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Becoming a beer expert: Is simple exposure with feedback sufficient to learn beer categories?

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ABSTRACT

Category learning is an important aspect of expertise development which had been little studied in the chemosensory field. The wine literature suggests that through repeated exposure to wines, sensory information is stored by experts as prototypes. The goal of this study was to further explore this issue using beers. We tested the ability of beer consumers to correctly categorize beers from two different categories (top- and bottom-fermented beers) before and after repeated exposure with feedback to beers from these categories. We found that participants learned to identify the category membership of beers to which they have been exposed but were unable to generalize their learning to other beers. A retrospective verbal protocol questionnaire administrated at the end of the experiment indicates that contrary to what was suggested in the wine literature, prototype extraction is probably not the only mechanism implicated in category learning of foods and beverages. Exemplar-similarity and feature-frequency models might provide a better account of the course of learning of the categorization task studied.

1. Introduction

Understanding experts' abilities is crucial for theoretical reasons but also for practical reasons such as developing efficient training programs. Among the experts' abilities, categorization is one of the most studied cognitive processes probably because it is the basis for so many other cognitive processes (e.g., recognition, identification, understanding, reasoning, and problem solving) and also because it is sensitive to the level of expertise (see, e.g., Ballester, Patris, Symoneaux, and Valentin (2008); Chase and Simon (1973); Chatard-Pannetier, Brauer, Chambres, and Niedenthal (2002); Chi, Feltovich, and Glaser (1981); Honeck, Firment, and Case (1987); Lynch, Coley, and Medin (2000); Shafto and Coley (2003); Solomon (1997); Tanaka and Taylor (1991)). So understanding how experts learn categories is critical for understanding expertise development.

Experts have been repeatedly exposed to stimuli from their domain of expertise and, from these repeated exposures, have learned to extract stimulus regularities. This idea was suggested in face processing by Dukes and Bevan (1967), (see, also, Posamentier and Abdi (2003)) who theorized that repeated exposures to different views of unfamiliar faces may help human observers extract the invariant face information. This type of learning is considered to reflect "perceptual learning," a term defined by Gibson (1969, p.3) as "an increase in the ability to extract information from the environment, as a result of experience and practice with stimulation coming from it." Language theorists prefer the expression "statistical learning" (a term coined by Saffran, Aslin, and Newport (1996)) to refer to the process of learning statistical regularities. According to Kellman and Garrigan (2009), perceptual learning is "one of the most, possibly the most, important component of human expertise" and would "serve in the development of expertise in multiple ways." One of these ways is to enable people to build categories of stimuli from the detected regularities of the stimuli they repeatedly encounter. During category learning, the observer pays more and more attention to stimulus aspects that are relevant for categorization and in contrast gradually pay less attention to irrelevant dimensions (Goldstone, 1998; Nosofsky, 1988). For example, in 1920, Hull trained human participants to learn to categorize deformed Chinese characters into categories. Each of the 12 categories was composed of exemplars that shared some invariant structural properties. For six exemplars of each category, participants were trained to associate the same arbitrary name corresponding to the category of these exemplars. Participants were then tested on six new exemplars and were able to accurately categorize these novel instances. This early experiment illustrates the importance of perceptual learning in category learning as a mechanism that extracts invariants from exemplars. Since this early work, perceptual and statistical learning have been well documented especially in the visual (Fiser & Aslin, 2001; Lu, Hua, Huang, Zhou, & Dosher, 2011), auditory (Saffran, Johnson, Aslin, & Newport, 1999; Wright & Zhang, 2009) and, to a lesser extent, tactile (Conway & Christiansen, 2005) domains.

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However, very few studies have dealt with chemosensory modalities such as olfaction and taste, even though repeated exposures to complex odorant molecules are an essential aspect of the expertise of, for example, perfumers, oenologists, and brewers. Understanding expertise in the chemical senses is a recent field of research and it has important implications for training experts because how these experts categorize their perceptions determines their abilities (Ballester, Dacremont, Le Fur, & Etiévant, 2005; Ballester et al., 2008; Hughson, 2003; Hughson & Boakes, 2002; Solomon, 1997). For example, wine experts categorize wines according to grape variety but novices do not (Ballester et al., 2008; Candelon, Ballester, Uscida, Blanquet, & Le Fur, 2004; Solomon, 1997). This effect could be explained by statistical learning: Through repeated exposures to wines from different colors or different grape varieties, wine professionals would extract the correlational structure of wine aromas linked to their colors or their grape varieties and so would develop categorical representations based on these characteristics (Ballester et al., 2008; Brochet & Dubourdieu, 2001; Gawel, 1997; Hughson, 2003; Parr, Valentin, Green, & Dacremont, 2010; Solomon, 1997).

