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VARIATION WITHIN CATEGORIES

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Part I

INTRODUCTION AND SCOPE OF THE THESIS

1. *Introduction*
2. *Historical development*
3. *Categorization: issues of the thesis*
4. *Uncertainty reduction and physiological activity*

1 INTRODUCTION

Everything flows and nothing remains. These famous words are generally ascribed to the Greek philosopher Heraclitus. He suggested that life is a swiftly changing flow of events, and that we never encounter exactly the same event twice ("it is impossible to step into the same river twice"). On the other hand, one of the Preacher's words says that there is no thing new under the sun (Ecclesiastes 1:9). The statements seem to contradict each other, yet both of them have been quoted approvingly many times. How can they be reconciled?

Indeed, each event or entity we experience is unique. However, we do not usually act as if we are constantly being overwhelmed by totally new impressions, not knowing how to respond to them. We recognize written words despite variation in handwriting, even handwriting we have never seen before. And when entering an animal shop, we identify some animals as puppies, other ones as parrots, and the salesperson as a man or a woman. Following this categorization, we know more about what we can reasonably expect from their behaviour. We know how to respond to them on the basis of past learning and categorization, due to the conceptual system most of us are endowed with.

The conceptual system encompasses a great deal of information about the environment. Information from the environment is reduced to behaviorally and cognitively usable proportions. Reduction of the complexity of the world around us is necessary, because -if not impossible- it is at least impractical to retain all of the specific information about each and everything we experience. Human memory stores representations derived from a wide class of perceived objects

that generally embody the frequently repeated themes of our experience. Knowledge in memory is organized around these representations, the category concepts. Concepts are essentially alinguistic. However, through language learning, concepts may acquire names. The use of categorical concepts is a most important factor in human life. It enables us to cope effectively with the environment by treating different things as the same, by abstracting from the ideosyncrasies of particular experiences. As Bruner, Goodnow and Austin (1956) put it:

> "To categorize is to render discriminably different things as equivalent, to group objects and events and people around us into classes, and to respond to them in terms of their class membership rather than their uniqueness." (p.1)

They pointed out that virtually all cognitive activity involves and is dependent on, the process of categorizing. In short, category concepts provide the classificatory system necessary to interact efficiently with the environment. Categories are essential as a means of handling large quantities of information. They determine the way we perceive, remember, communicate and think about objects and events.

What are the principles with which we divide up the world in the way that we do? How are categories put into memory, how are they coded? The type of categories studied in the present thesis, represent only part of the information people normally encounter. The categories of concern here are the kind of categories based on the grouping together of concrete physical objects. The study focuses on a number of factors with potential influence on learning and using categories. In Chapter 2, the historical development of theories and experimental studies on categorization will first be shortly considered. Then, in Chapter 3, the main theoretical issues addressed by the present study will be introduced.

A second topic of the study touches on the relationship of mind and brain. Connections between cognitive processes and neural functioning are explored. Attention will be given to this subject in Chapter 4.

The thesis is divided into three parts. Part I is an outline of the scope of the thesis. For convenience, the issues of the experimental studies are all put together in this Part. Next, each of the issues again will be dealt with in one or more of the Chapters of Part

II. Part II consists of the experimental studies. Chapter 5 and 6 have already been published in Acta Psychologica, 1981, 47, 1-24, and 1984, 57, 165-192, respectively (except for section 6.3.). Chapter 7 is in press, and is due to appear in Acta Psychologica, 1986, 63:1. In part III of the thesis, the results of the studies are compiled and discussed. Finally, a summary of the thesis is given.

1.1. References

Bruner, J.S., Goodnow, J.J., & Austin, G.A. (1956). A study of thinking. New York: Wiley.

2. HISTORICAL DEVELOPMENT

The study of categorization emerged within the field of psychological learning theory. A broad distinction can be made between earlier associationistic stimulus-response (S-R) theories and later hypothesis-testing theories. The post-1950s tradition of cognitive psychology led to a preference of the active hypothesis-testing models. The behaviourist tradition prior to the cognitive shift entailed the passive associationistic account of the category learning process.

2.1. Associationism

In the psychological literature, Hull (1920) advanced the "common element" view of category concepts. His theory was an associationistic S-R theory. In his theory, category learning involves the formation of an association between a certain response and an element common to a class of different stimuli. The category learner is viewed as passively undergoing a series of experiences which gradually bring about these associations, by reinforcement. Hull's opinions were formed in the behaviouristic climate of his time. In this tradition the unobservable internal processes of the organism were ignored and considered as a subject unsuitable for the scientific enterprise. Throughout the 1950s, the passive and mechanical associationistic account of the category learning process prevailed. S-R theories, however, appeared to be too simplistic to account for the processes of category learning. The S-R approach does not account for central, or thought processes that may influence the category learner's response

to the information presented in the stimulus.

2.2. Hypothesis testing

About 1955, the S-R concept became replaced by the input-output concept. This shift was not merely a linguistic one. It was recognized that a complex program controlled the input-output sequence (Miller, Galanter and Pribram, 1960), and this opened the way for new approaches to the study of cognitive processes. Another type of theory was proposed, according to which the organism is seen as actively seeking information. According to this view, categories are learned via an active, strategic process of forming and testing hypotheses. Bruner, Goodnow and Austin (1956) advanced this view. They provided an analysis of the nature of categorizing and its central role in cognition. They tried to externalize the thought processes of people when learning to categorize. They broke with the behaviouristic tradition by verifying the existence of hypothesis testing behaviour. From observed behaviour of the subjects they inferred certain patterns of purposive behaviour which they called "strategies". The notion of strategies enabled them to describe what the subject does "internally" when learning new classifications.

The work of Bruner c.s. brought about fundamental changes in category learning theory, and stimulated an intensive analysis of the variables affecting and of the processes underlying category learning. The process by which subjects learn a category concept was accepted to be one of forming hypotheses, which are tested and revised in the light of information from experience.

A typical method to study the process of category learning will be described next. It was realized that sometimes categories are learned by examples. People often have no control over which instances are presented to them. Exemplars and non-exemplars are pointed out to them as they happen to occur. In that case, a logical way to learn the category is by following a kind of reception strategy. This involves adopting a hypothesis, based on either the whole or a part of the first category example, and knowing how and when to alter it whenever new information is presented. To study the

strategies actually adopted by subjects in these circumstances, Bruner designed the following task. The task is described here because it has since been used as a standard procedure. Visual stimuli were constructed that subjects had to learn to classify into categories. Categories were defined by the experimenter. For example, the subject was shown a series of geometric figures that differed in the dimensions form (with values circle and square), colour (red and blue) and size (small and large). A category could then be defined by all red circles, for instance, leaving size as an irrelevant dimension. The subject was asked to classify each figure presented. Following each classification the subject was told whether or not it was correct. Learning took place from this feedback information. It was inferred that the subject had identified the category when no more classification errors were made. Therefore, learning trials continued until the subject consistently responded correctly.

The main measures of learning performance were the number of trials taken to reach a solution and the number of categorization errors made during learning. Stimulus factors, like the number of relevant and/or irrelevant dimensions, the number of values on the dimensions, and the type and complexity of the rule defining the category, were studied, as well as procedural factors, such as the order of presentation of the stimuli and the amount and nature of feedback to the subject. Many of these variables and their combinations have been shown to affect classification learning. The investigations also dealt with the kinds of hypotheses subjects entertained during learning and how these hypotheses were revised on the basis of feedback.

A number of models have been developed of the way in which a subject might choose among a pool of hypotheses. Early models (Restle, 1962; Bower and Trabasso, 1964) assumed that the subject begins a learning task with a universe of hypotheses from which he draws one. This hypothesis dictates his response. The subject retains the hypothesis if his response turns out to be correct, but discards it and selects another one if his response is wrong. A disconfirmed hypothesis is supposed to be returned to the pool. Later experiments refuted the assumption of no memory for previously tested hypotheses (a.o. Levine, 1966).

A more elaborate version of hypothesis-testing theory has been formulated by Levine (1969). This theory assumes that the subject begins a learning task by sampling a subset from the universe of hypotheses. He then takes one hypothesis from the subset as the working hypothesis, on which he bases his response. The working hypothesis is retained if the response is correct. If the response is wrong, the working hypothesis is discarded, and a new working hypothesis is chosen from the subset. If the subset is empty, the subject takes a new subset of several hypotheses and chooses a new working hypothesis from this subset. Other hypotheses from the subset are updated simultaneously after each feedback. These hypotheses are eliminated from the subset when they turn out to be wrong. In contrast to the no-memory assumption of the early models, Levine's theory assumed that subjects do eliminate hypotheses from the pool, at least for some time. In the course of time, subjects may forget that some of the hypotheses were disconfirmed. These hypotheses then become part of the pool again. The weight of empirical evidence supports Levine's theory (e.g. Levine, 1975; De Swart and Das-Smaal, 1976, 1979; Bourne, Dominowski and Loftus, 1979) We will return to the subset assumption of Levine's theory in experiment 2 and 4 in Chapter 5.

