Frames, Concepts, and Conceptual Fields

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In this chapter I propose that frames provide the fundamental representation of knowledge in human cognition. In the first section, I raise problems with the feature list representations often found in theories of knowledge, and I sketch the solutions that frames provide to them. In the second section, I examine the three fundamental components of frames: attribute-value sets, structural invariants, and constraints. Because frames also represent the attributes, values, structural invariants, and constraints within a frame, the mechanism that constructs frames builds them recursively. The frame theory I propose borrows heavily from previous frame theories, although its collection of representational components is somewhat unique. Furthermore, frame theorists generally assume that frames are rigid configurations of independent attributes, whereas I propose that frames are dynamic relational structures whose form is flexible and context dependent. In the third section, I illustrate how frames support a wide variety of representational tasks central to conceptual processing in natural and artificial intelligence. Frames can represent exemplars and propositions, prototypes and membership, subordinates and taxonomies. Frames can also represent conceptual combinations, event sequences, rules, and plans. In the fourth section, I show how frames define the extent of conceptual fields and how they provide a powerful productive mechanism for generating specific concepts within a field.

FEATURE LIST REPRESENTATIONS OF CATEGORIES

Before proceeding to a detailed discussion of frames, I first discuss their most obvious competitor—feature list representations. Later, we see that frames reme-
The fundamental problems of feature lists. Many theories across the cognitive sciences adopt feature list representations of categories. For example, work on natural categories and semantic memory in the 1970s typically employed feature list representations. Figure 1.1 contains examples of feature lists from the 1975 technical report that preceded Rosch, Mervis, Gray, Johnson, and Boyes-Braem's (1976) paper on basic level categories. As can be seen, each category representation is a list of features that subjects typically produce for the category, where a feature is any characteristic that category members possess. Rosch and Mervis (1975) similarly constructed feature list representations of categories, as did Ashcraft (1978), Glass and Holyoak (1975), and Hampton (1979). Many other researchers did not collect feature lists explicitly from subjects but nevertheless assumed feature lists in theoretical modeling. In the semantic memory literature, feature comparison models assumed that semantic decisions involve the comparison of feature lists, as in McCloskey and Glucksberg (1979), Meyer (1970), Smith, Shoben, and Rips (1974), and A. Tversky (1977) (see also Wyer & Srull, 1986, in the social cognition literature). Barsalou and Hale (in press) review the wide variety of forms that feature lists take in categorization models.

More recently, connectionist models have embedded feature lists in dynamic networks (e.g., McClelland & Rumelhart, 1986; Rumelhart & McClelland, 1986). Rather than being independent, features in a connectionist system become intercorrelated, with excitatory relations developing between features that typically cooccur, and inhibitory relations developing between features that do not. In Fig. 1.1, each feature would be related to every other feature in its list, with some relations being excitory and others being inhibitory. During categorization, input features activate correlated features and inhibit all others. As input features vary, they activate different feature subsets. Whereas traditional models represent a category with its entire feature list on every occasion, connectionist models represent a category dynamically with different feature subsets in different contexts.

![Fig. 1.1. Examples of feature lists for bird, apple, and socks from Rosch, Mervis, Gray, Johnson, and Boyes-Braem (1975). Copyright (1975) by the American Psychological Association. Reprinted by permission.](image)

In principle, numerous theories in psychology and linguistics assume that representations contain more than feature lists. In many cases, however, the additional structure—which tends to be frame-like—remains implicit theoretically and receives little attention empirically. As a result, these representations essentially reduce to feature lists. Consider work on artificial category learning in cognitive psychology. Typically, this work assumes the presence of frames in category representations. As described in much more detail shortly, a frame includes a cooccurring set of abstract attributes that adopt different values across exemplars. To see this, consider the category structures in Fig. 1.2, adapted from artificial categories in Medin and Schaffer (1978, p. 213). Notice that each exemplar in a category has one value on each of four attributes: color, form, size, and position. The frame in each category is this cooccurring set of abstract attributes, which take different values across category members. Work on artificial categories almost always uses frames in this manner to define category structures, as in the work of Estes (1986), Gluck and Bower (1988), Hayes-Roth and Hayes-Roth (1977), Hintzman (1986), Homa (1978), McClelland and Rumelhart (1985), and Nosofsky (1984).

Although frames typically structure artificial categories, they have played little role empirically or theoretically. Empirically, frames are irrelevant because every exemplar in every category has values on the same attributes. As can be seen from Fig. 1.2, Categories A and B are not distinguished by attributes but instead by values of these attributes. Consequently, the focus of work on artificial categories has been on how subjects learn patterns of values that predict category membership. Although subjects must be learning the frame as well—the fact that all exemplars have values on the same attributes—this form of learning has generally remained unaddressed. Moreover, attribute learning must be important in category learning, because attributes often differ across categories. For example, car has attributes for engine and transmission, whereas dog has attributes for fur and temperament. Rather than categorizing entities solely on the basis of specific values, people often categorize them on the basis of more abstract attributes.

Theoretically, the frames that researchers use to define artificial categories

![Fig. 1.2. The presence of frames in artificial categories. Adapted from Medin and Schaffer (1978, p. 213) by permission.](image)
have also received little attention. Theorists generally have nothing to say about
the psychological status of these frames. Nor have researchers specified whether
subjects view exemplar characteristics as attribute-value pairs or as a feature list.
Figure 1.3 illustrates this distinction. In the upper left, prototype representations
are essentially feature lists. Frames and the attribute-value sets that compose
them are not represented explicitly but are only implicit in the representation. In
contrast, the prototype representations in the upper right of Fig. 1.3 include an

![Diagram of frames and prototypes](image)

**FIG. 1.3.** Feature list and frame representations of prototypes (top) and of exemplars (bottom). Frames are enclosed in boxes.

The bottom half of Fig. 1.3 illustrates this distinction for exemplar representations. Because attributes are constant across
artificial categories, and because attribute learning has not been of interest, the distinction between attributes and values has not been salient or
explicit theoretically. As a result, representations in prototype and exemplar
models have essentially been reduced to feature lists, such as those on the left of
Fig. 1.3.

In exemplar models and multidimensional spaces that weight attributes
differentially, the distinction between attributes and values is more salient (e.g.,
Medin & Schaffer, 1978; Nosofsky, 1984; Shepard, 1974). However, these models
nevertheless fail to specify how subjects know that particular characteristics of
exemplars are values of one attribute and not another (e.g., how subjects know
that triangle is a shape). Because these models include no explicit representation
of attributes and their values, the ability to weight characteristics the same
amount because they are values of the same attribute remains unspecified. Such
an ability could rely on abstracted representations of attributes and their values;
or it could rely on an embedded level of exemplar processing for categorizing
characteristics as values of attribute categories.

Finally, work on componential analysis and semantic fields sometimes re-
duces semantic representations to feature lists. All of these theories assume that
entries within a semantic field have values on abstract, shared attributes (e.g.,
Grandy, 1987; Katz, 1972; Kittay, 1987; Lehrer, 1974; Lyons, 1977; Miller &
Johnson-Laird, 1976). However, semantic representations sometimes seem to
include only values of these attributes. For example, bachelor might be repre-
sented as adult, male, human, and unmarried, failing to specify the attributes of
age, sex, species, and marital status. Although these attributes are implicit, not
specifying them explicitly implies that semantic representations are feature lists.

### Evidence Against Feature Lists

The current psychological evidence against feature lists can be described alter-
natively as evidence for two structural properties of human knowledge: attribute-
value sets and relations.

**Evidence for Attribute-Value Sets.** Rather than coexisting at a single “flat”
level of analysis, the characteristics of exemplars typically form attribute-value
sets, with some characteristics (values) being instances of other characteristics
(attributes). For example, blue and green are values of color; swim and fly are
values of locomotion; six-cylinder and eight-cylinder are values of automobile
engine. Whereas features are independent representational components that con-
stitute a single level of analysis, attribute-value sets are interrelated sets of
representational components at two levels of analysis (at least). In this section, I
review several sources of evidence that people encode exemplar characteristics as values of more abstract attributes, rather than as independent features.¹

Extensive literatures offer compelling evidence that animals use attribute-value sets in discrimination learning (see Sutherland & Mackintosh, 1971, for a review). Consider intradimensional transfer. Animals receive stimuli that vary on two attributes and are conditioned to expect reward following a particular value on one of them. For example, animals might receive stimuli that vary in color (blue versus yellow) and shape (circle versus oval). In the process, they might learn that blue signals reward and that yellow does not, with shape being irrelevant. Once animals learn this first discrimination, they learn a second: The attributes remain the same, but their values are new. For example, the two attributes might still be color and shape, but their values might be red versus black and triangle versus square. When the second discrimination involves the same attribute as the first (intradimensional shift), learning is faster than when the discriminating attribute changes (extradimensional shift). For example, if color predicted reward for the first discrimination, learning is faster when the second discrimination involves color than when it involves shape. Even though all attribute values are new for the second discrimination, animals typically learn faster when the critical values are from the same attribute (but not always; Medin, 1975, 1976). Once animals learn that one attribute predicts reward, they continue attending to it, even when its values change. Such evidence suggests that animals encode the stimulus information as attribute values—rather than as independent features—and learn which attribute provides information about reward. Many other well-documented phenomena offer converging evidence, including reversal shift, overtraining or reversal shift, and transfer along a continuum. In addition, many such findings have been demonstrated with humans (e.g., T. S. Kendler & H. H. Kendler, 1970; Trabasso & Bower, 1968).

More recently, several new areas of work have further demonstrated the importance of attribute-value sets in human learning. Ross, Perkins, and Tenpenny (1990) found that an imaginary person with the characteristics, buys wood and likes sherbet, reminds subjects of another imaginary person with the characteristics, buys nails and likes ice cream. As a result, subjects place these two imaginary people in the same category and generalize that its members buy carpentry supplies and like dessert. These generalizations, in turn, function as frame attributes, such that later imaginary people belong to the category if their characteristics are values of these attributes. For example, someone who buys a chisel belongs to the category, whereas someone who buys sunglasses does not. Rather than representing the category with the simple features of exemplars, subjects represent it with more abstract attributes that take these characteristics as values. Thordnyke and Hayes-Roth (1979) reported a similar result (also see Watkins & Kerkar, 1985).

