STUDY GUIDE FOR ARTICLE-GROUP 3

HOW DO WE PARSE THE WORLD INTO CONCEPTS OR CATEGORIES?

First answer, “No one knows.”

Second answer, “This is an ancient topic of philosophy, a continuing topic of interest to psychology, and one of the great goals of research in neuroscience.”

The following pages in this document lay out a series of current theories, many of which are interconnected. My own research began close to the Prototype theory, and has moved toward Exemplar theory.

After perusing this document, please read the two articles in Group 3. The first is by Nosofsky, a major scholar of exemplar theory, the second is my me, and traces a contrapuntal schema taught to apprentice musicians in Bach’s time and earlier.

If the second of those articles seems reasonable, then the next step would be to begin reading Music in the Galant Style, which is available on this site (“The Galant Book”).

The Haydn and Mozart exemples from the music repertory (this site, “Repertory”) are discussed in Music in the Galant Style.

The twelve sonatas (about 36 movements) by Anna Bon are raw material for analysis. Many of her movements are almost uninterrupted presentations of the musical categories or schemata discussed in Music in the Galant Style.

By the way, Appendix A of that book is a Cliff’s Notes summary of the patterns. Using Appendix A, and flipping back to an exemplar or two from the main text should be sufficient to get an idea of the underlying category.
How do we learn categories or concepts?

Modern Psychological Theories of Concept Learning

It is difficult to make any general statements about human (or animal) concept learning without already assuming a particular psychological theory of concept learning. Although the classical views of concepts and concept learning in philosophy speak of a process of abstraction, data compression, simplification, and summarization, currently popular psychological theories of concept learning diverge on all these basic points.

Rule-Based Theories of Concept Learning

Rule-based theories of concept learning take classification data and a rule-based theory as input, which are the result of a rule-based learner with the hopes of producing a more accurate model of the data (Hekenaho 1997). The majority of rule-based models that have been developed are heuristic, meaning that rational analyses have not been provided and the models are not related to statistical approaches to induction. A rational analysis for rule-based models could presume that concepts are represented as rules, and would then ask what degree of belief a rational agent should be in agreement with each rule, provided some observed examples (Goodman, Griffiths, Feldman, and Tenenbaum). Rule-based theories of concept learning are focused more on perceptual learning and less on definition learning. Rules can be used in learning when the stimuli are confusable as opposed to simple. When rules are used in learning, the decisions are made based on properties alone and rely on simple criteria that do require a lot of memory (Rouder and Ratcliff, 2006).

Example of Rule based theory:

“A radiologist using rule-based categorization would observe whether specific properties of the X-ray meet certain criteria; for example, is there an extreme difference in brightness in a suspicious region relative to the other regions? A decision is then based on this property alone” (Rouder and Ratcliff 2006)
The prototype view on concept learning holds that people abstract out the central tendency (or prototype) of the experienced examples, and use this as a basis for their categorization decisions.

Prototype theory:

The prototype view on concept learning holds that people categorize based on one or more central examples of a given category followed by a penumbra of decreasingly typical examples. This implies that people do not categorize based on a list of things that all correspond to a definition; rather, a hierarchical inventory based on semantic similarity to the central example(s).

To illustrate this, imagine the following mental representations of the category: Sports

The first illustration may demonstrate a mental representation if we were to categorize by definition:

Definition of Sports: an athletic activity requiring skill or physical prowess and often of a competitive nature.

The second illustration may demonstrate a mental representation that Prototype Theory would predict:

1. Baseball
2. Football
3. Basketball
4. Soccer
5. Hockey
6. Tennis
7. Golf
...
15. Bike-racing
16. Weightlifting
17. Skateboarding
18. Snowboarding
19. Boxing
20. Wrestling
...
32. Fishing
33. Hunting
34. Hiking
35. sky-diving
36. bunji-jumping
...
62. cooking
63. walking
As you can see the Prototype theory hypothesizes a more continuous (less discrete) way of categorization in which we don’t limit the list to things that match the category’s definition.

**Exemplar Theories of Concept Learning**

Exemplar theory is the storage of specific instances (exemplars), with new objects evaluated only with respect to how closely they resemble specific known members (and nonmembers) of the category. This theory hypothesizes that learners store examples verbatim. This theory views concept learning as highly simplistic. Only individual properties are represented. These individual properties are not abstract and they do not create rules. An example of what Exemplar theory would look at is, “water is wet;” it simply knows that some (or one, or all) stored examples of water have the property wet. Exemplar based theories have become more empirically popular over the years with some evidence suggesting that human learners use exemplar based strategies only in early learning, forming prototypes and generalizations later in life. An important result of exemplar models in psychological literature has been a de-emphasis of complexity in concept learning. Some of the best known exemplar theory of concept learning are the Generalized Context Model (GCM), Nosofsky’s (1986) generalization of Medin ans Schaffer’s (1978) Context Model. A connectionist version of the GCM, called ALCOVE, has been developed by Kruschke (1992). The ALCOVE model addresses trial-by-trial concept learning. On each training trial, ALCOVE is presented with a stimulus, makes a prediction of the distribution of category choices, is presented with the correct classification, and then adjusts its associative weights and dimensional attention strengths. All of these models are matching models that exemplar sets for a category contains all of the category’s exemplars.

**Problems with Exemplar Theory**

Exemplar models critically depend on two measures:

1. Similarity between exemplars
2. Rule to determine Group Membership

Sometimes it is difficult to attain or distinguish these measures.