2.3. Criticism on traditional studies

The question of the nature of the information that is stored in memory when a category concept is learned did not receive much attention in the earlier studies. It was taken for granted that categories simply consist of defining values and it was assumed that categorization is based on rules for combining these values. The emphasis was laid on the learning process rather than on structure. In the last decade, the trend of research on categorization changed to focus on the issue of what is stored in memory, thereby questioning the idea of defining value representation. The shift went together with more interest in natural, real-life categories.

The stimulus material traditionally used has been criticized for its artificiality and its simplicity. Stimuli were based on a few discrete values on a small number of completely independent stimulus

dimensions. Boundaries between dimensional values were always clear-cut, and no variation occurred within values. However, these boundaries in daily life are often unclear. An illustration of fuzzy boundaries comes from an experiment of Labov (1973). Labov studied the boundaries of the cup category. He was interested in the items that subjects, given a series of items, would call cups, and which ones they would call bowls. The items reflected an increasing ratio of width to depth. Subjects were asked to classify pictures of the objects. With increasing relative width there was a gradual shift from cup to bowl responses, but there was no clear-cut point where subjects stopped using cup. Even more interesting was that when subjects were asked to imagine the object placed on a table and filled with food, more bowl responses were given, though the same gradual shift appeared from cup to bowl. Thus, boundaries not only can be unclear, but they can also be influenced by the context in which something is placed. Unclear boundaries between dimensional values are also illustrated by the colour dimension. Colours vary along a continuum in which for instance, red gradually becomes orange, and orange gradually becomes yellow.

Apart from unclear boundaries, there is another significant point to discuss. Even with variants of a dimensional value that everyone would agree belongs to the same value, some variants are more typical of the value than others. Thus, a good red is more typical of the colour red than some less focal shade of red.

Finally, in natural categories, dimensional values are not always independent of each other. Some values more often occur together in a category than they occur with other values. As Bruner et al. (1956) already put it in their discussion of complexity of learning materials, the (defining) values of most objects are redundant with respect to each other. Four wheels and metal, for example, more often co-occur in cars than three wheels and plastic.

Simple artificial material may thus lack relevance or ecological validity. However, with complex everyday material an objective assessment of categorization behaviour may not be possible, since it is not known what information is available for making the categorization, because the stimuli cannot be exactly specified. In the earlier

studies, ecological validity tended to be sacrificed. There has been a reversal of this trend the last decade.

The traditional studies were also criticized for the "defining values" view of category concepts on which they were based. Instead it was felt that natural language categories often lack a common defining element. This idea is borrowed from Wittgenstein (e.g. Johnson-Laird and Wason, 1977). It is usually illustrated with the example of the proceedings that we call 'games' (board-games, card-games, ball-games, Olympic Games, and so on). 'Games' are not all classified according to the same defining property. Rather, games are linked by a family resemblance. In a family resemblance structure, category exemplars share a large proportion of their values, but do not necessarily agree in any one value.

2.4. New approach

Implicit in the earlier studies was the idea that categories are specified by necessary and sufficient conditions for membership, and that all category members are equally typical or representative of the category. In the new approach to the study of categories, the validity of these assumptions has been questioned. The new approach was instigated by the work of Rosch (Rosch, 1973, 1975; Rosch and Mervis, 1975). Rosch studied the characteristics of natural categories. Her work combined ideas from different social sciences, i.e. linguistics, anthropology, psychology, and particularly from two research areas, viz. semantic memory and schema formation.

At the time, semantic memory models still assumed that categories exist of sets of defining values. Nevertheless, it began to be recognized that not all category exemplars are equally typical. Lakoff (1973) suggested that the absolute dichotomy between truth and falsity regarding category membership should be replaced by a continuous truth dimension. In his view, semantic relations are a matter of degree rather than all-or-none. Lakoff showed that various qualifying terms, such as "almost", "true", "technically", "regular", each are applicable to only a subset of category exemplars. Speakers use the terms to signal degrees of category membership. For instance, it is acceptable

to say that a whale is technically a mammal, but not that a cow is technically a mammal, because a cow is more than just that, it is a typical instance of a mammal. Likewise, the sentence "a sparrow is a true bird" is acceptable, but "a penguin is a true bird" is not. In order to account for these expressions, it is necessary to recognize the nonequivalence of instances. This is what Smith, Shoben and Rips (1974) did in their model of semantic memory, the feature-comparison model. According to this model, categories are represented not only by defining values, but also by so called characteristic, non-necessary values. Exemplars that have many of the characteristic values of a category are considered to be more typical than those that do not. Rosch joined the idea of typicality differences among exemplars as a feature of natural categories.

The other assumption in traditional studies that bothered Rosch was that of necessary and sufficient conditions for membership. This assumption was avoided in the prototype models. Prototype models stemmed from the area of schema formation research. The view that information is stored by means of a schema was advocated by Bartlett (1932). According to Bartlett, information is not simply retained in its full detail. Instead, a schema is abstracted, which subsequently organizes incoming information.

Posner and Keele (1968, 1970) studied prototype abstraction with nonverbal, ill-defined categories. They used simple dot patterns, that did not allow for an obvious classification rule. Categories were produced by applying distortions to a prototype, that represented the central tendency of the category (i.c. the average of the set of distortions). The distortions implied that dots of the prototype moved to new positions in accordance with some statistical rule. Subjects learned to categorize the distorted patterns. Posner and Keele showed that subjects generate a mental representation of the prototype even when that specific pattern was never actually presented to them during learning. It has also been found that the unseen prototype was more resistant to forgetting than were the originally presented patterns (Strange et al., 1970).

In the prototype approach, the representation of a category is thus taken to be the result of an abstraction process. It is

generally assumed that different category exemplars are integrated into one memory structure, i.e. a summary description of the category. This description is used whenever a decision about category membership has to be made. In contrast to the traditional view it is furthermore thought that category representation is not restricted to a set of defining values. For a value to be included in the summary, it need only be characteristic of the category. Prototype models agree on that. However, the models differ in their assumption on exactly what is abstracted. They differ in the nature of the summary description. Posner and Keele have made a case for the abstraction of average values on the exemplars that were experienced during category learning. The prototype need not be an existing exemplar. It might be composed of values never experienced, because it has the mean value on every dimension that varies among the experienced exemplars. Another conception of prototype composition can be found in frequency models (a.o. Neumann, 1974). In these models, a prototype is assumed to be based on frequency of occurrence of values among the experienced exemplars, and not on the average of values along a dimension. People form prototypes composed of the modal frequencies of the values of the experienced members of the category. Although the values themselves must have often been experienced, the combination of the values need not actually be perceived.

It is the work of Rosch that applied prototype theory to natural categories, the implicit concepts of daily life. Rosch proposed that natural categories are represented as prototypes or best exemplars, surrounded by other members of decreasing representativeness. The more typical members have more of the characteristic values than others. Specifically, Rosch hypothesized that typicality of a category member is determined by its family resemblance to other members of the same category. A high family resemblance means that a large number of values is shared with the other members, while at the same time few values are shared with contrasting categories. Thus, the best examples of one category will not be good representatives of other categories. Furthermore, atypical exemplars or category members on the boundaries, are not clearly either members or non-members.

Boundaries are usually fuzzy.

With a variety of experimental methods, Rosch and her associates investigated the memory representation of natural categories. From their experiments it appeared, for instance, that subjects can reliably rate the extent to which a member of a category fits their idea of the meaning of the category name. Typicality differences were found, like a chair being a better example of furniture than a lamp or a piano. They also used the priming technique. Priming in studies of cognition refers to the triggering of specific memories by a particular cue. Thus, the advance presentation of a category name may to a greater or lesser degree, facilitate subsequent matching performance with cues related to the prime. With this technique they have shown that the representation generated by the category name is more like members rated as good examples than those rated as poor examples of the category. Furthermore, feature listings and typicality ratings of various items within a given category showed that the more features an item has in common with other members, the more it is considered a typical member of the category. The results generally support the empirical validity of Rosch's idea that natural categories have an internal structure, in which members are ordered according to the degree to which they are judged to be "good examples" of the category.

The internal structure is governed by principles of categorization. Categorizing is aimed at what Rosch calls "cognitive economy". This means that on one hand categories should preserve information about the environment as much as possible, but on the other hand - to minimize cognitive load - they should reduce the infinite differences among stimuli to manageable proportions. In other words, the aim is to maximize the information accounted for, and to keep at a minimum the number of categories that have to be distinguished. Economy also implies a maximization of intercategorical differences, so that the categories will be maximally distinctive. In this context the conception of hierarchical organization of categories is of relevance. Rosch claims that natural categories are hierarchically related. Larger categories usually contain a number of smaller ones. Three levels are distinguished. Superordinate categories, such as clothing, contain basic-level categories (e.g. trousers), which in turn contain

subordinate categories (e.g. Levi's). Cognitive economy is maximized at the basic level. Therefore, the basic level is considered the most important. At this level, more information is preserved than at the higher level because members of a basic category have more in common. At the same time, differences among objects are reduced as compared with the lower level categories. The subcategories of a basic category have only small specific differences because their members share many values. Basic categories are most important in language and they are the first categories we learn. The claims concerning a basic level can be formalized in terms of cue validity (a.o. Beach, 1964). Cue validity is a probabilistic concept indicating the predictive validity of a dimensional value of a category. Cue validity is based on frequency of occurrence of values both in the focal and in other categories. A category exemplar with a high total cue validity is more differentiated from other categories than one of lower total cue validity. Cue validity is maximized at the basic level. In this thesis the concept of cue validity will be used and further described in Chapter 6 and 7.