¹My use of “attribute” is essentially equivalent to other theorists’ use of “dimension,” “variable,” and “slot.” I assume that all of these terms are at least roughly synonymous.

Wisniewski and Medin (1991) reported evidence for attribute-value sets in categories of children’s drawings. Rather than representing these categories with features from visual images (e.g., concrete lines, shapes, squiggles), subjects instead represented them with abstract attributes. For example, subjects represent the category, drawings by creative children, with the attributes, detailed and unusual. When a drawing’s visual characteristics provide evidence for these abstract attributes, it belongs in the category.

Finally, much work on story understanding shows that people use abstract attributes to code the specific components of stories (Stein, 1982; Stein & Trabasso, 1982). For example, people assign story components to attributes such as setting, goal, protagonist, obstacle, plan, and outcome. When a story presents values of these attributes in coherent patterns, understanding and recollection proceed smoothly. When values of these attributes are missing, not easily recognized, or organized incoherently, story processing is difficult and nonoptimal.

Evidence for Relations. Contrary to feature lists, people do not store representational components independently of one another. Instead, people have extensive knowledge about relations between them. For example, Malt and Smith (1984) found that people’s knowledge of bird contains a correlation between sing as a value of sound and small as a value of size. Medin, Altom, Edelson, and Freko (1982) found that people learn correlations of symptoms that define disease categories (e.g., the cooccurrence of discolored gums and nosebleeds defines burillosis). L. J. Chapman and J. P. Chapman (1969) and Murphy and Wisniewski (1989) showed that people readily learn relations that are consistent with background beliefs and intuitive theories. Billman and Heit (1988) demonstrated that learning a relation proceeds more rapidly when it is embedded in a system of relations than when it occurs in isolation. Gentner (1989) reviewed the importance of relations in constructing analogies. Medin, Goldstone, and Gentner (1990) and Goldstone, Medin, and Gentner (1991) demonstrated the importance of relations in similarity judgments. Finally, people do not encode the events within a story independently of one another but integrate them with causal relations (Trabasso & Sperry, 1985; Trabasso & van den Broek, 1985; Trabasso, van den Broek, & Suh, 1989).

Some of the aforementioned work assumes that relations are simply correlations between representational components. Connectionist models similarly view relations as various forms of correlation. However, people clearly represent many relations conceptually. Although robin and feather are both highly correlated with bird, people know that a robin is a bird and that a feather is part of a bird—people would never claim that a feather is a bird or that a robin is part of a bird. Fodor and Pylyshyn (1988) provided detailed and convincing arguments that relations between representational components are often conceptual and not just correlational.

Because connectionist nets typically do not represent conceptual relations, they have difficulty representing attribute-value sets, which require conceptual
relations between attributes and values (e.g., circle is a type of shape, not a part of one). Rumelhart, Smolensky, McClelland, and Hinton (1986, p. 33) claim the opposite, proposing that attribute-value sets occur in a connectionist net when inhibitory relations exist between mutually exclusive features. For example, Rumelhart et al. argue that inhibitory relations between small, medium, and large in their “schema” for room produce an attribute for room size. Because a value for one attribute can have inhibitory relations with values of different attributes, however, inhibitory relations are not sufficient for defining attribute-value sets. Although an inhibitory relation exists between shower for room fixtures and piano for room furniture, shower and piano are not values of a common attribute. Nor are inhibitory relations necessary for attribute-value sets, because the values of many attributes are not mutually exclusive (e.g., color is simultaneously brown and red for robin). As a result, Rumelhart et al.’s schemata are simply dynamic feature lists. Features may suppress one another across contexts, but this only represents cooccurrence relations—not conceptually related attribute-value sets. Moreover, the notion of competing “values” provides no account of the more general attributes that integrate these values (but see Rumelhart et al., 1986, p. 25, for the hint of an intriguing possibility).

Frames

Because frames contain attribute-value sets and relations, they provide natural solutions to the problems of feature lists. The construct of frames is hardly new in the cognitive sciences. In classic work, Fillmore suggested that frames underlie people’s syntactic knowledge of verbs (Fillmore, 1968; more recently, Fillmore, this volume; Jackendoff, 1987; Wilkins, 1988). The frame for buy specifies that an active sentence containing “buy” must include an agent and a theme and may optionally have a source and an instrument, as in:

The artist (agent) buys paint (theme) at the art store (source) with a credit card (instrument).

Fillmore’s account of frames focused primarily on the syntactic structure of verbs, although he frequently stressed the importance of underlying conceptual structure (e.g., Fillmore, 1977, 1984, 1985). Complementary to Fillmore’s work, Norman and Rumelhart (1975) developed explicit accounts of the conceptual structures that underlie syntactic frames. Schank (1975, 1982) and Schank and Abelson (1977) developed the conceptual approach further. Minsky (1977) developed an account of frames relevant to vision, which, too, has received wide application. Bobrow and Winograd (1977), Lenat and Guha (1989), and Minsky (1985) provided additional accounts of frames. The technical definition of frame in artificial intelligence has evolved to mean something like a fixed set of named slots whose values vary across applications (e.g., Charniak & McDermott, 1985). Hayes (1979) argued that frames bear many deep resemblances to first-order predicate calculus.

In cognitive psychology, frames have received much attention in research on the essentially identical construct of schema (Bartlett, 1932). Theorists who have attempted to articulate the structure of schemata have generally identified the same structural properties proposed for frames (e.g., Cohen & Murphy, 1984; Rumelhart & Ortony, 1978). However, much undesirable baggage has become associated with “schema.” Psychologists frequently demonstrate the ubiquity of schemata in human knowledge (for reviews, see Alba & Hasher, 1983; Brewer & Nakamura, 1984). Yet, their studies rarely attempt to provide evidence for the structural characteristics of schemata proposed in more theoretical analyses (e.g., attribute-value sets, relations). As a result, “schema” is often criticized as being vague and unspecified. Moreover, “schema” has come to mean many different things to many different people. Most problematic is the frequent use of “schema” to mean a feature list prototype (e.g., as illustrated in the upper left of Figure 1.3). Researchers sometimes assume that a schema is simply those features most common across a category’s exemplars (e.g., Cohen, 1981; Markus, Smith, & Moreland, 1985; Posner & Keele, 1968). Because of these problems, I use “frame” to highlight the well-specified, structural properties common to formal analyses of frames and schemata.²


COMPONENTS OF FRAMES

I next examine three basic components of frames: attribute-value sets, structural invariants, and constraints. I assume that frames represent all types of categories, including categories for animates, objects, locations, physical events, mental events, and so forth. As we shall see, the representation of adjectives, adverbs, and quantifiers is feasible within the context of frames as well. In all cases, my examples of frames greatly underestimate their actual complexity. Although these simplified examples keep presentation tractable, it is important to remember that constructing a complete conceptual frame for a single category is a

²Some psychologists have provided evidence for structural properties of schemata. Examples include careful analyses of story schemata (Stein, 1982; Stein & Trabasso, 1982; Trabasso & Sperry, 1985; Trabasso & van den Broek, 1985; Trabasso et al., 1989) and careful analyses of verb frames (Tanenhaus & Carlson, 1989; Tanenhaus, Carlson, & Trueswell, 1989).
challenging and sobering experience. For examples of how complex frames can become, see Lenat and Guha (1989).

Attributes and Values

A cooccurring set of attributes constitutes the core of a frame. Consider the partial frame for car in Fig. 1.4, whose attributes include driver, fuel, engine, transmission, and wheels. Again, note that this frame is simplified considerably to facilitate presentation, with many attributes being absent (e.g., color, seats). As a frame represents different exemplars, its attributes adopt different values. When the frame for car is applied to one particular car, its attributes might adopt values of Liz for driver, gasoline for fuel, four-cylinder for engine, standard for transmission, and alloy for wheels. When applied to another car, the same attributes might adopt different values.

A fundamental task for frame theorists is to provide satisfactory definitions for attribute and value. I define an attribute as a concept that describes an aspect of at least some category members. For example, color describes an aspect of birds, and location describes an aspect of vacations. A concept is only an attribute when it describes an aspect of a larger whole. When people consider color in isolation (e.g., thinking about their favorite color), it is not an attribute but is simply a concept. Similarly, when people think about location in isolation (e.g., in geography), it is not an attribute. A concept is only an attribute when viewed as describing some aspect of a category's members. Color becomes an attribute when viewed as an aspect of bird, and location becomes an attribute when viewed as an aspect of vacation. In this regard, the definition of attribute is extrinsic, depending on a concept's aspectual relation to a category.

By concept I mean the descriptive information that people represent cognitively for a category, including definitional information, prototypical information, functionally important information, and probably other types of information as well. In this regard, my use of concept vaguely resembles intension and sense. In general, I assume that frames represent all types of concepts, whether they are free-standing concepts, such as bird and vacation, or whether they are attributes, such as color for bird and location for vacation. Later sections address frames for attributes in greater detail.³

What aspects of a category can be attributes? Clearly, this depends significantly on a category's ontological domain (Keil, 1979, 1981). For physical objects, attributes are likely to include color, shape, and weight; whereas for events, attributes are likely to include location, time, and goal. Attributes are often parts of category members. As discussed by Chaffin (this volume) and Winston, Chaffin, and Herrmann (1987), part is a highly polysemous relation. According to their analysis, part can refer to a physical part of an object (leg–chair), the material of an object (metal–ring), a member of a collection (flower–bouquet), an action in an activity (pitch–baseball), an object in an activity (food–eat), a location in an activity (destination–drive), and so forth. However, I assume that attributes can represent many other aspects of category members beside their parts. For example, attributes include evaluations (enjoyment–music), quantities (cardinality–family), costs (sacrifice–career), benefits (skills–education), and so forth. As I argue later, people are highly creative in their construction of attributes, often producing new ones relevant to specific contexts.