**Multiple-Prototype Theories of Concept Learning**

More recently, cognitive psychologists have begun to explore the idea that the prototype and exemplar models form two extremes. It has been suggested that people are able to form a multiple prototype representation, besides the two extreme representations. For example, consider the category spoon. There are two distinct subgroups or conceptual clusters: spoons tend to be either large and wooden or small and made of steel. The prototypical spoon would then be a medium-size object made of a mixture of steel and wood, which is clearly an unrealistic proposal. A more natural representation of the category spoon would instead consist of multiple (at least two) prototypes, one for each cluster. A number of different proposals have been made in this regard (Anderson, 1991; Griffiths, Canini, Sanborn & Navarro, 2007; Love, Medin & Gureckis, 2004; Vanpaemel & Storms, 2008). These models can be regarded as providing a compromise between exemplar and prototype models.
EXPLANATION-BASED THEORIES OF CONCEPT LEARNING

The basic idea of explanation-based learning suggests that a new concept is acquired by experiencing examples of it and forming a basic outline. Put simply, by observing or receiving the qualities of a thing the mind forms a concept which possesses and is identified by those qualities.

The original theory proposed by Mitchell, Keller, and Kedar-Cabelli in 1986, called explanation-based generalization, is that learning occurs through progressive generalizing. This theory was first developed to program machines to learn. When applied to human cognition, it translates as such - the mind actively separates information that applies to more than one thing and enters it into a broader description of a category of things. This is done by identifying sufficient conditions for a thing fitting a category, similar to schematizing.

The revised model revolves around the integration of four mental processes – generalization, chunking, operationalization, and analogy.

- Generalization is the process by which the characteristics of a concept which are fundamental to it are recognized and labeled. For example, birds have feathers and wings. Any thing with feathers and wings will be identified as ‘bird’.
- When information is grouped mentally, whether by similarity or relatedness, the group is called a chunk. Chunks can vary in size from a single item with parts or many items with many parts.
- A concept is operationalized when the mind is able to actively recognize examples of it by characteristics and label it appropriately.
- Analogy is the recognition of similarities between potential examples.

This particular theory of concept learning is relatively new and more research is now being conducted to test it.

BAYESIAN THEORIES OF CONCEPT LEARNING

Bayesian theories are those which directly apply normative probability theory to achieve optimal learning. They generally base their categorization of data on the posterior probability for each category, where for category i, this posterior is given by Bayes rule,

\[ P(C_i | D) = \frac{P(D | C_i) P(C_i)}{P(D)} \]

where \( P(D | C_i) \) is the probability of observing the given data on the assumption it was generated from category \( C_i \), \( P(C_i) \) is the prior probability of category \( C_i \), and \( P(D) \) is the marginal probability of observing the data, which usually does not enter into consideration. In general, the category possessing the maximum posterior \( P(C_i | D) \) would be the category selected for the given data.

Bayes’ theorem is important because it provides a powerful tool for understanding, manipulating and controlling data that takes a larger view that is not limited to data analysis alone. The approach is subjective and this requires the assessment of prior probabilities, making it also very complex. However, if Bayesian’s show that the accumulated evidence and the application of Bayes’s law are sufficient the work will overcome the subjectivity of the inputs involved. Bayesian inference can be used for any honestly collected data and has a major advantage because of its scientific focus.

One model that incorporates the Bayesian theory of concept learning is the ACT-R model, developed by John R. Anderson. The ACT-R model is a programming language that works to define the basic cognitive and perceptual operations that enable the human mind by producing a step-by-step simulation of human behavior. This theory works along with the idea that each task humans perform should consist of a series of discrete operations. The model has been applied to learning and memory, higher level cognition, natural language, perception and attention, human-computer interaction, education and computer generated forces.
In addition to John R. Anderson, Joshua Tenenbaum has been a contributor to the field of concept learning; studying the computational basis of human learning and inference using behavioral testing of adults, children, and machines from Bayesian statistics and probability theory, but also from geometry, graph theory, and linear algebra. Tenenbaum is working to achieve a better understanding of human learning in computational terms and trying to build computational systems that come closer to the capacities of human learners.

COMPONENT DISPLAY THEORY

M. D. Merrill’s Component Display Theory (CDT) is a cognitive matrix that focuses on the interaction between two dimensions: the level of performance expected from the learner and the types of content of the material to be learned. Merrill classifies learner’s level of performance as find, use, remember and material content as facts, concepts, procedures, and principles. The theory also calls upon four primary presentation forms, and several other secondary presentation forms. The primary presentation forms include: rules, examples, recall, and practice. Secondary presentation forms include: prerequisites, objectives, helps, mnemonics, and feedback. A complete lesson should include a combination of these primary and secondary presentation forms, but the most effective combination varies from learner to learner and also from concept to concept. Another significant aspect of the CDT model is that it allows for the learner to control the instructional strategies used and adapt them to meet his or her own learning style and preference. A major goal of this model was to reduce three common errors in concept formation: over-generalization, under-generalization and misconception.

Main principles of this theory are:

1. Having all three primary learner level of performance forms (find, use, and remember) present yields the most effective instruction.
2. Primary presentation forms can either be presented through an explanation learning strategy or through an investigation learning strategy.
3. As long as all of the primary presentation forms are present in the instruction, the order in which the primary presentation forms are presented does not matter.
4. Learners should have control over the number of instances or practice items that they receive.