These mental representations are often described as "prototypes" or central tendencies, as put forward by Parr, Green, White, and Sherlock (2007, p.859): "The positive association between typicality rating and wine quality […] suggests that New Zealand wine professionals do indeed have a prototypical or ideal Sauvignon Blanc wine in mind, and that this prototype closely matches what wine professionals consider when they use the term 'good varietal definition'." Prototype models (Posner & Keele, 1968; Reed, 1972) assume that people abstract a central representation (prototype) from the presented exemplars of a category. Then categorization judgments about exemplars are based on distances computed between the prototype and the exemplars. But, contrary to previous studies on language acquisition or face or shape processing, these studies on wine did not provide evidence for prototype extraction and some alternative explanations could be entertained.

The feature-frequency theory (Kellogg, 1981; Neumann, 1974; Reed, 1972) proposes other close models based on abstracted information. These models assume that people register how often features or combinations of features occur among instances of a category and then base their categorization judgment on these frequency measures.

From abstracted information, experts could also have built some explicit rules about the characteristics of products (Rouder & Ratcliff, 2006; Smith & Sloman, 1994) and apply these rules to decide whether a product belongs to a category by selecting out some specific features and determining whether the product satisfies a rule suggested by these features.

Another possible mechanism could be stated in term of exemplar memorization. During their training, experts would memorize all the individual exemplars they encounter (Medin & Shaffer, 1978; Nosofsky, 1988). All these theories have been previously largely compared in different reviews of the literature (e.g. Ashby & Maddox, 2005; Goldstone & Kersten, 2003).

To sum up, it seems clear that exposure and statistical learning play an important role in the way experts in the chemosensory domain categorize their perceptions. Authors working on wine have observed category-specific changes in professionals (compared to novices) and interpreted their results in terms of learning statistical regularities and wine prototype construction. But these interpretations are quite restrictive and some alternative learning mechanisms could explain the observed results.

In the present study, rather than testing recognized experts whose training protocols are unknown, we used non-expert participants namely people who had not previously participated in formal tastings, and had no previous technical knowledge about beers (e.g., brewery visits or exposure to specialized literature)— and repeatedly exposed with feedback these participants to beers from two different categories (top and bottom fermented beers). At the end of each exposition session, participants were provided feedback about the category of each beer. We then tested if these participants were able 1) to learn the beer categories and 2) to generalize their learning to other non-learned beers.

In order to evaluate if alternative mechanisms to prototypes could occur during this category learning, participants were also asked to fill out a retrospective verbal protocol questionnaire.

2. Material and methods

2.1. Assessors

Participants were nineteen students (6 women and 13 men, mean age: 21.5, $SD = 1.0$ years) from the ISA-Lille ("Institut Supérieur d'Agriculture de Lille"). The experiment took place as part of a 70-hour-long course on the discovery of various occupations related to brewing. During this course, students were introduced to various technical and sensory aspects of beer. At the beginning of the study, students only knew the technical definition of the studied beers (given in the next paragraph).

2.2. Discussion on stimuli selection

One critical point when studying categorization and category learning is the choice of the stimuli because it is necessary to present unfamiliar categories to participants and observe their behavior during the learning period. To ensure that the participants are unfamiliar with the categories, one option is to create new, arbitrary categories of objects, but these categories may not be ecologically valid (Ashby & Maddox, 2005; Close, Hahn, Hodgetts, & Pothos, 2010). To use new, but ecologically valid categories, we chose real ill-defined chemosensory categories unknown to naïve beer consumers: the fermentation beer categories (a technical feature when brewing beers). In this framework, a beer can be categorized as a top-fermented, bottom-fermented, or a spontaneous-fermented beer, depending on the yeast used for the fermentation step. Top-fermented beers are fermented with yeasts called *Saccharomyces cervesiae* at temperatures of between 15 °C and 25 °C. These yeasts rise to the surface of the vat at the end of the fermentation, hence the name "top." Bottom-fermented beers are fermented with yeasts called *Saccharomyces carlsbergensis* or *pastorianus* at a temperature of between 5 °C and 10 °C. The yeasts migrate to the bottom of the vat, hence the name "bottom fermentation." Spontaneous fermentation is an ancestral method hardly used except for the production of specific beers (e.g., lambic, gueuze, kriek). The beer sensory characteristics depend largely on the type of fermentation. Most of the bottom-fermented beers are blond, not very alcoholic, and not very aromatic. Among top-fermented beers, we find blond, amber, and dark beers that are more alcoholic, more aromatic, and often perceived as more "dense." But these general sensory characteristics cannot be applied to all the beers of each category because of the large within category sensory variability of these beers and because there are several counter examples of beers from one category having characteristics of the other category. We call these counter-example beers: "trap beers."

2.3. Stimuli

Thirty-six beers (18 top-fermented "TF" beers and 18 bottom-fermented "BF" beers) were evaluated (Table 1). The TF and BF beers were chosen so as to best represent the beer market in terms of color and alcohol content but one "trap beer" was inserted into each category. For TF beers, the trap beer was "Hoegaarden"—a wheat beer that shares more sensory properties with BF than with TF beers (low degree of alcohol, light blond color). For BF beers, the trap beer was "Bière du Démon" whose high alcohol degree (12% vol.) makes it more similar to TF than to BF beers.

A quantity of 25 ml of each beer was presented in three-digit coded white plastic tumblers and served at 10 °C with a white light. This