	NoClas
25	intens	cwn	825	**708**	20	**10**	71	109
25	intens	c	440	**370**	17	**16**	38	54

Table 10: Only the 3 greatest values are taken with intensities 0.8, 0.6, 0.4

4.3 Results for other groups

Experiments have been done with other groups. Group GS has only 3 descriptors which describe odors very superficially. Compared with the so far obtained classification results, table 11 shows that results are worse. This indicates that it is almost impossible to discriminate the 25 odors only with this 3 descriptors. It seems that results depend on the learning base size, more than on categories involved. However, results are too close to a random anwer (1/25) to be meaningful.

Nr.odors	value	category	LearnEx	**Nr.Proto**	Right	%	Wrong	NoClas
25	intens	cwn	850	**764**	14	**7**	178	8
25	intens	c	435	**392**	2	**2**	95	9
25	intens	cn	642	**582**	6	**4**	138	15

Table 11: GS: Classification results

Another group is GSP which has 19 descriptors to choose from. These descriptors are the same as for GP1 and GS. Compared with the results of GP1, classification results are a

bit better. Adding the 3 *surface* descriptors raises results from 20 % to 25 % (compare tables refall24 and 4.3).

Nr.odors	value	category	LearnEx	**Nr.Proto**	Right	%	Wrong	NoClas
25	intens	cwn	825	**632**	34	**17**	157	9
25	intens	c	459	**343**	28	**25**	81	2
25	intens	cn	585	**441**	29	**20**	112	6

Table 12: GSP: Classification results

5 Conclusion

Results This report examines experimental data with a neural incremental classifier. Because of the relatively small number of subjects (from 24 to 42) in a group there is only a small number of examples for each odor available. Furthermore a great number of descriptors (16 for GP1) faces a small number of actively chosen descriptors (about 3). The great differences between examples of one odor and the similarity of examples of different odors makes the problem hard to learn. Facing this data, it seems very difficult to distinguish the different classes. Best classification results stay under 30 %. It is interesting to note that the best result has been reach by an algorithm less sensitive with difficult examples. According to underlined problems, it is not clear that a greater number of examples for each odor would help to reinforce differences between odors and so facilitate classification.

Useful notes to help future works

- Descriptor intensities is a far more reliable information that response times.
- *Surface* descriptors of group GS are not able to discriminate odors. However, they are helpful in addition with *profound* descriptors (group GSP).

Future works Several works are scheduled on collected data. Further works will deal with modular aspects of memorization. Some works are engaged in associative memory, properties evocation, or priming. The spade-work done in this report will be useful. Knowing that odors cannot be discriminate by proposed descriptors will avoid time consuming experimentations.

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