The definition of value follows from the definition of attribute: Values are subordinate concepts of an attribute. Because values are subordinate concepts, they inherit information from their respective attribute concepts. In the frame for car, values of engine (e.g., four-cylinder) inherit properties of engine (e.g., consumes fuel, produces force). Values further inherit the extrinsic fact that they are an aspect of category members. Because engine is an aspect of car, its values are aspects of car as well. Values contain additional information not in their respective attributes, thereby making them more specific concepts. Four-cylinder and six-cylinder contain information that makes them more specific than engine and that differentiates them from each other.

³In previous papers, I have proposed that concepts are temporary representations of categories in working memory (Barsalou, 1987, 1989). Because the emphasis in the current chapter is on the structure of knowledge in long-term memory, I use concept more generally to mean any descriptive information about a category or attribute, either in long-term memory or working memory. I remain committed to the view that people use relatively stable knowledge in long-term memory to construct temporary representations in working memory, with these temporary representations exhibiting extensive flexibility and context sensitivity. I present numerous examples of how frames produce flexibility in later sections.

FIG. 1.4. A partial frame for car that illustrates attribute-value sets and relations in frames.
Attribute Taxonomies. Because values are concepts, they in turn can be attributes having still more specific values. For example, the frame for animal might include an attribute for means of locomotion, whose values include legs, wings, and fins. In turn, the frame for land mammal might include an attribute for legs, whose values include human legs, horse legs, and dog legs. Whereas legs is a value in the frame for animal, it is an attribute in the frame for land mammal. As Fig. 1.5 illustrates, the increasing specificity of values may produce an attribute taxonomy having many levels. For example, human legs can be an attribute whose values include female human legs and male human legs.

Attribute taxonomies exhibit many of the same properties as object taxonomies (e.g., animals, fruit, clothing). Like object taxonomies, attribute taxonomies exhibit typicality. For example, people may egocentrically perceive legs to be more typical of means of locomotion than fins or wings. Like object taxonomies, attribute taxonomies exhibit a basic level (B. Tversky & Hemenway, 1985). Legs, wings, and fins constitute the basic level for locomotion, because each is monomorphic, constitutes a large information gain, shares a common shape, and exhibits a common action. Like object taxonomies, attribute taxonomies depend on nested sets of properties. Legs inherit the properties of locomotion but include additional properties that distinguish them from wings and fins.

These analogies between attribute and object taxonomies are perhaps surprising. On the one hand, attributes constitute the building blocks of object taxonomies. On the other hand, attributes form taxonomies just like those for object taxonomies. Attributes mirror the taxonomic structure they produce. The extent to which people represent attribute taxonomies explicitly is an open question. If people regularly process taxonomic relations between attributes and values across multiple levels, they may establish attribute taxonomies in memory. However, if people generally process attributes and values more locally, they may fail to integrate them into taxonomies. Although Barsalou and Ross (1986) provide evidence for this more local view, their Experiment 4 illustrates that people can compute new relations in attribute taxonomies. On the other hand, Hampton's (1982) demonstrations of intransitivity in object taxonomies suggest that people may sometimes fail to integrate distant levels in attribute taxonomies.

Attribute Frames. Not only do attributes mirror the taxonomies to which they contribute, they also mirror the frames that contain them. Within a frame, each attribute may be associated with its own frame of more specific attributes. In Fig. 1.6, consider the frame for companion embedded in the frame for vacation (Barsalou, 1991). Rather than being a simple unidimensional attribute, companion is an embedded frame containing a more specific set of attributes, such as age, relation, free time, and preferred activities (in this and all later figures, dotted boxes, such as those around vacation and companion, enclose frames). Similarly in our recent work on real estate planning, the frame for house has an attribute for location, which in turn is a frame whose attributes include convenience, utilities, zoning, and security. These secondary attributes often have frames as well. For example, convenience is a frame whose attributes include proximity to employment, proximity to entertainment, proximity to educational facilities, and proximity to shopping. Even these attributes continue to have frames. For example, proximity to employment is a frame whose attributes might include driving duration, which in turn is a frame whose attributes might include traffic conditions. Later figures provide many further examples of frames for attributes.

Attribute Construction. People frequently create new attributes to achieve goals, much like they create ad hoc categories to achieve goals (Barsalou, 1991). Consider the frame for the companion attribute of the vacation frame in Fig. 1.6. One attribute of companion that subjects often mention is free time, because companions must be free at the same time to take a shared vacation. If we asked people to describe characteristics of companion in a neutral context, they might

![FIG. 1.5. Example of an attribute taxonomy for means of locomotion.](image)

![FIG. 1.6. Example of an attribute frame for companion embedded in a frame for vacation.](image)
never produce this attribute. When people consider companion in the context of vacation, however, they consider free time to coordinate the schedules of possible companions. Similarly, consider the frame for the time attribute of the vacation frame. Planners frequently consider the attribute amount of work disruption for each possible vacation time, preferring times that produce minimal disruption. If we asked subjects to produce attributes of time in isolation, they would probably never produce amount of work disruption. Instead, people produce this attribute because of its relevance to time in the context of vacation.

Do people construct these specialized attributes or retrieve them from memory? When new aspects of exemplars become relevant in novel contexts, people may construct new attributes to represent them. The extensiveness of highly idiosyncratic attributes in our planning data suggests that people readily construct new attributes as they need them. As a side effect of the construction process, however, these attributes are likely to become stored in memory, such that they can be retrieved later in similar contexts.

Clearly, an infinite number of attributes could be constructed for a category (Goodman, 1955). In this regard, the human conceptual system is highly productive, although no person constructs all or even many of these potential attributes. Experience, goals, and intuitive theories play important roles in constraining attribute construction. If people experience different exemplars of a category, they may represent different attributes for it. For example, if cars have smog devices in one country but not in another, only citizens of the former country may typically represent smog device as an attribute of car. If people have different goals while interacting with exemplars, they may represent different attributes for them. For example, a wine connoisseur may represent wood used for aging as an attribute of wine, whereas someone who counsels alcoholics may not. If people have different intuitive theories about a category, they may represent different attributes for it. For example, people who know scientific theories of biology may represent genes as an attribute of animal, whereas people who do not know these theories may not.

Once particular attributes become represented for a category, they determine relevance. If two people represent a category with different attributes, they encode its exemplars differently. Different aspects of the exemplar are relevant, because the perceivers’ respective frames orient perception to different information.

**Attribute Systematicity.** Frames often contain core attributes that cooccur frequently, what Barsalou and Billman (1989) call attribute systematicity. Whenever a frame applies, its core attributes are all usually relevant and considered in the current context. Consider core attributes in the frame for buy: buyer, seller, merchandise, and payment. When an instance of buying occurs, values for these attributes are usually known. If some are not known, perceivers often infer default values, thereby considering all attributes regularly across exemplars.

Because psychological cooccurrence produces associative strength, these attributes become integrated in memory to form an established structure, namely, the core of a frame.

Attribute systematicity is not all-or-none but varies continuously as attributes cooccur to different extents. Consider a country in which smog devices occur only in some cars. Because smog device does not cooccur with engine and wheels as highly as they cooccur with each other, it exhibits less attribute systematicity than they. Similarly, loan source exhibits low systematicity for buy, because not all exemplars have values for this attribute. Because the attributes associated with a frame vary in systematicity, frames are not rigid structures. Although many frame theorists assume that a frame entails the presence of its attributes (e.g., Hayes, 1979), I assume that the presence of attributes is probabilistic. Across contexts, different subsets of attributes are active in a frame, depending on the specific exemplar and the surrounding context (cf. Murphy, 1990, Experiments 3 and 4). Nevertheless, core sets of attributes may be active for most if not all exemplars.

Why do some attributes and not others constitute a frame’s core? Certain attributes may have a value for every exemplar, such that encoding these values causes their attributes to be processed together frequently, thereby forming an experiential core. However, some attributes may be necessary conceptually, such that it is impossible to understand the concept without considering them, even when values are absent. For example, buy cannot be understood fully without considering buyer, seller, merchandise, and payment. Both frequency of occurrence and conceptual necessity probably contribute to the cores of frames.

**Structural Invariants**

Attributes in a frame are not independent slots but are often related correlationally and conceptually. As we saw in the previous section, a frame’s core attributes correlate highly, often appearing together across contexts. As a result, correlational relations develop between them, somewhat like those in connectionist nets. However, the relations between frame attributes generally reflect more than cooccurrence, reflecting conceptual information as well (Barsalou & Billman, 1989, pp. 158–159). Consider the car frame in Fig. 1.4. The operates relation between driver and engine reflects people’s conceptual understanding that the driver controls the engine’s speed. Similarly, the rotates relation between engine and transmission represents the knowledge that the engine spins components of the transmission. Because such relations generally hold across most exemplars of a concept, providing relatively invariant structure between attributes, I refer to them as structural invariants.

Structural invariants capture a wide variety of relational concepts, including spatial relations (e.g., between seat and back in the frame for chair), temporal relations (e.g., between eating and paying in the frame for dining out), causal
relations (e.g., between fertilization and birth in the frame for reproduction), and intentional relations (e.g., between motive and attack in the frame for murder). Miller and Johnson-Laird (1976) review the tremendous amount of work that has addressed these relations and others.

Most theorists view the relations that underlie structural invariants as primitives. However, Chaffin and his colleagues argue convincingly that these relations are not primitives but instead decompose into more specific attributes (Chaffin, this volume; Winston, Chaffin, & Herrmann, 1987; also see Cruse, this volume). On Chaffin's analysis, the part relation, which integrates a wide variety of attributes in frames, decomposes into attributes for functionality, separability, homeomerony, and spatio-temporal extent. Functionality reflects whether a part's function in the whole determines its location. Separability reflects whether a part can be separated from the whole. Homeomerony reflects whether all parts are the same kind of thing as the whole. Spatio-temporal extent reflects whether the position of a part in space or time is more salient. Consider:

A roof is part of a house.