Another principle of categorization asserts that the environment is perceived to possess a correlational structure. In the criticism on traditional studies we have already mentioned that the combinations of what we perceive as dimensional values are not equiprobable. Rather, some values co-occur more than others. Rosch argues that categories tend to be formed that mirror the structure perceived in the environment. However, elsewhere she recognizes that it may also be the case that this structure is something that is imposed on regularities in nature by our conceptualizing minds (Rosch, 1978). Co-occurrence of dimensional values will be one of the main issues in Chapter 7.

The point of correlational structure is also emphasized by Anderson (1985). Anderson describes the structure of natural categories as a schematic structure, and asserts that schemas represent (among other things) our knowledge about how dimensional values tend to go together to define objects. Thus according to Anderson, it is the interrelational structure, the configuration of dimensional values, rather than just a list of values that defines a category. Incidentally, Anderson

states that part of the object schema may also be functional information. This is an aspect that both traditional and prototype theorists have often neglected (de Swart, 1982).

The use of a schema framework has become widespread in psychological research. At the same time interest is now growing in complex, composite categories (Millward, 1980; Mandler, 1984; Medin and Smith, 1984). Research on categorization has been dominated by the usage of simple categories. However, these categories can be further integrated and related to each other to form more complex organizations of knowledge. Such elaborated, interconnected knowledge structures are most generally referred to as schemas, although the schema notion implies also an active organizing principle. Not just categories can be coded by schemas. Events, stories and scenes, can also be represented by schematic forms of organization. In that case, spatio-temporal relations are important parts of the schemas. These complex knowledge structures, however, are beyond the scope of this thesis. We will now turn to the issues to be studied in this dissertation.

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3. CATEGORIZATION

3.1. Theoretical issues

In Chapter 2.4 it was mentioned that the classical view on categories entails the idea of category representation by defining values. Defining values are both necessary and (jointly) sufficient to define the category. If there is more than one defining value, the values are combined by some rule (e.g. conjunction or disjunction) to determine category membership. The classical view has been severely criticized for the defining value notion (e.g. Rosch, 1975), and although none of the criticisms has been utterly decisive (see for instance Martin and Caramazza, 1980), it has led many investigators to alternative views, mainly prototype ones. New research questions came up, such as what determines a prototype and what information is used in the classification of new exemplars. Stimulus materials were changed. Instead of artificial stimuli, e.g. geometrical figures, subjects became importuned with real life materials, such as birds, faces and pieces of furniture. Furthermore, different experimental paradigms were adopted in order to meet the research questions.

However, before totally shifting the helm and abandoning the defining values notion entirely, it would be interesting to know what the influence of typicality is on a traditional category learning task with defining values. The question of interest is whether it can be shown that categories that are learned in the traditional way, with membership being sufficiently specified just by defining values, may nevertheless acquire an internal structure that favours typical members over less typical ones. Of course, this can only come about

if subjects are given proper information from which it is possible to derive typicality differences among exemplars. With well-defined categories, it is then quite conceivable that defining values enter into the category representation, but this does not rule out the possibility that other information is also represented. Thus, typicality effects may not be inconsistent with the traditional view if they can be shown to occur with a category learning task that conforms to the traditional Brunerian design.

However, apart from that, it may be the case that it is not definingness in a strict sense that makes up the crucial variable. This could be rather some related but less rigid measure of variability, such as for instance the degree to which a dimensional value is representative, i.e. occurring often but not always among category members. Definingness may then simply be the maximum degree of representativeness. This avoids the problem of whether or not people are able to specify the defining values or whether or not they ultimately have defining values represented. At the same time it has the advantage of accounting for differences among category members in goodness of example. The problem then remains just what it is that determines representativeness or typicality. This will be investigated in the experiments in Chapter 6 and 7 of the present thesis.

As a starting point, two experiments in Chapter 5 have been designed to apply typicality variation to a classical learning problem with defining values, employing both traditional and more realistic stimulus materials. Thus the experiments attempt to provide a bridge between the traditional concept identification studies and the more recent developments on the organization of knowledge in more natural categories.

Natural category exemplars may vary in the degree to which they are typical of the category. An apple, for instance, is thought to be more "fruit-like" than a watermelon, and a sparrow is a more typical bird than a turkey. Typicality differences among category members have been established in numerous studies (a.o. Smith et al., 1974; Rosch, 1975). In these studies it has, for instance, been shown that subjects agree in their typicality judgments of category members, and that the typicality ratings predict reaction time to verify category

membership. The question of what determines this typicality variation is important because its answer will offer insights into the basis of category structure. The central concern of the present dissertation is variation amongst exemplars within the same category. Different aspects of within-category variation may contribute to the way that a category is remembered following experience with exemplars and non-exemplars. The present study addresses these aspects and their influence on learning and subsequent usage of categories.

In particular, two main aspects are focused on. One aspect concerns the frequency of occurrence of dimensional values. The other aspect is the similarity of variants of a dimensional value to a prototypical value (e.g. various triangular forms to a prototype triangle). This aspect will be called typicality of value variants. To distinguish between typicality based on frequency of values and variant typicality, these typicalities will next be referred to as representativeness and (variant) typicality, respectively.

3.1 Frequency of occurrence in contrast categories

Maximization of cue validity was suggested by Rosch (1973) to be a determining factor regarding the internal structure of a category. According to this principle, the best examples of categories are those exemplars that have the most in common with other members of the same category, and share the least with contrasting categories. It is the latter addition that constitutes a particularly important research issue in the present thesis. When people learn a category, do they use information on contrasting categories at all when forming the focal category? And if so, then what information do they use, what effect does it have on the category to be learned?

It is often assumed that in learning a category, the learner keeps track of the frequencies with which values occur within that category. Indeed, there is substantial evidence for accumulation of frequency information during category learning (a.o. Neumann, 1974; Goldman & Homa, 1977; Hayes-Roth & Hayes-Roth, 1977; Chumbley et al., 1978; Kellogg et al., 1978). One could argue then, that in a category representation the dimensional values represented are the ones that

occur most often among category members. This is in fact what Neumann (1974) for instance proposed in his attribute-frequency model. According to his model, a category prototype is formed that contains the maximal number of the most frequently experienced values.

Occurrence of values within one category may be of relevance in the representation of that category. However, it could equally well be the case that it is just what distinguishes a category from other categories that makes up the important information. In this view, when a category is being learned, the learner pays particular attention to those values that provide the sharpest contrast with other, related categories. These so-called distinctive values may next become central to the category representation. In that view, a category representation not only contains information on occurrence in the focal category, but also on occurrence in contrasting categories. The latter information can of course only be learned when contrasting categories are experienced in addition to the category to be learned. In the latter view, contrasting categories are useful in a learning phase, because they provide information on the occurrence of dimensional values outside the focal category. Distinctiveness from other categories is not always accounted for in categorization models. It is however accounted for in models that have cue validity as a critical term, such as for instance the property-set model proposed by Hayes-Roth and Hayes-Roth (1977). As mentioned in 2.4, cue validity can be defined as the frequency with which a cue, or a dimensional value, occurs in one category, divided by the total frequency of that cue across all categories. Cue validity thus takes into account the resemblance within a category, as well as distinctiveness from contrasting categories.

In the category learning tasks of the experiments described in Chapter 6 and 7, frequency of dimensional values will be varied both in the focal and in the contrasting category. As for occurrence in the focal category, a high frequency of values is assumed to facilitate categorization performance. In addition, the influence of occurrence in a contrasting category will be investigated extensively on the following hypothesis. Frequency of values in the contrasting category will affect categorization performance and representativeness

ratings. Category exemplars will be categorized more easily and will be judged more representative, the lower the frequency of their composing values in the contrasting category was during learning. The influence will be studied both by varying frequency in the contrasting category and by either including or not including a contrast category in the learning task.

In Chapter 6 also a delay of testing variable will be introduced in order to test whether values that appear to be most important to categorization are also the most resistant to forgetting.

3.1.2. Conjoint frequency

Another controversial issue regarding frequency of occurrence is whether or not subjects learn about each dimensional value independently of the other values. The question is, whether or not frequency of co-occurrence of dimensional values affects category formation. Rosch et al. (1976) have claimed that the perceived world comes as structured information rather than as arbitrary, equiprobable co-occurring values. Values that characterize the members of natural categories are often correlated, and these conjoint frequencies are mirrored in the categories that people form. The suggestion that conjoint frequency affects categorization has also been made by Hayes-Roth and Hayes-Roth (1977) and by Medin and Schaffer (1978).