Functionality has the value of restricted, because the roof's function determines its location in a house; separability has the value of separable, because the roof can be removed from the house; homeomerony has the value of non-homeomeronomous, because the entire house is not made of roofing material; spatio-temporal extent has the value of spatial, because the roof's spatial position in a house is salient. In contrast, consider:

Wood is part of a baseball bat.

Contrary to the previous example, functionality has the value of unrestricted, separability has the value of inseparable, and homeomerony has the value of homeomeronomous. Although it is unlikely that people label these attributes with terms such as homeomerony, Chaffin's findings suggest the human conceptual system distinguishes and represents them in some manner.

Clearly, this analysis assumes that a frame represents the part relation, where the frame's attributes are functionality, separability, homeomerony, and spatio-temporal extent. Different instances of the part relation take different values on these attributes, depending on the part and the whole. Once again we see recursion in frames representing frames. Just as frames represent the attributes of a frame, so too do they represent its structural invariants.

For the sake of simplifying presentation, I gloss over differences between various forms of part (and other relations) from here on. Also, to simplify presentation in all later figures, I omit structural invariants between attributes, such as operates and rotates in Fig. 1.4. Instead, I generally use aspect and type to integrate frame components in a simpler manner. If more complete representa-

tions were constructed for these frames, better articulated relations between attributes would be required, as would subtle distinctions among them.

Constraints

The structural invariants described in the previous section represent relatively constant relations between a frame's attributes. In Fig. 1.4, the relation of flows between fuel and engine is generally true of cars, as is the relation of rotates between engine and transmission. Such relations capture normative truths about relations between attributes.

Constraints, too, are relations but of a different type. Rather than being normative, constraints produce systematic variability in attribute values. The central assumption underlying constraints is that values of frame attributes are not independent of one another. Instead, values constrain each other in powerful and complex manners. In the following sections, I describe various types of constraints, including attribute constraints, value constraints, contextual constraints, and optimizations. Figure 1.7 illustrates examples of constraints in a partial frame for vacation (Barsalou, 1991). Note again that structural invariants between attributes are omitted for simplicity of presentation (e.g., occurs between activity and location).

Attribute Constraints. Attribute constraints are rules that constrain attribute values globally. The transportation frame of Fig. 1.7 contains a negative attribute constraint (−) between speed and duration:

As a form of transportation becomes faster, its duration becomes shorter (over a constant distance).

Figure 1.7 also includes positive attribute constraints (+):

As a form of transportation becomes faster, its cost becomes higher.
As a location's distance from home increases, transportation becomes faster.

Note that these attribute constraints need neither be logical nor empirical truths. Although some are (e.g., the inverse relations between speed and duration), others are not (e.g., the requirement that long distances from home covary with fast transportation). Instead, attribute constraints often represent statistical patterns or personal preferences, which may be contradicted on occasion. For a change of pace, someone may want to travel slowly over a long distance to see beautiful scenery.

Value Constraints. Whereas attribute constraints are general rules that constrain attribute values globally, value constraints are specific rules that relate
particular sets of values locally. Consider the 

enables relation between San Diego and 
surfing in Fig. 1.7. This relation specifies that a particular value of the 

direction attribute constrains a particular value of the activity attribute. Another 

value constraint similarly relates Rockies and snow skiing. The requires relations 

between snow ski and mountains and between surfing and ocean beach illustrate 

somewhat more complex value constraints that cross levels within the frame 

representation. Similar to attribute constraints, value constraints may often represent statistical patterns and personal preferences, rather than necessary truths.

Contextual Constraints. A distinction between contextual constraints and 
optimizations is orthogonal to the distinction between attribute constraints and 
value constraints. Contextual constraints occur when one aspect of a situation constrains another, such as physical constraints in nature. For example, speed of 

transportation constrains its duration over a fixed distance. Similarly, the activity of 
surfing requires an ocean beach. Contextual constraints also reflect cultural 
conventions. For example, people’s income and the taxes they pay may bear a relationship to one another. Similarly, swimming as an activity may require a 

swimsuit as clothing. In general, the various aspects of a particular situation are 

not independent of one another. Instead, physical and cultural mechanisms place 

constraints on combinations of compatible attribute values. As the preceding 

examples illustrate, contextual constraints can either be attribute constraints or 
value constraints.

Optimizations. Whereas contextual constraints reflect physical and cultural 
mechanisms, optimizations are constraints that reflect an agent’s goals. Consider 

how the agent’s goals in Fig. 1.7 constrain the values of various attributes. The 

agent’s goal of good exercise constrains the value of exertion in the activity frame 
to be high. Similarly, the agent’s goals of short travel and low cost constrain the 
duration and cost variables in the transportation frame to be short and low, 
respectively. Although all of the optimizations shown in Fig. 1.7 are value 
constraints, optimizations can also be attribute constraints. For example, the 
value of an agent’s desire to achieve a goal generally constrains the value of the 
agent’s effort in pursuing it.

Whereas contextual constraints typically require that values satisfy them, 
optimizations typically require that one value excel beyond all others. For example, 
just about any kind of swimsuit will satisfy the contextual constraint that 
clothing be worn while swimming. In contrast, the cheapest form of transportation optimizes the goal of inexpensive travel. Whereas people generally select 
values that satisfy contextual constraints, they generally seek values that excel when optimizing goals.

People often attempt to optimize multiple goals simultaneously for an attribute. For transportation, someone might optimize cost, speed, and comfort simultaneously—not just cost alone. As a result, the optimal value may not be
optimal for any one goal in isolation. The optimal form of transportation may not be the cheapest, because a slightly more expensive form optimizes cost, speed, and comfort together.

*Propagating Constraints Through Frames.* Constraints often propagate themselves through frame systems in complex manners. To see this, consider how low cost propagates constraints in Fig. 1.7. To optimize cost, the agent first propagates low cost as a goal to low cost for transportation. Next, through the attribute constraint that relates cost and speed, low as the value of cost selects slow as the value of speed. In turn, the attribute constraint between speed and distance from home selects close as the value of distance. Once close has been selected, it constrains the instance of location to be San Diego, because a satisfactory instance of location must match values established in the location frame. Once San Diego has been selected, a value constraint selects surfing as the instantiation of activity. What began as an attempt to optimize the goal of low cost propagated constraints through the frame system to select surfing. Such reasoning appears to occur ubiquitously in human cognition (Barsalou, 1991). Although the preceding description of constraint propagation had a serial flavor, much constraint propagation may occur in parallel.

*Constraint Frames.* In previous sections, we saw that frames represent attributes and structural invariants. Frames, too, represent constraints. Consider the constraint:

**Swimming requires swimsuits.**

The requires relation in this constraint is actually a frame containing attributes such as likelihood, source, conditions, and so forth. Likelihood states the intuitive probability that the constraint applies. For the swimsuit requirement, the likelihood that it applies may be high, at least in some cultures. Source states the origin of the constraint. For the swimsuit requirement, the source is usually a government or its agents. Conditions specifies conditions under which the requirement holds. For the swimsuit requirement, conditions might be all contexts except for privately owned swimming areas and nude beaches.

**Representational Primitives**

Human conceptual knowledge appears to be frames all the way down. Frames are composed of attributes, structural invariants, and constraints, which in turn are represented by frames themselves. Such recursion and "self-similarity" bear an intriguing resemblance to the fractal structures found across a wide variety of physical systems (Gleik, 1987).

Does the representation of frames at some terminal level of analysis ever become grounded in perceptual, motor, and conceptual primitives as theorists often assume (cf. Miller & Johnson-Laird, 1976)? Are there terminal components out of which all frames are constructed? I suspect not, because of the following general principle: For any attribute, structural invariant, or constraint, people can always construct further attributes, structural invariants, and constraints that capture variability across instances. Although an attribute, relation, or constraint may start out as a holistic, unanalyzed primitive, aspects of its variability may subsequently be noted, represented with attribute-value sets, and integrated by structural invariants between attributes, and constraints between values. What was once a simple, unitary primitive becomes analyzed and elaborated, such that it becomes a complex concept.

To see this, consider a possible representational primitive red, which occurs across an enormous set of instances. Various animals, fruits, and artifacts are red, at least to some extent. People could represent red as a primitive in each of the concepts that represent these entities. Alternatively, people could isolate aspects of red through analysis and elaborate these aspects with attribute-value sets. For example, intensity could be identified as an aspect of red and be elaborated with a description of its values across known instances. Similarly, the shape of a red area, its location, and its time of occurrence could each be represented as attribute-value sets. As a result, red is no longer a holistic, unanalyzed, representational primitive but instead becomes a complex frame, taking different values across categories. In robin, for example, the frame could specify that intensity is low, shape is oval, location is breast, and time is at maturity. Or for stop sign, the frame could specify that intensity is high, shape is hexagonal, location is front, and time is permanent. As a result, no simple primitive represents red for all red things (cf. Halff, Ortony, & Anderson, 1976; Wierzbicka, this volume).

One can view Chaiken's analysis as demonstrating a similar point for structural invariants. Part could be viewed as a primitive relation that takes the same form across uses, but as we saw earlier, such relations appear considerably more complex, being represented by a frame whose attributes include functionality, separability, homeomorphy, and spatio-temporal extent. Whereas these attributes take one set of values for a roof as part of a house, they take another set for wood as part of a bat. Because constraints are also relations, a similar argument applies to them. For both structural invariants and constraints, frames develop to represent the variability across their respective instances.

For any representational component—whether it be an attribute, structural invariant, constraint, or something else—people can always note a new source of variability across instances, and add further frame structure to capture it. Through the continuing process of analysis and elaboration, people transform what were once holistic, unanalyzed primitives into complex frames. As a result,
primitives that serve as simple, elementary building blocks no longer exist. Note that this is not an ontological claim about the structure of the physical world but instead a psychological conjecture about how people represent it.

If primitive building blocks do not exist psychologically, then what kinds of primitives might there be? Perhaps a primitive is a general, abstract, unanalyzed concept that typically appears initially at some point during early development. Through experience, it becomes analyzed and elaborated, acquiring the ability to spawn a wide diversity of more specific, complex concepts from which other concepts are built. These primitives might include ontological categories such as location, object, event, person, and mental state; semantic roles such as agent, instrument, and source; activities such as see, move, and get; qualities such as color, intensity, shape, and size; and relations such as is, part, in, before, cause, and intend. Wierzbicka (this volume) and Jackendoff (this volume) suggest a variety of other possible primitives.

Rather than being the elementary building blocks of knowledge, primitives may instead be larger wholes, the analysis of which produces an indefinitely large set of complex building blocks. Rather than lying at the representational “bottom,” these primitives may lie at the representational “top.” For example, location may begin as a primitive that simply means something like region. But with experience, it may be analyzed and elaborated to include attribute-value sets for terrain, climate, altitude, and so forth. As a result, the location frame acquires the ability to produce a wide variety of specialized location concepts. For example, the location frame might take mountains, cold, and high as values of terrain, climate, and elevation to produce a specialized location concept for snow skiing. Similarly, the location frame might take values of beach, warm, and low to produce a specialized location concept for body surfing. Once the location primitive becomes analyzed and elaborated with attribute-value sets, it develops the ability to produce a wide variety of more specialized location concepts that can be used to build new frames.

As the examples for snow skiing and body surfing illustrate, different values across a common set of attributes can represent different types of locations. But some locations differ so much that they may not even share attributes. Consider location in the frames for fire hydrant, star, and electron. Whereas street is an important attribute of location in the frame for fire hydrant, it is not an important attribute of location in the frames for star or electron. Instead, galaxy is an important attribute of location for star, and distance from the nucleus is an important attribute of location for electron. Because different entities often occur in very different spatial reference systems, the location frame must develop different attributes to capture the variability in each.

Perhaps the most difficult issue is: Which particular attributes, relations, and constraints become established in frames? This is indeed a deep and difficult issue upon which the success of this enterprise rests. Suffice it to say for now that perceptual salience, goal-relevance, intuitive theories, and memory entrench-

ment are all important (Barsalou, 1992). Just what the specifics of these factors might be continues to constitute one of the most significant challenges facing the study of knowledge (see Barsalou, in press, for further discussion).

Summary and Critique

At their core, frames contain attribute-value sets. Attributes are concepts that represent aspects of a category’s members, and values are subordinate concepts of attributes. Because values are concepts, they in turn can be attributes by having still more specific values. People appear to construct new attributes and values as new aspects of categories become apparent or relevant. Unlike previous theories, frames are not rigid configurations of independent attributes. Instead, attributes vary in systematicity, with the relevant attributes varying across contexts. Frames further contain a variety of relations. Structural invariants in a frame capture relations in the world that tend to be relatively constant between attributes. Conversely, constraints capture systematic patterns of variability between attribute values. Because frames represent attributes, structural invariants, and constraints themselves, the mechanism that constructs frames builds them recursively. Frames for what were once primitive concepts produce complex concepts that are used to build new, more specific concepts.

Absent from this account is a coherent view of frame processing. Before a computational system can build the frames described here, it needs a powerful processing environment capable of performing many difficult tasks. This processing environment must notice new aspects of a category to form new attributes. It must detect values of these attributes to form attribute-value sets. It must integrate cooccurring attributes into frames. It must update attribute-value sets with experience. It must detect structural invariants between attributes. It must detect and update constraints. It must build frames recursively for the components of existing frames.

Another significant challenge concerns the power of frames. Hayes (1979) argues that frames are an implementation of first-order predicate calculus (also see Charniak & McDermott, 1985). In addition, Hayes entertains the possibilities that frames extend into higher order logics and that nondeductive procedures operate on frames (actually, such procedures often exist in other theorists’ frame implementations). Given these properties, frames clearly have substantial expressive power, and it is difficult to see what constrains them.

One way to tackle this issue is to distinguish between the content and form of frames. Psychologically, the content of frames seems highly constrained in one regard and relatively unconstrained in another. Biologically, humans and other organisms have predispositions to perceive and represent certain attributes (cf. Jackendoff, this volume; Wierzbicka, this volume). In humans, there are clear biological bases for attributes such as color, pitch, location, and so forth. Similarly, some relations seem to have biological bases, including simple spatial
relations, temporal relations, and causal relations. These attributes and relations appear privileged in many ways, including ease of perception, presence in early development, and so forth. Consequently, one way to constrain a frame theory is to limit the initial attributes and relations in frames to some set of primitives and then assess whether all subsequent frames can be derived from them.

Although early frames in human development may be relatively constrained to biological attributes and relations, later frames in adult knowledge seem relatively unconstrained. At least as far as we can imagine, people seem capable of constructing frames for any content (cf. Fodor, 1983). Consequently, the fact that the content of frames is formally unconstrained seems quite compatible with the observation that people’s ability to conceptualize content seems relatively unconstrained. Perhaps surprisingly, the unconstrained content of frames is psychologically valid.

Regarding form, frames are constrained in important ways. According to my analysis, frames contain three basic components: attribute-value sets, structural invariants, and constraints. If this analysis is correct, then evidence for these components should be ubiquitous. Moreover, hypotheses about these components are falsifiable. We might find evidence for isolated features rather than for more structured, attribute-value sets. We might not observe structural invariants between attributes nor constraints between values. We might observe structural invariants and constraints to be correlational—as in connectionist models—rather than conceptual. Even if we obtain evidence for these three components, we might not observe them to be organized in the way I propose. Clearly, the properties of frames are distinct and testable. In addition, these properties can probably be constrained further. For example, the capacity of working memory might constrain the number of core attributes in a frame to around five. Similarly, capacity and performance limits in human cognition might limit the recursive depth of frames and the length of constraint chains. In principle, developing a constrained and falsifiable theory of frames appears quite feasible. What remains is to implement such a theory and acquire rigorous empirical evidence for its components.

REPRESENTING CONCEPTS WITH FRAMES

Frames support a wide variety of conceptual tasks that are fundamental for natural and artificial intelligence. In this section, I illustrate how frames can represent exemplars and propositions, prototypes and membership, subordinates and taxonomies. I also illustrate how frames can represent conceptual combinations, event sequences, rules, and plans.

Representing Exemplars and Propositions


Fig. 1.8, which shows a subset of the attributes that a person might represent for bird. Exemplars of bird, such as bird-1 and bird-2, are represented as cooccurring sets of attribute values. For example, bird-1 has values of small, brown, and straight for the attributes of size, color, and beak. As each new exemplar is encountered, its values are integrated into the frame, similar to bird-1 and bird-2. If exemplars have values for different attributes, they instantiate different subsets of attributes. For example, if the silhouette of a bird were perceived at dusk and color were imperceptible, values might be stored only for size and beak.

In most exemplar models, exemplars are stored independently of one another, not being stored together or associated in any way (as in the bottom left of Fig. 1.3). In contrast, frames provide a natural means of organizing exemplars. As Fig. 1.8 illustrates, exemplars that have values on the same attributes are integrated into the same frame, thereby being stored together. Because exemplars with values on other attributes would be stored elsewhere in memory, frames organize exemplars according to similarity. Exemplars with many shared attributes are stored closer to one another in memory than exemplars with few shared attributes. Integrating an exemplar into a frame does not necessarily lose exemplar information, because an exemplar’s values remain interconnected. Nevertheless, integrating exemplars into frames provides natural mechanisms for forgetting exemplar information. Cooccurrence relations between an exemplar’s values could become lost, leaving the values associated to attributes independent of any particular exemplar. Or values of an exemplar might become inaccessible from the frame’s attributes, thereby precluding retrieval of the exemplar.

One can view an exemplar in a frame system as an existential proposition: There exists an entity $x$ in category $C$ that has values $p$, $q$, and $r$ for attributes $P$, $Q$, and $R$ (cf. Hayes, 1979). More specifically:

$$\exists x \quad C(x) \land P(x,p) \land Q(x,q) \land R(x,r)$$

FIG. 1.8. Example of using a frame to represent exemplars of bird.
Applying this notation to *bird-1* in Fig. 1.10 produces:

\[ \exists x \text{ BIRD}(x) \land \text{COLOR}(x, \text{brown}) \land \text{SIZE}(x, \text{small}) \land \text{BEAK}(x, \text{straight}) \]

Following many philosophers, existential propositions could reflect purported claims about the physical world. Or, following many psychologists, existential propositions could simply be psychological representations, whose truth value is largely irrelevant.

Through the integration of existential propositions, frames can represent the complex propositional structure of discourse, as has been known for some time (Kintsch & van Dijk, 1978). Consider the following short discourse from Barsalou (1992):

Rick, feeling festive, rented a house near a tropical reef. He had recently built a house worth three million dollars. Rick had visited the reef long ago. The fish had been beautiful, and many divers were present (pp. 210–211).

![Diagram of frames for RENT, BUILD, VISIT, DIVE, RICK, HOUSE, REEF, FISH, and DIVERS](image)

Figure 1.9 illustrates how frames for *rent*, *build*, *visit*, *dive*, *Rick*, *house*, *reef*, *fish*, and *divers* can represent this text. As suggested in Barsalou (1992, chs. 8 and 9), activating and instantiating conceptual frames is the central process in language comprehension. As comprehenders encounter nouns, verbs, and propositions, they activate frames, whose attributes may become instantiated through later text. Upon encountering *Rick* and *rented* in the aforementioned text, for example, readers activate a frame for each. Information about Rick’s mood is integrated into the *mood* attribute in the frame for *Rick*. In turn, the frame for *Rick* is integrated into the *agent* attribute in the frame for *rent*. Barsalou (1992) describes the process of frame activation and instantiation in further detail (see also Just & Carpenter, 1987).

Representing Prototypes and Membership

*Prototypes.* Frames not only provide a natural means of representing specific exemplars but also of representing general information across exemplars. We have seen already how frames represent general attributes that typically take values for a category. However, frames can also represent typical values and typical patterns of values across category members. Consider Fig. 1.10. As can be seen, one value for each attribute is more likely than the other value across exemplars (e.g., *brown* occurs for five exemplars, whereas *white* occurs for three). The prototype is simply the set of most frequent values across attributes. In Fig. 1.10, the prototypical *bird* is *small* in *size*, *brown* in *color*, and has a *straight beak*.