Kellogg (1981), on the other hand, states that stimulus dimensions are independently represented, and that only simple frequencies are counted. There has not much research been done on this topic. One study, a category learning experiment of Kellogg (1981), failed to produce conjoint frequency effects. In Kellogg's study, however, the values with which conjoint frequency was varied, were all irrelevant to categorization. The possibility remains that conjoint frequency effects will show up when relevant values are concerned. This question will be tackled in Chapter 7.

3.1.3. Feedback information

Feedback information in category learning experiments usually offers the subject information on the category to which an item belongs. Any other information, such as "this is a good example", or "this one is not very representative of the category"' is withheld. However, suppose that the category learner is given such additional information as to the goodness of example of an item. Would this information be useful, i.e. by facilitating the process of category learning, or by improving categorization performance afterwards? It is conceivable that the learner will profit from this extra information, because information on the category structure is now directly given, whereas otherwise this can only be experienced indirectly from the exemplars themselves. The hypothesis on the use of information on representativeness of an exemplar in addition to the normal feedback will be investigated in the experiments described in Chapter 6 and 7.

3.1.4. Typicality of value variants

As mentioned in 3.1.1., frequency of occurrence of values has been shown to be an important variable in category learning, and models have been based on this. However, in contrast to frequency models, distance models of categorization predict that prototypes are formed on the basis of some multidimensional mean rather than mode. Studies that have compared both types of model do not unequivocally favour one or the other type of model (Martin & Caramazza, 1980; Reed, 1972), although frequency models seem to have the most empirical support (Goldman & Homa, 1977; Hayes-Roth & Hayes-Roth, 1977; Neumann, 1977; Chumbley et al., 1978). The kind of dimensional values used in a category learning task may be relevant to this state of affairs.

The kind of dimensional values -discrete or continuous- places constraints on what information can be gathered to represent categories. When discrete values are employed, variability in category exemplars most probably results from varying the frequency of occurrence of those values. On the other hand, when continuous values are used, variation amongst category exemplars may also result from

varying the typicality of value variants. If dimensional values vary continuously, then each value is determined by some allowable range of variation. Continuous values may vary in typicality within certain ranges, but apart from that they may vary regarding their overall frequency of occurrence in a category. Thus there may be a case for both models. The human classificatory system may be flexible enough to allow both for frequency and for variant typicality variation. It is the concurrent influence of frequency and variant typicality variation that will be investigated in the present dissertation. The idea is that both types of model apply. However, they do so in different aspects of within-category variation. Frequency variation has been described in 3.1.1 and 3.1.2. In the same learning tasks in which frequency will be varied, typicality of variants will be manipulated in order to determine concurrent effects. If it can be shown that both variables are effective in the same category, then it can be concluded that these variables are not mutually exclusive, but rather that they represent different aspects of the same category learning process.

Typicality of value variants for all kinds of stimulus materials to be used in the experiments of the present thesis, were established in preliminary studies. In Chapter 5, the main purpose of typicality variation is to examine whether the typicality phenomenon that exists in natural categories, can be also demonstrated within the kind of well-defined categories traditionally employed in studies on category learning. Next, in Chapter 6 and 7, typicality of variants will be manipulated together with frequency of occurrence of dimensional values. The focal categories in these experiments are ill-defined in that dimensional values are combined in a way that excludes a category representation by common and defining values. Typicality is expected to influence categorization, such that increasing variant typicality has a facilitating effect on categorization performance. Typicality effects will be further studied by varying the range on which variant typicality is varied in the learning task.

3.1.5. Range of typicality

Another problem that has not received much attention in studies on category learning is the formation of category boundaries. This issue is obviously related to within-category variation. One may assume that categories are represented by prototypes, surrounded by exemplars of decreasing representativeness. One may further acknowledge that category boundaries are mostly vague rather than clear-cut. However, this leaves open the question of the ultimate range of discrepancies among category exemplars that a person is willing to accept. For example, an opening in a wall with glass in it is usually called a window. However, it is questionable whether, if the opening is only one inch wide, it would still be categorized as a window. Context may be of relevance here. In 2.3. we mentioned the study of Labov on boundaries of the cup category. In that study, one factor influencing the boundary appeared to be context. The cup boundary was not the same in different contexts. Likewise, the one inch opening may be called a window depending on the context. For instance, it is a regular window when it is part of a doll's house. This is an example of a factor of influence on category boundaries once they are formed. It shows that boundaries are flexible because they are context dependent. The problem to be studied in this thesis, however, concerns boundary formation. How is experience related to category width? People can use narrow, moderate, or wide categories for classification, and it is hypothesized that this is influenced by prior experience on category exemplars.

3.2. Line of research

3.2.1. Extension of the classical line

The experiments described in Chapter 5 form an extension of the classical line of experimentation in category learning to more complex and more realistic category members. Employing a conventional category learning paradigm (see 2.2), typicality of value variants is manipulated in traditional well-defined categories. Typicality will

be varied both for relevant (defining) and for irrelevant values. In this situation, like in traditional studies, subjects most probably learn the relevant values, which amounts to solving the learning problem. However, it is also hypothesized that learning performance will be influenced by value typicality. That is, learning will be easier when the relevant values are typical rather than atypical, but the reverse will hold for irrelevant values. Furthermore, the idea that subjects have about category members following learning is supposed to be affected by typicality.

To study the effects of typicality, the meaningless artificial stimuli traditionally used were employed in one study. These consisted of unconnected, arbitrarily arranged separable dimensions. In order to compare traditional material with more real-life stimuli, the experiment was replicated with more meaningful realistic unitary material.

The older research tradition on categorization has been especially profitable because it studied hypothesis formation. From many traditional studies it appeared that people solve concept identification problems by formulating and testing hypotheses (e.g. Bower and Trabasso, 1964; Levine, 1975; De Swart and Das-Smaal, 1976; 1979). However, people usually are not capable of keeping track of all possible hypotheses at one time. Levine (1969) suggested that from all possible hypotheses a subset is chosen. This multiple-hypothesis sampling theory was described in Chapter 2. The category learning tasks to be described in Chapter 5 offer an opportunity to test an implication of Levine's theory.

3.2.2. Aspects of within-category variation

Concurrent effects of frequency of occurrence of dimensional values and typicality of value variants are the subject in the experiments described in Chapter 6 and 7. The experimental paradigm used to study these effects consists of a learning phase, followed by a test phase.

In the learning phase, subjects are shown items one by one from a mixed set of both category exemplars and non-exemplars. The

categories are experimenter-defined. Feedback indicates the correct classification for each item, thereby providing the information necessary for category learning.

In the test phase, subjects are asked to categorize all kinds of items, including novel instances that they have not studied. The nature of the information acquired during experience with the learning items will be evaluated from performance on the test items. The test phase is comprised of a categorization test and also a pairwise comparison task. In this task, exemplars from the focal category are to be compared on representativeness of that category. At the conclusion of each experiment, subjects are asked to mention the characteristic features of the category to be learned, in order of decreasing importance to categorization. Manipulation of the learning set is expected to yield information about the influence of a number of variables on category learning and on subsequent categorization performance.

Frequency of values in the contrasting category will be varied among values having the same focal frequency. Besides, in Chapter 6, a delay of testing variable is introduced to examine differential forgetting of values of different cue validities. In Chapter 7, the effect of contrasting category experience will also be studied by providing, apart from the focal category, either or not a contrasting category in the learning task. Furthermore, co-occurrence of relevant and irrelevant values is varied during learning, in order to test the effects of conjoint frequency.

Effects of typicality of variants are studied both in Chapter 6 and 7. The range of typicality experienced during learning is varied by presenting exemplars composed of either a small range of typical variants only, or a broad range of both typical and atypical variants. Atypical variants may slow down the learning rate, but on the other hand they may result in a better representation of the category boundaries. The question will be addressed whether the latter means only a better categorization of new atypical members of the focal category, or whether it also means facilitation on boundary items of the contrasting category.

Finally, both in Chapter 6 and 7, effects of the kind of information given to the subjects during learning will be studied. Feedback

information is either specific or nonspecific: in addition to the proper category, an item's degree of category membership may or may not be indicated. Problems on the interpretation of the results concerning this topic in Chapter 6, are the reason to introduce an observational category learning paradigm in Chapter 7. In an observational paradigm, confusion of response and feedback information, which may be complex in the specific information condition, is prevented because subjects need not give a categorization response during learning in this paradigm. They are required just to look at stimuli and the feedback information in self-paced trials. In between the learning blocks, subjects are tested a few times using short classification tasks. Information on representativeness of an item is expected to facilitate categorization performance.

3.2.3. Main questions of research

The central concern of the study is what it is that determines an item's representativeness or typicality to a category. As a starting point, and in an attempt to provide a bridge between traditional concept identification studies and the more recent accounts of natural category representations, typicality variation will be applied to a classical learning problem with defining values. Typicality effects may not be inconsistent with the traditional view if they can be shown to occur in such learning tasks. Next, two main aspects of variation within categories and their concurrent effects on categorization are further investigated. These are frequency of occurrence of dimensional values, and the typicality of the variants with which they occur.

Regarding frequency, the question is whether and how frequency of occurrence of values affects category representation. An important question is whether people use information on occurrence of values in contrasting categories when they learn some category, and whether there are differential effects of forgetting on this point. Conjoint frequency represents another important issue. Does conjoint frequency affect categorization? Will an irrelevant value be judged more representative when it correlates with a relevant value as compared

with zero correlation between these values? Furthermore, the question is addressed whether feedback information on representativeness of an item has a benificial effect on category learning. Affirmative answers are expected on all of these questions.

On variant typicality, the issue of boundary formation is raised. How is experience related to category width? Categorization performance on category boundary exemplars will be studied on subjects varying in the range of variants they experienced during learening. Broad rather than small range experience is expected to hamper category learning, but to result in better categorization of atypical boundary exemplars, both of the focal and of the contrast category.

Another research topic of the present thesis is the relationship between information processing and physiological activity. The research question on this issue will be specified in the next chapter.

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4. UNCERTAINTY REDUCTION AND PHYSIOLOGICAL ACTIVITY

In this Chapter, the relationship between information processing in cognitive tasks and autonomic physiological activity is introduced. From time to time, cognitive psychologists are reminded that there is more to human intelligence than just the pure cognitive system. The importance of paying more attention to the physiology of cognitive processes has lately been emphasized a.o. by Rumelhart and Norman (1981), Iran-Nejad and Ortony (1984), Nilsson (1984), and Posner (1984). The present thesis does pay attention to this relationship by studying the Galvanic Skin Response (GSR) as a possible index of uncertainty reduction.

Cognitive processes are sometimes manifested in overt behavior. However, more often they are not, in which case a variety of different experimental methods is employed to infer these processes. It is at this point that measurement of physiological indices of cognitive processes can offer a substantive contribution. Physiological variables may serve as objective measures of specific cognitive processes. This study focuses on one of these measures, the GSR.

The GSR has been traditionally used as an indicator of the Orienting Response (OR), and can be considered to be a reliable index of this concept (e.g. van Olst, 1971; Maltzman, 1979; Barry, 1984). When studying the OR literature, the frequency of occurrence of the name of Sokolov is striking. Sokolov (e.g. 1969) has developed a large body of theory based on his investigations of the OR. Central in his theory is the idea that neural models, i.e. representations of experience, are built up in the brain. Neural models represent systems of expectancies or hypotheses. New experiences are compared to

these models The OR is suppressed if a match occurs. In case of a mismatch a discrepancy between hypothesis and actual incoming an OR is produced. This is manifested in physiological ity.

The theory of Sokolov has received substantial support, but on the other hand it has not been completely without its critics. For instance, Bernstein and Taylor (1981) have argued that Sokolov failed to specify the influence of stimulus significance on the OR. They stated that although the literature demonstrates clearly that mismatch can produce an OR, there is nothing to indicate that mismatch must do so. Instead it is said that mismatch results in an OR only when the stimulus is judged to be potentially useful or significant in addition to conveying informational value. The stimulus must play a distinct role in the subject's task. The importance of stimulus significance has recently been supported by Wingard and Maltzman (1980). They showed that subjects with a particular recreational interest (e.g. surfing or chess), displayed significantly larger GSRs to slides depicting scenes related to their specific interest, as compared to other recreations.

Continuing the studies of De Swart and Das-Smaal (1976; 1979 a,b) and of De Swart et al. (1981), the present thesis elaborates further on the hypothesis that GSR reflects uncertainty reduction provided by feedback during category learning. Thus the question is whether or not the GSR amplitude is related to the change in subjective probability of hypotheses held by the subject. The relationship is important because of the central role of expectancy or uncertainty in current models of information processing (e.g. Neisser, 1978).

Different operations have been used in the measurement of uncertainty or expectancy. In contrast to studies in which expectancy is inferred from the a priori probability of a stimulus, the present study relies on changes in subjective posterior probability. In category learning tasks, changes in probabilities of hypotheses result from feedback. Many studies have shown that subjects change their hypothesis only after disconfirmation (e.g. Falmagne, 1970; Coltheart, 1973; White, 1974; De Swart and Das-Smaal, 1976, 1979a). If a categorization turns out to be incorrect (disconfirmation), the

probability that the selected hypothesis is true reduces to zero. In case of correct categorizations (confirmations), the subject gains some confidence and stays with his hypothesis. Usings Bayes' theorem, De Swart and Das-Smaal (1979b) showed that these different kinds of feedback result in different amounts of uncertainty reduction. The current study investigated the effects of different types of feedback (i.e. noninformative, confirming, and disconfirming), on GSR during a category learning task. GSR is expected to increase from noninformative to confirming to disconfirming feedback.

Moreover, subjects' confidence about categorization is measured directly in the present studies. De Swart and Das-Smaal (1979b) and De Swart et al. (1981) showed that sorting the data according to confidence ratings leads to an even better understanding of the effects of confirming and disconfirming feedback on physiological indices in terms of uncertainty reduction. In the present study, therefore, subjects will continually be asked to estimate the certainty that their categorization was right. The hypothesis that the GSR amplitude varies systematically with the confidence of the subject in his hypothesis and the type of feedback he receives, will be tested in a variety of ways both in chapter 5 and 6 of the present thesis.

Regarding the "significance hypothesis" of Bernstein and Taylor (1981) mentioned above, in the present studies significance is ensured by task relevance. In category learning tasks, confirming and disconfirming feedback are highly task relevant since the different types of feedback play a distinct role in the information processing activities of the subject.

In conclusion, the aim of GSR measurement in the present study is to test the hypothesis that GSR reflects the amount of uncertainty reduced by feedback in a category learning task.

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Part II

STUDIES

5. *Typicality, physiological activity and concept identification*
6. *Variation within categories*
7. *Effects of contrast category, conjoint frequency and typicality on categorization*

N.B.: for this Chapter see journal article as indicated below

5. TYPICALITY, PHYSIOLOGICAL ACTIVITY AND CONCEPT IDENTIFICATION*

5.1. Synopsis

The extent to which instances are good or poor examples of their categories (typicality) was varied in a concept identification (CI) task. Typicality was first established for the kind of artificial material traditionally used in CI tasks (experiment 1). This material was employed in a CI task (experiment 2) with a variety of dependent variables, including the galvanic skin response (GSR). To test the generality of the results, more realistic stimuli were employed (experiment 3 and 4). The results showed that typicality influenced performance on the CI task, that the GSR is primarily related to uncertainty reduction, that the findings with arbitrary materials are replicated with more meaningful materials, and that the multi-hypothesis sampling theory of Levine is supported by the findings.

5.2. Introduction

Most of the "classical" studies of concept identification (CI) in the tradition of Bruner et al. (1956) can be criticized on several points. In a CI task the subject is presented with a series of stimuli, some of which are instances of the concept, and others of which are not. The subject is asked to categorize each stimulus. Subsequently feedback is given regarding the correct categorization. One point of criticism concerns the equivalence of instances as members of a category, and the discreteness of their attributes. In many of the traditional studies the discrete values of each dimension were chosen because of their discriminability, and the chosen values remained constant during the experiment (e.g. only one value of red,

*) E.A. Das-Smaal & J.H. De Swart. Typicality, physiological activity and concept identification. Acta Psychologica, 1981, 47, 1-24.

N.B.: for this Chapter see journal article as indicated below

6. VARIATION WITHIN CATEGORIES*

6.1. Synopsis

Two aspects of variation within categories, relating to different models of categorization, were investigated - frequency of dimensional values and typicality differences within values. The influence of range of typicality experienced during learning and of informational value of feedback was also studied. Finally, differential forgetting of values was examined.

In the experiment subjects learned to categorize faces, and then performed a classification test task and pairwise comparisons of faces. A variety of dependent variables was employed, including the galvanic skin response (GSR).

Typicality and frequency of values appeared to influence categorization performance independent of each other. It was concluded that both prototype distance models and frequency models explain different aspects of variation within the same categories, and that models of categorization should account for frequency of values in contrasting categories. Results showed furthermore (1) the influence of typicality range on the extension of a category; (2) no influence of specific feedback regarding representativeness of a face; (3) less decay with a distinctive value; and (4) a positive relationship between uncertainty reduction and GSR.

6.2. INTRODUCTION

Traditional work on categorization treated all exemplars of a category as equally good examples of the category. This view has been criticized a.o. by Rosch (1973) and by Das-Smaal and De Swart (1981), who argued that categorization models must be capable of representing

*) E.A. Das-Smaal & J.H. De Swart. Variation within categories. Acta Psychologica, 1984, 57, 165-192.