Prototypes can be computed in a number of ways. After integrating a new exemplar into a frame, a procedure could determine the most frequent value of every attribute and represent these values as an explicit prototype (e.g., as in Fig. 1.10). Or, this same procedure could update an explicit prototype only when needed, rather than after every new exemplar. Or, prototypes might not be represented explicitly at all. Instead, prototypes might only emerge implicitly when exemplars are used in category processing, because the most frequent values dominate across exemplars (Medin & Schaffer, 1978).

Regardless of how prototypes arise, frames naturally produce typicality effects: If an exemplar’s values occur frequently across the exemplars integrated into a frame, then it is typical (e.g., *bird-1* in Fig. 1.10). In contrast, exemplars whose values occur infrequently are atypical (e.g., *bird-7*). Additionally, if exemplars vary in the attributes for which they have values, then an exemplar’s typicality also depends on how frequently its attributes have values across exem-
Frames can also represent typical patterns of values, using the various constraints described earlier. In Fig. 1.10, a value constraint explicitly represents the correlation between small size and brown color across exemplars. As discussed in Barsalou (1990), cooccurrence information can be computed in many possible ways. Analogous to prototypes, cooccurrence relations could be updated explicitly with each new exemplar; they could be computed only when needed, or they could exist implicitly, emerging as frequent patterns of values across exemplars. Because exponential amounts of cooccurrence information exist, computing all of it is probably unrealistic. One reasonable approach is only to compute cooccurrence information that is relevant to the goals and background knowledge of the perceiver (Murphy & Medin, 1985). Another is to compute only cooccurrence information discovered during remindings (Medin & Ross, 1989; Ross & Spalding, 1991). Much cooccurrence information may generally be ignored and not become stored in a frame system. If ignored cooccurrence information should become relevant at a later time, it can be computed from whatever exemplars are currently accessible.

Prototypes and cooccurrence relations provide default information about a category when values for frame attributes are not specified explicitly. Consider the sentence:

When Hank came home, a bird was sitting on his porch.

Although this sentence does not describe any characteristics of the bird that Hank observed, a frame can produce inferences about it. First, the reader can infer that the bird has values on attributes such as size, color, and beak, given these attributes generally take values across birds. Second, the reader can infer default values for these attributes, based on prototypical values extracted from previous exemplars. If the reader's knowledge were similar to Fig. 1.10, he or she could infer that the bird is small, brown, and has a straight beak. To see how cooccurrence relations provide defaults, consider:

When Hank came home, a white bird was sitting on his porch.

Because white color cooccurs with curved beak in Fig. 1.10, the reader can infer that the bird has a curved beak. Note that straight beak is prototypical but is overridden by the correlation between white color and curved beak that occurs across bird-4, bird-5, and bird-7. Because white does not correlate with any value for size, the reader could use the prototype to infer that the bird is small.

Cooccurrence relations enable frames to generate defaults dynamically, as occurs in the norms described by Kahneman and Miller (1986). For example, if partial information about a bird is encountered, cooccurrence relations may generate defaults for attributes whose values remain unspecified. For any pattern of provided attribute values, a frame system can fill in the remaining attribute.
values (much like a connectionist net). As the provided attribute values vary, the inferred defaults can vary dynamically as well. Rather than being limited to values in the prototype, defaults are contextually sensitive, being determined by the particular pattern of cooccurrence relations that the input activates.

Membership. Frames provide a wide variety of mechanisms for representing category membership. First, possession of certain attributes can count as evidence for belonging to a category. For example, having any value on the attribute of color counts as evidence for being a physical entity (Keil, 1979, 1981). Second, possession of certain attribute values can count as evidence for category membership. For example, having the values of human, female, and adult for species, sex, and age counts as evidence for being a woman. Third possessing values within a certain range can count as evidence for category membership. For example, having values of cost that range from $125,000 to $175,000 could count as evidence for someone's category of potential houses to buy (Flannigan, Fried, & Holyoak, 1986). Fourth, possession of values lying beyond a reference point can count as evidence for category membership. For example, legal U.S. voters are 18 years or older (Medin & Barsalou, 1987).

Through the use of various constraints, frames can represent a wide variety of membership decision rules. For example, a requires constraint from a frame's root node to an attribute value specifies that the value is necessary for category membership (e.g., man requires adult as the value of age). Conversely, a requires constraint from a value to the root node of a frame specifies that the value is sufficient for membership. Typically, a joint set of values may determine sufficiency, as for human, child, and female being jointly sufficient for girl. To represent joint sufficiency, values must be integrated by a cooccurrence relation, from which a requires constraint projects to the root node. Frames can also represent disjunctive and biconditional categories. To represent the disjunctive category of baseball strike, three independent requires constraints must project to the root node: one from swings and misses for hitter's action, one from swings and fouls for hitter's action, and one from the cooccurrence of in the strike zone for pitch location and hitter does not swing for hitter's action. To represent the biconditional category of gay relationship, one requires constraint must relate male for partner 1 and male for partner 2, and another must relate female for partner 1 and female for partner 2.

All of the requires constraints in the previous categories produce well-defined categories. In the absence of such constraints, categories are fuzzy. Under these conditions, an exemplar's similarity to the attribute and value information stored in a frame may control categorization. As an exemplar's attributes and values increasingly match those in a frame, the frame becomes increasingly likely to provide the exemplar's categorization. Following Murphy and Medin (1985), constraints from background knowledge to frames may specify that some attributes and values in a frame are more relevant to similarity comparisons than others.  

Representing Subordinates and Taxonomies

Subordinate concepts emerge naturally in frame systems. Consider the representation of fowl as a subordinate of bird in Fig. 1.11. According to this much simplified example, birds are those entities that have the particular attributes and values in the frame for bird. In turn, fowl is the subset of birds whose values for size, color, and beak are typically restricted to large, white, and large, respectively. Subordinates are sets of exemplars whose values constitute a subset of frame information. Through the representation of increasingly specific subordinates, taxonomies emerge in frames. To see this, consider the representations of water fowl and duck in Fig. 1.11. Water fowl are those birds that typically have large, white, large, and paddles as values for size, color, beak, and locomotion, respectively. Ducks are those birds that typically have large, white, large, paddles, and short as values for size, color, beak, locomotion and neck, respectively. Because water fowl have all the values of fowl plus an additional value for paddles, water fowl are subordinates of fowl. Similarly, because ducks have all the values of water fowl plus an additional value for short neck, ducks are subordinates of water fowl. Through the representation of nested attribute values, taxonomies evolve naturally within frames.

Figure 1.11 represents taxonomic relations explicitly (i.e., the type relations from fowl to bird, from water fowl to fowl, and from duck to water fowl). If type relations were not represented explicitly, however, this taxonomy would still be represented implicitly, based on value nestings alone. By assessing whether one subordinate's attribute values are nested within another's, a procedure could identify taxonomic relations. Given such flexibility, frame systems can represent both prestructured taxonomies and computable taxonomies (Smith, 1978).

5By further assuming that different attributes and values can underlie membership and typicality, frames readily account for the dissociation that sometimes occurs between typicality and membership. For odd numbers, membership requires that a number have one as its value of remainder when divided by two. In contrast, typicality may reflect an exemplar's value on frequency of occurrence or its proximity to the ideal of minimal magnitude (cf. Armstrong, Gleitman, & Gleitman 1983). When typicality and membership are directly related, the same attributes and values underlie both. For example, Barsalou (1985) found that typicality in weapons increases with destructiveness, which is clearly related to membership (also see Fehr & Russell, 1984, Experiment 5; Hampton, 1988).

6The examples in Fig. 1.11 are much simplified for the sake of presentation (e.g., some fowl are not white).
nouns frame retain their defaults (e.g., size retains its default of small). However, selective modification fails to account for interactions that often occur between modified and unmodified attributes (Medin & Shoben, 1988; Murphy, 1988, 1990). In white bird, for example, size as well as color is likely to be modified, because white birds are generally large, thereby overriding the default of small for size.

The examples in Fig. 1.12 illustrate how frames represent conceptual combinations and the interactions that often accompany them. As can be seen, one meaning of bird house can be represented by integrating frames for bird and house into the agent and location attributes in the frame for live (cf. Gleitman & Gleitman, 1970). Constraints capture the interactive inferences that people are
likely to make about bird house. Because the birds who typically live in such houses are small and fly, these defaults enable the house to be small and off the ground. As Fig. 1.12 also illustrates, constraints similarly capture interactive inferences that underlie apartment dog (cf. Murphy, 1988). Frames for dog and apartment are integrated into the agent and location attributes of the frame for live. The constraint that medium and large dogs typically require a yard enables the inference that small dogs tend to live in apartments. Because apartments do not have yards, they generally preclude dogs that are medium or large, with small remaining as the most plausible size.

Representing Event Sequences

So far, I have been using frames to represent timeless states of the world. Yet, frames also lend themselves to representing the dynamic flow of events over time, what many refer to as scripts (Schank & Abelson, 1977) and mental models (Johnson-Laird, 1983). Consider the partial frame for a simple four-stroke engine, which might include attributes for carburetor, ignition system, and cylinder. In an atemporal frame representation, the values of these attributes are the specific carburetors, ignition systems, and cylinders of particular engines. However, the values of frame attributes can be used in a much different way to simulate engine behavior.