N.B.: for this Chapter see journal article as indicated below

7. EFFECTS OF CONTRASTING CATEGORY, CONJOINT FREQUENCY AND TYPICALITY ON CATEGORIZATION*

7.1. Synopsis

Two experiments were conducted to investigate whether (a) experience with a contrasting category, (b) conjoint frequency of dimensional values, (c) range of typicality of values, and (d) type of information administered during learning influenced subsequent test performance.

Each experiment began with an observational category learning task, employing faces as stimuli. This was followed by a categorization test task and by pairwise comparisons of faces. Influence of a contrasting category was studied in Experiment 1 by varying frequency of values of the contrasting category, and in Experiment 2 by either including or not including a contrasting category in the learning task.

Results indicated that (a) categorization is influenced by experience with a contrasting category, (b) conjoint frequency enhances the importance of values to a category, (c) broad typicality range experience reduces typicality differences among exemplars of a category, whereas small range experience diminishes differences in a contrasting category, and (d) information on representativeness of exemplars does not facilitate subsequent test performance.

The implications of the results for categorization models are discussed.

7.2. Introduction

Various models have been proposed as to the basis of categorization, several of which appear to be viable. One class of models, prototype-distance models (e.g. Reed, 1972), hold that a central representation (prototype) is abstracted from the experienced

*) E.A. Das-Smaal & J.H. de Swart. Effects of contrasting category, conjoint frequency and typicality on categorization. Due to be published in: Acta Psychologica, 1986, 63: 1.

Part III

CONCLUSION

8. Retrospect

Summary

Samenvatting

8. RETROSPECT

One way to deal with the variety of information in our environment is to form and make use of category representations, as was argued in Chapter 1. The issue regarding category representation that is focused upon in this study, concerns the memory storage of within-category variation. The two opposite theoretical positions relevant to this subject are the classical view with the defining values assumption, and the prototype approach (see Chapter 2). In the former view no aspect of within-category variation is represented, whereas the latter position in its extreme version holds that every aspect of within-category variation is represented. However, as Palmer (1978) already noted, underlying this dichotomy is a broad range of possible theories.

To attack the question of what aspects of variation within categories are represented, and how specifically they are represented, the present study considered the storage of information on frequency of dimensional values, and on typicality of the variants with which they occur. These variables represent different aspects of variation within categories (see Chapter 3). Their relative contribution to the learning of categories and the formation of category boundaries was studied, as well as their influence following learning on categorization and typicality judgments of old and novel exemplars and non-exemplars.

8.1. Frequency and cue validity

Frequency of occurrence of values in the focal category as compared to their occurrence in the contrasting category, was expressed in terms of cue validity. This measure gives an objective indication of the degree to which a value provides a correct basis for a categorization decision. The question is what subjects learn from this state of affairs about the actual goodness of a value; i.e. to what degree is it used and relied upon in subjective judgments following learning. In answering this question, special attention was paid to the influence of occurrence of a value in a contrast category, and to conjoint frequencies of values.

The influence of frequency of occurrence of values among contrasting category items on categorizing focal category exemplars was a very robust finding, coming from converging sources. It has been demonstrated repeatedly, employing a variety of learning paradigms, methods of testing, and dependent variables. In all experiments described in Chapter 6 and 7, high total cue validity of exemplars facilitated learning and classification following learning. The results on categorization with value omission as well as on the additional task of mentioning the characteristic values add to the evidence. Furthermore, when learning had to take place from focal category exemplars only, without experiencing a contrast category, categorization was guided by focal frequency of the dimensional values.

When values with the same cue validity but with different frequencies of occurrence were compared, focal frequency showed its own influence, apart from cue validity. Values of higher frequency were judged more typical. However, distinctive values -that is, dimensional values that occur frequently and exclusively in the focal category- appeared to be the most typical and most important ones to classification following learning. Delay of testing (see Chapter 6) showed that this was even more so with the passing of time.

The apparent conclusion from the findings is that people collect considerable knowledge of the frequency with which dimensional values occur in particular categories during learning. This knowledge is not

restricted to just the focal category, but also extends to the contrast category. People are able to use this knowledge in order to evaluate relative frequencies, that is, occurrence in one category as compared with occurrence in a contrast category. Three remarks have to be made on this conclusion, and we will turn to them next.

8.1.1. Automatic encoding of frequency information

The results on additional feedback information on frequency are relevant to the question whether or not frequency information is learned automatically. Some cognitive processes require sustained effort or conscious control on the part of the subject. Other cognitive operations can be accomplished automatically, requiring little cognitive capacity (e.g. Shiffrin and Schneider, 1977). Hasher and Chromiak (1977), Kellogg et al. (1978), and Zacks et al. (1982) have suggested that frequency information is processed automatically during learning. On the other hand, Greene (1984) and Hockley (1984) argued that there is not enough evidence for automatic encoding of frequency information. Experiments in Chapter 6 and 7 showed that subjects encoded frequency information effectively under conditions of non-specific feedback, despite the fact that they did not receive direct information concerning frequency of occurrence. Beyond that, the present results showed that decisions involving frequency judgments are not enhanced by the availability of direct information on frequency. In the experiment described in Chapter 7, measures were taken to exclude a possible explanation in terms of shortage of processing time and confusion of response and feedback. In spite of these precautions, advantage of presenting additional information on frequency was not forthcoming. These results argue that the encoding of frequency information is an automatic process. For, in contrast to automatic operations, effortful processes are assumed to profit from additional help.

Frequency information may be encoded automatically. However, it should be recognized that the frequency information stored can be used to further conscious processing, for instance, to generate hypotheses, which may be done consciously (Kellogg, 1982). Evidence that people

do, in fact, generate hypotheses about the relevant values of a category by selecting high-frequency values comes from experiments by, for instance, Haygood et al. (1970) and by Kellogg (1980). In category learning tasks, subjects appeared to hypothesize high-frequency values much more often as would be expected by chance.

8.1.2. Task demands

A second remark on the conclusion regarding frequency effects is the following. An unanticipated finding was the following difference between the categorization and the pairwise comparison task. Differential performance on focal category exemplars of lower total cue validity was found between these two tasks in all experiments. The results suggest that frequency in the contrast category is weighted more heavily in categorization tasks than in tasks that require judgments of representativeness of exemplars regarding the focal category. Unlike in categorization decisions, differences among categories are not so much the issue in the latter kind of task. Therefore, in that case, distinctiveness, as determined by occurrence in contrast categories, is deemed less important and receives less weight. This is not to say that influence of occurrence in a contrast category is not at all important in a paired comparisons task or in the additional task of mentioning the values typical to the focal category. The present studies have shown that it is. However, because the above mentioned disparity showed up repeatedly, this points to the relevance of task analysis.

Effects of task demands are also described by Medin and Smith (1984). They borrowed a distinction from Miller and Johnson-Laird. Miller and Johnson-Laird (1976) distinguished between the core and the identification procedure of a category. The core, according to Medin and Smith, contains the defining values of a category. The identification procedure contains values that are used in categorization, and these need not be the defining values. Medin and Smith further suggest, and cite some evidence, that different tasks may demand different information usage. The identification procedure is used to identify objects, whereas the core will be used whenever someone is

asked to back-up or justify the categorization decision (e.g. how do you know this is an exemplar of category X?). In the present view, this means that information on distinctiveness, which is used in the categorization decision, is of less relevance with justification, because this implies concentration on only one category.

As outlined in the discussion of Chapter 6, one interesting implication of the finding on task demands is that information on frequency in the focal category and information on frequency in contrast categories has to be separately accessible in memory, and not already joined in the measure of cue validity. Cue validity then, may be either computed when neccessary, or stored in addition to frequencies in focal and contrast category. Perhaps what is required is a distinction such as made by Miller and Johnson-Laird, between categories and procedures for using categories. Having knowledge of occurrence in contrasting categories does not imply that this knowledge is always used in performance.

Thus the contention that a category consists of certain values is not enough. It does not say how those values are weighted or integrated when people use that category in some particular situation. An account is needed of the manner in which a whole is constructed from the parts in each case. And as for storage, the information must be stored such that it enables us to use that information in a flexible way. Task and contextual factors may give rise to a kind of momentary relevant activation pattern in which certain values may temporarily be of more importance than others. For instance, different values are distinctive when a chicken (as a domestic animal) is compared with a horse than when a chicken (as food) is compared with another kind of meat. Regarding context, Barsalou (1982) makes a distinction between context-independent and context-dependent information in categories. Context-independency arises automatically from a high frequency of occurrence in the focal category. Context-independent information is activated on all occasions. Context-dependent information, on the other hand, refers to properties that are activated only in certain contexts. In this view, information on distinctiveness, and on degree of occurrence of a value in a contrast category, can be considered context-dependent information.

A post-hoc interpretation of the findings on a more elementary level of theorizing may serve to integrate the frequency results. Suppose the following. As a part of a momentary activation pattern, dimensional values activate categories in which they have occurred, to an extent corresponding with registered prior frequency of occurrence. Thus, a common value activates both the focal and the contrast category, although the focal category will be activated more. A distinctive value, however, activates only the focal category, because it has never occurred in the contrast category. It is furthermore assumed that contrasting categories inhibit each other when they are activated, a suggestion that comes from Wickelgren (1981) and from Rumelhart and McClelland (1982). It follows that the net activation of the focal category will be higher from a distinctive value than from a common value, even if they occur with the same frequency in the focal category, like in the present study. In a categorization task, the decision may then involve determination of which one of the categories at issue is activated most. A pairwise comparison task, on the other hand, concentrates on the focal category. It involves determining which one of two exemplars is more strongly related to the focal category. In such a task the focal category may be primed, and this diminishes the relative influence of inhibition by way of the contrast category.

8.1.3. Conjoint frequency

In the interpretation just mentioned, the effects of conjoint frequency, which were evidenced in the present study, also have to be accounted for. Therefore, it is necessary to assume excitatory relations between values, increasing in strength or number with increasing co-occurrence frequency. This assumption can clear up a controversy on conjoint frequency effects. As was pointed out in the discussion of Experiment 2 in Chapter 7, the effectivity of conjoint frequency shows up when at least one of the values is important to categorization. Conjoint frequency increases the typicality of an irrelevant value when it correlates with a value that is important to categorization. This explains why Kellogg (1981) did not find any conjoint

frequency effect using values that were all irrelevant to categorization. Excitatory relations between two irrelevant values do nothing of significance to increase the activation of the category. However, when at least one relevant value is concerned, an increased activation of the category is the result, facilitating categorization and increasing typicality judgments. The irrelevant value activates the category by way of its relationship with the highly characteristic value.

The assumption that effects of conjoint frequency are constrained to situations in which at least one of the joint values is relevant or characteristic to the category also solves a major problem signaled both by Reed (1982) and by Medin an Smith (1984). They argue that it is not probable that all possible correlations among values are taken into account, because they are too numerous. The condition of relevancy of at least one of the conjoint values may also in this respect appear to be an important constraint on the correlations that are taken into account.

Another interesting potential explanation bears on the Gestalt claim that "the whole is more than the sum of the parts". It may be speculated that the formation of interrelations by conjoint frequency, and the resulting additional activation through mutual excitation, gives rise to some of these effects. The results of the present study indicate that correlation of values enhances the typicality of the "whole" stimulus containing the correlated values, relative to non-redundant combinatations. This shows that conjoint occurrence of values during learning can cause the whole to be perceived as more than the sum of its parts. The existence of a predominant manner of organizing the parts of a stimulus may, in a comparable way, be due to special interrelations between values in memory, whether they are learned or physiologically prewired. Effects of learning the interrelations have been established in the present study.

8.2. Two aspects of variation

The frequency aspect of within-category variation has been considered in some detail. What has not as yet been accounted for is the

aspect of variance within dimensional values, the range of variants that are permissible for a certain value. This is another aspect that has been investigated in the present study. It pertains to variants that differ in typicality. The contribution of each aspect, frequency and variant typicality, to categorization was assessed by varying them together in the same experiments on the same values. Each form of variation had its own type of influence, and the aspects appeared not to interact. As described in section 3.1.4., the frequency and variant typicality aspects have been accounted for by a frequency and a prototype-distance model, respectively. The conclusion from the present studies is that the two types of model are complementary rather than contradictory. Both aspects together should be accounted for in one categorization model, if it is to be a viable one.

As was suggested in the general discussion of Chapter 7, a frequency model can be used for discrete as well as continuous values when it is assumed that the continuous dimensions are made up of intervals (Neumann, 1977). Such a model can be equally employed for categories with and without defining values.

The term well-defined describes those categories which have values that are both necessary and sufficient for determining category membership. Categories without such values, that instead have values that are only more or less representative of a category, can be termed fuzzy or ill-defined. Although for these categories it would always be possible to find some complicated "scientific" rule that could be used for classification (Martin & Caramazza, 1980), the rule for ill-defined categories may be so complex that subjects will have too much difficulty in determining it. Following this definition, the category structure employed in the experiments of Chapter 6 and 7 is an ill-defined one, whereas the categories used in the Chapter 5 experiments can be considered well-defined.

It appeared from various postacquisition tasks in the present experiments that also for ill-defined categories holds that the most frequent values, with lowest frequency in a contrasting category, are learned and considered most important to a category. This result does not deny the possibility, but argues against the necessity of defining values as part of a category representation. The latter account also

suggests that there is less difference between well-defined and ill-defined categories than has been argued for instance by Rosch (1975).

8.3. Exemplar representation

In discussing the various approaches to categorization, we have not yet mentioned the possibility that, rather than information being integrated in some fashion, each experienced exemplar may be stored and remembered individually. Support for such a model comes from Medin & Schaffer (1978). The exemplar view, however, has several weaknesses. First of all it predicts good memory for all the learned exemplars. In contrast, it has in fact been demonstrated repeatedly that memory for specific items is very poor (a.o. Bourne & O'Banion, 1969). Furthermore, having categories represented by exemplars only, provides none of the advantages of categorization mentioned by Bruner et al. (1956), such as efficiency and uncertainty reduction (see Chapter 1). The exemplar view also has severe problems in representing generalized knowledge that pertains to dimensional values, such as knowledge on conjoint frequencies, or frequency of values in contrasting categories. The special importance of distinctive values, which was established in the present studies, as well as the effects of conjoint frequency are not in favour of a category representation based on exemplars only. Of course, everything that in other models is supposed to be abstracted, can in principle be computed rather than stored directly, but this would require a great amount of computation in each case, which is not very parsimonious. Also the result from the experiments in Chapter 5, that typicality has differential influence for relevant and for irrelevant dimensional values within the same exemplars, argues against exemplar representation. Finally, as Smith and Medin (1980) pointed out, there are two special problems. In the first place, the question is what is left that joins the exemplars into one category. It is not clear what constitutes a category at all when only exemplars are represented. In the second place, there is a problem about what is done when only summary information about a category is given and no exemplars are experienced, such as is the case when a category is learned by being told rather than by

examples. The solution of these problems requires some kind of information abstraction.

8.4. Typicality of value variants

Dimensional values may vary in their frequency of occurrence, and this has consequences for categorization as discussed previously. However, for continuous values holds that the values may vary in typicality of the variants with which they occur, of course within certain ranges. The present study showed that this, apart from frequency has other, unrelated consequences, to which we will now turn.

Typicality variation was applied to well-defined as well as to ill-defined categories. Typicality effects have been established in both kinds of category structure, indicating that even the formation of traditional, well-defined categories is affected by the typicality of value variants with which the category is learned. This argues against a strictly all-or-none structure of categories, in the sense that no instance is a better exemplar than any other. Categories do possess internal structure, as indicated by the typicality effects. However, the effects were restricted to values that were relevant to the categorization decision. It should be noted here that typicality and relevance are not the same thing. Typicality has to do with the range of a value, whereas relevance has to do with its probability of occurrence. Category learning was facilitated by high rather than low typical value variants when relevant values were concerned. No such difference was found with irrelevant values. The discrepancy may be explained by an interaction between the selectivity of attention and the knowledge that is built up (e.g. Das-Smaal et al., in preparation). In the beginning of category learning, there is no category information available in memory to direct attention to specific stimulus values. The analysis of the stimulus is data driven, probably influenced by salience of values. However, in the course of learning, the analysis becomes more "top down", guided by hypotheses or expectations. The information that has been gathered is used to direct attention to values deemed relevant, the latter being guided by frequency. Finally, the learner will end up with detailed

representations of information on at least the focused values. The information that is stored includes various details about frequencies as well as information on their typicality ranges, as has been shown in the present study. Values considered irrelevant to category abstraction may be represented incompletely or may not be remembered at all. This is indicated by a recognition experiment of Nickerson and Adams (1979). They showed that whereas knowledge of colour and size of a U.S. penny is good, knowledge of its visual details is poor. Dimensions such as colour and size are relevant to the distinction between a penny and other coins. On the contrary, the additional details are irrelevant to the purposes for which pennies are employed. Hence they apparently do not receive much attention.

The idea of stimulus analysis being guided by expectations is central to schema theories (Neisser, 1967). Current experiences are assimilated to past experiences, and what we subsequently perceive is influenced by these experiences. Thus, perception contains the memory of earlier encounters, as Arnold, (1984) put it. As a result, the accounts of stimuli may be different from the stimuli that evoked them. The present study's findings on the effects of typicality range experience serve to illustrate this point. Two groups of subjects differed in range of typicality over which the value variants of the stimuli were varied during learning. The groups subsequently appeared to respond in different ways to the same interstimulus distance. The "psychological" distance between the stimuli from two categories was larger when a small rather than broad range of typical variants was experienced during learning. It shows that prior experience can make a significant difference in typicality judgments and in subjective intercategorical distance.