To see how frames can represent event sequences, consider the much simplified frame for a one-cylinder, four-stroke engine in Fig. 1.13 (cf. Barsalou, Hale, & Cox, 1989). Instead of the frame's attributes taking values for the components of a specific engine, the attributes take values for states of operation (e.g., the carburetor can either be in the state of forming fuel vapor or of being empty). To see the difference, compare the values of engine attributes in Fig. 1.4 with the values of engine attributes in Fig. 1.13.²

Because the frame in Fig. 1.13 represents a four-stroke engine, the engine can be in one of four states, which are represented as the four strokes of the engine cycle. Each stroke in Fig. 1.13 is represented by a vertical line (i.e., a "stroke line"). Each horizontal line connected to a stroke line by a solid circle indicates a value of a frame attribute that occurs during that stroke. Those horizontal lines with "wickets" over a stroke line do not occur during that stroke. In stroke 1, for example, the carburetor is in the state of forming fuel vapor, the ignition system is in the state of charging, the intake valve is in the state of open, the exhaust valve is in the state of closed, the piston is in the state of decompressing, and the action of the cylinder is to suction fuel vapor into the cylinder. The states of the engine's components on each of the remaining three cycles can be determined by noting the state values connected to each of the remaining three stroke lines. As can be seen, this event sequence is represented by crossing the frame for the engine with the frame for the engine cycle and noting all "intersections." As examples in Figs. 1.14, 1.15, and 1.16 illustrate further, crossing one frame for a

²Simultaneous representation of particular engine components and states could be achieved by having particular components emanate directly from the attributes, with states being defined over these components instead of over the attributes. For example, carburetor could have the carburetor in Phil's car's engine as its component value, which could be in the state of either forming fuel vapor or of being empty.
physical domain with a second frame for time provides frames with a general means of representing event sequences. 8

Figure 1.14 illustrates how frames represent the temporal sequence of states in an interpersonal event, namely, buying a used car for $2,000. Each vertical line

8The representation of engine states in Fig. 1.13 is formally identical to the representation of exemplars in Figs. 1.8 and 1.10: In each case, a state/exemplar is a collection of attribute values. The only difference is that the states in an event sequence are temporally related, whereas exemplars are typically not connected to each other in any manner (although they could be).

represents one state in the event sequence constituting the sale. This frame representation of an event attempts to account for the same type of information as Schank and Abelson's (1977) scripts, but in a somewhat different manner.

Representing Rules

Rules provide a common mechanism for producing event sequences. Applying a rule to an initial state transforms it into a subsequent state. In turn, applying a second rule (or perhaps the first rule again) produces a third state. Through a series of rule applications, an event sequence ensues, where each event is the transformation of one state into another. In production systems, production rules produce a wide variety of event sequences in this manner (Anderson, 1983). In theories of qualitative reasoning, rules propagate forces and substances over device topographies to produce device functions (de Kleer & Brown, 1984; diSessa, 1983; Forbus, 1984; Hayes, 1985). In story grammars, rules produce the plot transitions that form a story (e.g., Stein, Kilgore, & Albro, 1990; Stein & Levine, 1990; Trabasso & Sperry, 1985; Trabasso & van den Broek, 1985; Trabasso et al., 1989).

Frames for event sequences contain rules implicitly. Consider the stroke lines for stroke 1 and stroke 2 in Fig. 1.13, which can be integrated to form the following rule:

Rule 1: CAUSE (condition: stroke 1, outcome: stroke 2).

Three additional rules can be constructed for the engine cycle in Fig. 1.13:

Rule 2: CAUSE (condition: stroke 2, outcome: stroke 3).


Rule 4: CAUSE (condition: stroke 4, outcome: stroke 1).

Using frame notation, each rule could be represented as an independent production. Rule 1 would contain all of Fig. 1.13, excluding the stroke lines for strokes 3 and 4. In addition, a cause frame could be added, with its attributes for condition and outcome bound to stroke 1 and stroke 2, respectively. Rules 2, 3, and 4 could be represented similarly. If the condition for a rule were met, then the rule would fire as a production, producing its outcome.

Rather than storing rules as separate productions, they can be stored more efficiently in a frame that integrates them. Consider Fig. 1.15, where the frame for the engine cycle contains four causal events, one for each rule. Note that the complete stroke lines and the frame for the engine from Fig. 1.13 are not shown but are assumed to be present. Each stroke line is the outcome of one causal event and the condition for the next causal event.
Representing Rules 1 through 4 in this manner differs in important ways from production systems. Whereas these rules are integrated in a frame representation, they would be independent entities in a production system. As a consequence, the frame representation is more economical. Each stroke line is only represented once in Fig. 1.15 but would have to be represented twice in a production system: once as a condition, and once as an outcome (similar to Rules 1 through 4 preceding). Moreover, the frame representation provides a more coherent and global account of the engine cycle, because relations among the four rules are shown explicitly. However, an individual rule can still fire separately of the others. Rule 3 rule could fire, if its condition occurs, even if Rules 1 and 2 have not. Additionally, automatic firing of rules could be represented as the extent to which the relevant causal relations become strengthened in memory (Shiffrin & Schneider, 1977), or as the extent to which exemplars are integrated with rules (similar to Figs. 1.8 and 1.10; Logan, 1988). Nevertheless, the representation in Fig. 1.15 suggests that rules embedded in frames should be harder to access than isolated rules in production systems, if surrounding rules in an integrated frame provide interference. Evidence from Carlson and Yarue's (1990) blocking condition demonstrates such difficulty.

Figure 1.16 illustrates two further examples of frames representing rules. At the top, an intuitive view of combustion is represented as a causal relation between two sets of states defined over fuel, air, and heat source. At the bottom, the epitome of a rule, modus ponens, is represented as a relation between two sets of states defined over \( X \rightarrow Y, X, \) and \( Y \). As these examples illustrate, frames can represent a wide variety of rules.

Representing Plans

Frames are central to the initial planning of events (Barsalou, 1991). When people plan events such as trips, purchases, social events, and repairs, they often begin by partially activating a frame for the event being planned. In planning a vacation, people might activate the partial frame in Fig. 1.17.

The primary activity during the initial planning of an event is to instantiate frame attributes. As illustrated in Fig. 1.17, a planner might select snow skiing as
If a plan to snow ski in August is to succeed, satisfactory locations must be identified, such as mountainous regions with ski resorts in the southern hemisphere. If departure were changed to January, however, then new locations must be identified, such as mountainous regions with ski resorts in the northern hemisphere. Similarly, if departure and activity were changed to March and sunbathing, still new locations must be identified, such as beaches near the equator. In general, the already instantiated values of frame attributes contextualize the goal-derived categories used to instantiate later attributes.

Optimizations of a planner's goals further contextualize categories. As can be seen from Fig. 1.17, the agent has goals of privacy and aesthetic enjoyment, which propagate additional constraints to the vacation frame in the form of ideals (Barsalou, 1985, cf. Lehrer, this volume). Specifically, the ideals, maximally beautiful, and minimally popular, become established in the frame for location. To optimize the planner's goals, locations should approximate these ideals as much as possible. In contrast, if the planner's goals were to socialize and be warm, a different set of locations would be ideal. As a planner's goals vary, they contextualize the categories used to instantiate frame attributes.

THE STRUCTURE OF CONCEPTUAL FIELDS

The previous section focused primarily on how frames structure concepts, including concepts for exemplars, prototypes, subordinates, conceptual combinations, event sequences, rules, and plans. This final section explores how frames structure large fields of concepts. In particular, it explores how frames define the implicit extent of a conceptual field, how specific concepts within a field come to be represented explicitly, and how frames support the adaptation of concepts within a field. As we shall see, a frame is a finite generative mechanism capable of producing a large field of related concepts.

Defining the Extent of Conceptual Fields

Every frame defines an implicit conceptual field. To see this, consider the partial frame for animal in Fig. 1.18. If someone knew only these attributes and values for animal, its field would have 100 potential concepts, each having 1 value on each of the 4 attributes (i.e., 5 species × 2 sexes × 5 ages × 2 states of neutering = 100 combinations). These concepts include human–male–child–unneutered

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As discussed earlier, constraints are often statistical patterns rather than logical necessities. As a result, exceptions to the constraints in Fig. 1.17 are possible. For example, an August departure does not necessarily require that the location be in the southern hemisphere, given summer skiing is possible in the European Alps. Statistically, however, most summer skiing locations may be in the southern hemisphere.
sively at many levels. To see the potential explosion in growth, imagine that a frame of 5 attributes, each having 2 values, represents each of the original 14 values for animal in Fig. 1.18. Adding this level of embedded frames increases the total number of concepts in the field from 100 to 104,857,600.\footnote{The number of forms that each of the original 14 values can take is $2^5$ (i.e., 32 combinations of 5 attributes, each having 2 possible values). The number of forms that each of the original 100 combinations of 4 values can take is therefore $32^4$ (i.e., 1,058,576). Because there were 100 original combinations, the total number of concepts possible in the extended field is 105,857,600.} If frames for relations and constraints are included as well, the field would continue to grow. Assembling frames in conceptual combinations, event sequencings, and plans produces still larger conceptual fields. For example, friend can embed recursively within itself to form conceptual combinations for the friend of a friend, the friend of a friend's friend, the friend of a friend's friend's friend, and so forth. In principle, a frame that can take itself as an attribute value produces a conceptual field that is infinite in size. Obviously, such frames do not define their fields of potential concepts exhaustively.

As these examples illustrate, frames are highly generative mechanisms. From explicitly representing a small number of frame components in memory, a person develops the ability to represent an indefinitely large number of concepts in the frame’s field. Although individuals may only represent a few of these concepts explicitly, they can construct any of the remainder by forming new combinations of values across attributes.

Semantic Fields. Some of the concepts in a conceptual field become lexicalized to form a semantic field (Grandy, 1987; Kittay, 1987; Lehrer, 1974; Lyons, 1977; Miller & Johnson-Laird, 1976). In the semantic field for animal, the word “eunuch” means human–male–adult–neutered, “mare” means horse–female–adult, and “puppy” means dog–infant. Most research on semantic fields has addressed conceptual fields that are heavily lexicalized, as well as their most densely, lexicalized regions. When part of a field is unlexicalized, it constitutes a lexical gap. For example, no lexical item exists for horse–female–adult–unneutered or dog–male–infant–neutered. References to these concepts require more complex clausal expressions, such as “unneutered mare” and “male puppy that has been neutered.”