8.5. Category boundaries

One problem that has been neglected in models of categorization that allow for variation within categories, is the problem of category boundaries. It may occur that an item is not clearly either a member or a non-member of a category. The problem is how much discrepancy is allowable among members of a category. In section 2.2. we argued that

boundaries are dependent on context. The question addressed in this study concerns the influence of learning on the range of discrepancies that is still acceptable. Atypical exemplars are sooner accepted as category members if one's category ranges are wide rather than narrow. Although there may be individual differences in the category ranges that people keep for themselves (Detweiler, 1975), the present results generally show how ranges can be determined by learning, and how range experience influences within-category variation. As was to be expected, experience with a broad variant range resulted in a relatively large extension of the focal category. It also resulted in better categorization of novel atypical focal category exemplars. Atypical boundary instances of the contrast category, however, were not categorized better by broad than by small range experienced subjects. This may have been due to fast categorization of contrast items by default following learning in the small range condition. The explanation is that because of the small extension that small range subjects formed of the focal category, contrasting category items clearly are not members of such a small focal category. Therefore, once the small focal category is learned, contrast items can be relatively easily rejected. This could have compensated a benificial effect of broad rather than small range experience on categorization of the contrast items. The categorization by default explanation following small range learning experience was tested and supported by several results described in Chapter 7.

The range of variants that was experienced, influenced typicality judgments. A recurrent finding was the lack of typicality differences in the focal category following broad range experience. A third range condition, with broad range experience but a limited number of different variants within this range, showed that the lack of typicality differences was indeed due to the width of the category, and not to the greater number of variants. Thus extending the range of variants causes a reduction of typicality differences among focal category exemplars. This finding agrees with the model of stimulus discrimination of Gravetter and Lockhead (1973), which was mentioned in Chapter 6.

The results on typicality range show how the manner in which something is perceived or interpreted can change as a result of experience. Category learning can bring about such changes in the cognitive system, causing a different interaction of the cognitive system with recurring stimuli than before learning took place.

8.6. Hypothesis testing

Regarding the way in which people proceed when they learn categories by examples, a very influential idea states that people acquire categories by a process of selecting and testing hypotheses (e.g. Bruner et al., 1956; Levine, 1975). As mentioned before, the findings on storage and usage of information on frequency of occurrence in a categorization learning task can be reconciled with hypothesis testing theory by the assumption that frequency information is used to select hypotheses. Haygood et al. (1970) a.o., and more recently Kellogg (1980), have evidenced this view. One special theory on hypothesis formation, Levine's (1969) multi-hypothesis sampling theory, was supported in the present study by results described in Chapter 5. An illustration of multi-hypothesis sampling in a real-life situation is given by Reed (1982). Reed describes how hypothesis testing is applicated in a task that involves diagnosing medical problems. Results on how physicians attempt to diagnose a disease agree with Levine's theory. It appeared that physicians start to form hypotheses early in the examination. Then they monitor a subset of about three hypotheses at a time, and this subset remains fairly constant through different stages of examination. The results show that more than one hypothesis or expectation can be active and evaluated simultaneously. As was outlined in Chapter 4, many studies have shown that in a category learning paradigm such as was used in the present studies, one of these hypotheses is employed as a basis for response, and that subjects reject this hypothesis only after disconfirmation of the categorization response.

8.7. Uncertainty reduction and GSR

It has been proposed, on the basis of earlier categorization experiments (De Swart and Das-Smaal, 1976; 1979a, b), that the amplitude of the Galvanic Skin Response (GSR), is a manifestation of the amount of uncertainty reduction caused by feedback in such tasks. This is consistent with Sokolov's (1969) model of the Orienting Response (OR), which provides an analogue at the neural level of the cognitive process of testing hypotheses. As discussed in chapter 4, it also agrees with Bernstein's (1969) significance hypothesis, since feedback clearly provides highly task-relevant information. Stated in terms of Pribram and McGuiness (1975), the evaluation of the feedback information value indicates the degree to which it calls for "context updating", and it is argued here that this is reflected by GSR.

In the present study, subjects were required to categorize stimuli and to indicate the extent of their confidence in their categorization response. Following these responses, feedback was given. GSR was measured during this feedback. Thus, influence from response selection and execution processes on GSR measurement was canceled out here. GSR appeared to vary with the subjective amount of information delivered by physically identical feedback stimuli. In a variety of ways it has been shown that the higher the subjective information value of the feedback, the higher the GSR.

The results described in Chapter 5 show that GSR indicates uncertainty reduction more than task difficulty. The former aspect of information processing bears an aspect of expectation, based on a subject's hypothesis which is to be evaluated. The latter aspect of information processing refers to mental load or cognitive effort that has to be spent on a task. It is conceivable that different physiological variables have different psychological correlates. Whereas GSR may be primarily understood as an indicator of uncertainty reduction, Janisse (1977) suggested that the pupillary response is superior to GSR as an index of task difficulty. In a category learning task, employing both GSR and Heart Rate (HR) as an indicator of autonomic physiological activity, De Swart and Das-Smaal (1976a) showed that HR is a less suitable measure in such a cognitive task. On the other

hand, the amplitude of P300, like GSR, has been evidenced as an indicator of uncertainty reduction about hypotheses under test (De Swart et al., 1981; Donchin, 1975). The exact relationship among these and other physiological indices has to be cleared up by future research.

In Chapter 6, the specific feedback condition provided an opportunity to test the relationship between GSR and uncertainty reduction in yet another way than was done in our previous studies, and in an ill- rather than well-defined category learning task. Again, support was found on the idea that GSR reflects the amount of uncertainty reduced by feedback in a category learning task. A physiological measure like GSR as an index of a special cognitive activity in such tasks, has the advantage above other dependent measures that it provides direct information on covert cognitive processes. Therefore it is concluded that GSR amplitude provides a useful supplementary instrument in cognitive research.

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SUMMARY

This thesis concerns the memory storage of category information. It presents an analysis of several aspects of variation among category exemplars. For each of these aspects the effects on the way that a category is remembered following experience with exemplars and non-exemplars were assessed. In addition, the study considers the connection between cognitive processes and physiological activity.

In the experiments described in Chapter 5, typicality of value variants was varied in traditional category learning problems with defining values. Typicality of value variants appeared to influence learning performance. The effect, however, differed for relevant and irrelevant values. Typicality of relevant values facilitated category learning, whereas typicality of irrelevant values did not affect categorization performance. The latter discrepancy can be explained by interaction between selective attention and the developing category representation (see 8.4).

Different aspects of within-category variation in categories without defining values are the focus of Chapter 6 and 7. Two types of categorization models that are often contrasted are relevant in this respect. These are frequency models and prototype-distance models (see Chapter 2). In accordance with these models, two main aspects of within-category variation were investigated, i.e. frequency of dimensional values and the typicality of the variants with which they occur. A variety of methods was employed to examine their influence on category learning and its results. Frequency of values and variant typicality appeared to independently influence categorization performance. It was concluded that frequency and prototype-distance models are complementary rather than contradictory. They explain different aspects of variation within the same categories.

Regarding specific frequency effects, the experiments showed how frequency of values not only in the focal, but also in the contrast category influences category representation. The latter aspect is an important one that should be, but is not always accounted for in categorization models. A task effect appeared with respect to the influence of frequency in the contrast category. Implications are discussed in section 8.1.2.

The question whether or not conjoint occurrence of values affects categorization, represents another theoretically controversial issue (see 3.1.2.). From the present results it appeared that the typicality of an irrelevant value is enhanced when it correlates with a value that is important to categorization. The latter aspect may offer a solution to the above-mentioned controversy (see 8.1.3.). In all, subjective importance of values to categorization was clearly demonstrated to be determined by these frequency variables. Another variable, delay of testing, showed that distinctive values are more resistant to decay.

Finally, an experimental manipulation related to frequency was whether or not subjects received additional feedback information on

frequency. Additional information had no benificial effect on category learning. In section 8.1.1. this finding is discussed in connection with automatic encoding of frequency information.

With variant typicality the problem of category bounderies was raised. This is an often neglected issue in models of categorization. In the present study, the influence of range of variant typicality experienced during learning was investigated. As expected, broad rather than narrow range experience resulted in a larger extension of the focal category, with better categorization of atypical focal category boundery exemplars. However, atypical boundery items of the contrast category were not categorized better. The range of variants also influenced item typicality judgments. Within the focal category these judgments diverged relatively more following small range experience. Narrow as compared with broad range experience furthermore had the effect of polarizing the categories, i.e. the same physical distances were judged differently depending range experience.

Finally, the relationship was investigated between information processing in categorization tasks, and physiological activity as measured by the amplitude of the Galvanic Skin Response (GSR). In a variety of ways it was shown in Chapter 5 and 6 that the higher the subjective information value of the feedback, the higher the GSR. It is argued that GSR measurement as an indication of uncertainty reduction provides a useful supplementary instrument in cognitive research.