The partial frame for mare in Fig. 1.18 further illustrates the large space of lexical gaps often found within a field. As far as I know, none of the concepts in this field is lexicalized. People do not have lexical terms for a mare that is roan–Arabian–small–spirited or for a mare that is white–docile. Instead, people express these concepts in more complex linguistic constructions, such as “roan Arabian mare that is small and spirited.” Lexicalized concepts in a semantic field only capture a small fragment of the concepts in the conceptual field.

and cat–female–adult–neutered. Additional concepts of fewer than four values are also possible, such as horse–child–male, horse–child, and horse. Concepts of more than four values are possible as well, such as horse/donkey–female–
adult–unneutered for a subset of mules. If a frame contains all of the attributes and values possible within a conceptual field, then the frame defines the potential concepts that can be produced exhaustively.

The field for animal is much more complex than Fig. 1.18 implies. Because the frame for animal also contains frames for its values, relations, and constraints, the field of animal concepts is considerably larger. For example, frames could represent the value of male, a relation between neutered and sex, and so forth. Furthermore, frames could continue to represent frame components recursi-
The partial frame for vacation in Fig. 1.18 illustrates how a frame defines the conceptual field for an event, which includes the concepts described by “a vacation with a grandmother to relax in Hawaii in August” and “a vacation with a friend to ski in Colorado in December.” Although none of the concepts in the field for vacation is lexicalized, lexicalization sometimes occurs in event fields. In the field for cook, “simmer” lexicalizes the concept of cooking with water, gentle action, no oil, and no vapor (Lehrer, 1974). Similar to “mare” in the field for animal, however, many unlexicalized concepts for simmer exist, such as the one described by “simmering mushrooms in vegetable stock and garlic over gas heat.”

Constructing Specific Concepts within a Field

Frames are finite generative mechanisms. A modest amount of explicit frame information in memory enables the computation of a tremendously large number of concepts. By combining attribute values in new ways, people construct new concepts implicit within existing frame knowledge. Although all of these concepts are potentially computable, not even experts are likely to consider more than a small subset. This next section explores several factors that may lead to the construction of specific concepts within a conceptual field.

Experience and Concept Construction. As the result of experiencing particular exemplars, a person populates the respective conceptual field with exemplar representations. Each exemplar representation is the combination of attribute values that defines it as a particular point within the field. Figures 1.8 and 1.10 illustrate one form that exemplar representations can take.11

The combination of values used to code an exemplar depends on the content of the relevant frame. For example, a novice’s frame for horse might contain fewer attributes and values than an expert’s frame. In coding a particular horse, a novice might only encode color, size, and stockiness. In contrast, an expert might code additional attributes, such as breed, sex, age, back sway, and so forth. As a result, the expert’s coding of a particular horse as a point in the conceptual field carries more information, in an information theoretic sense. Analogously, different cultures may have different frames for the same field that produce different codings of the same exemplar. In this way, frames define relevance with respect to particular perceivers.

The content of frames also determines the distinguishability of exemplars. Imagine that a novice’s frame for horse only contains attributes for color, size, and stockiness. As long as different horses have different combinations of values for these attributes, no two horses are encoded identically, and exemplars remain distinguishable. However, to the extent that two or more horses are coded with the same set of values, they are not distinct. As multiple exemplars become coded identically, they may establish an increasingly entrenched representation of a subordinate concept of horse, as discussed earlier for Fig. 1.11.

Because experts encounter many more exemplars than novices, yet have richer frames, the key factor in expert knowledge concerns the relation between exemplar density and frame content. If exemplars are distributed evenly throughout a conceptual field, an expert may rarely code them identically, because so many possible attributes apply. As a result, an expert’s frame system produces “deeper” processing of exemplars, thereby producing better memory (cf. Chiesi, Spilich, & Voss, 1979; Craik & Tulving, 1975; Ross, 1981; Spilich, Vesonder, Chiesi, & Voss, 1979). If exemplars populate a few small areas of a field densely, however, an expert may code many exemplars identically, such that poor memory results. A more likely possibility is that attribute-value sets are best articulated in the most densely populated regions of a field. Exemplars in these regions receive fine-grained codings that rarely overlap, whereas exemplars in less populated regions receive coarser codings. Densely populated regions of a field may also exhibited greater taxonomic depth (cf. Rosch et al., 1976).

Constraints on Exemplars. Not all combinations of attribute values in a conceptual field are physically possible. Because exemplars exhibiting these combinations never occur, concepts for them may not develop. In the field of cooking utensils, for example, frying pans made of paper are impossible. Similarly, vacations with Caribbean beach and snow skiing as values of location and activity are impossible. Many other concepts are physically possible yet never occur. Although a frying pan made of platinum is possible, it may never occur. Similarly, a vacation to Japan with one’s grandmother is possible but never occur. Because people never encounter such exemplars, they rarely consider the respective concepts, except perhaps in imagination. As a result, extensive “conceptual gaps” exist in conceptual fields, analogous to the lexical gaps in semantic fields.

Two factors appear central to the realization of specific concepts: natural forces and goal optimization. Natural forces constrain the patterns of attribute values that occur in zoological, botanical, and geological fields. For example, genetic mechanisms constrain patterns of phenotypic traits in organisms. Because the genes of robins cause straight beaks and red breasts to cooccur, people do not know them to have curved beaks and red breasts. Similarly, physical forces constrain the characteristics of inorganic substances. Because atomic mechanisms cause gold to be relatively yellow and soft, people do not know it to be blue and soft.

For artifacts, goal optimization constrains the patterns of attribute values that occur. In constructing tools, the patterns that people encounter are those that

11In this section, I only discuss how exemplars instantiate points within a conceptual field. I do not discuss how states instantiate points within an event field, although the same proposals apply (Figs. 1.33, 1.14, 1.15, and 1.16).
optimize their goals. For example, hammers generally have wooden handles and steel heads. Hammers typically do not have solid steel handles, because the added weight tires the arm. Nor do hammers typically have platinum heads, because the extra expense has little benefit in durability. Similarly, the plans that people construct for events are those that optimize their goals. In planning trips, people do not experience limousine and grocery store as values of vehicle and destination, because the benefits of taking a limousine to buy groceries do not outweigh the costs. Similarly in brushing, people do not experience one hour and teeth as values of duration and object, again because of low payoff.

Imagination and Concept Construction. Experienced exemplars are not necessary for constructing concepts within a field. Clearly, people can imagine concepts for nonexistent exemplars. In evaluating typicality, people construct concepts of ideal category members, whose realization in experience would optimize a goal (Barsalou, 1985). In planning, people imagine events that do not exist (Barsalou, 1991). In decision making, people imagine possible choices (Kahneman, Slovic, & Tversky, 1982). In evaluating actual events, people imagine alternative events that might have occurred instead (Kahneman & Miller, 1986). The computational power of the human cognitive system reflects its ability to imagine concepts within conceptual fields. Through mental simulation, people develop insights into past events and predictions for future events. By comparing multiple possibilities, people identify optimal alternatives. By combining concepts in new ways, people invent new devices and procedures. Much of what is unique in human nature rests on the ability to combine conceptual information creatively.

Frames readily support the creative combination of information. As we saw earlier, frames define huge spaces of implicit concepts. Because most of these concepts are never considered but nevertheless computable, they provide extensive opportunities for creativity. By combining attribute values in new ways, people explore explicitly what were once implicit regions of a conceptual field. Moreover, every new attribute or frame added to memory offers further opportunities for creativity. When people learn about genes, learning does not end with this concept. Instead, people can combine genes with any plant or animal frame to construct a new conception of each. Furthermore, people can apply genes to other frames metaphorically, as did Holland (1975) in his conception of genetic algorithms for machine learning. Frames provide the combinatorics that support constructing reality in myriad ways and conceiving of the possible worlds that lie beyond it.

Adapting Concepts within a Field

Frames readily allow people to adapt their knowledge to a changing world. Imagine that robins evolve to have purple instead of red breasts. To represent this, people simply have to change the value of color from red to purple in their frame for robin. Because all other values remain the same, nothing else in the frame need be altered. Similarly, imagine that people begin using hammers with solid steel handles to develop arm strength. The addition of steel as a value of handle material in the frame for hammer captures this change, along with an enables relation to develop arm strength as a value of goal.

Because people constantly experience new things in the world, and because the world is constantly changing, human knowledge should be of a form that adapts to change readily. Frames offer a type of flexibility that is "genetic" in character. Similar to the somewhat orthogonal structure of genes in organisms, attributes can function orthogonally in frames. Because values for attributes can vary independently—to the extent that they do not violate constraints—they can capture whatever orthogonal variation occurs in nature. If values of hair color and eye color vary independently in a species, frames can readily capture this variation, because the respective attribute-value sets can function orthogonally. On the other hand, when correlations exist in nature, frames can capture them with structural invariants and constraints.

Representing change in experience and evolution is much like representing event sequences: For each, a frame's attributes remain relatively constant, with changes in values capturing change over time (cf. Hayes, 1985). As we saw earlier, frames can represent the evolution of a system over a short time period, as in the successive states of a four-stroke engine. However, frames can also represent change over much longer time periods, as in the physical growth of a person over their life span, change in cultural convention over history, or change in a species over evolution.

CONCLUSION

Frames capture constancy and variability across exemplars and time. The same basic, frame-producing mechanism applies virtually to any domain. Moreover, it applies recursively, producing frames within frames at any point where new aspects of variability are noted. As a result, frames represent the attributes, values, structural invariants, and constraints that compose frames. What may begin as a relatively undifferentiated "primitive" domain becomes increasingly articulated as frames develop to represent it. So far, the evidence for a fundamental frame-producing mechanism in human cognition rests mostly on informal examples and intuition. A much stronger empirical case remains to be developed. In addition, much remains to be learned about the mechanisms that produce and process frames. Although frames may provide a fairly uniform representation across tasks and domains, a wide variety of processing mechanisms may underlie their utilization in human intelligence.
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REFERENCES


2 Toward a Frame-Based Lexicon: The Semantics of RISK and its Neighbors

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In these pages we present some initial results of a large-scale inquiry into a semantic field centered in the English lexeme RISK. The kind of description we seek to justify could not easily be represented in a standard print dictionary, for reasons that soon become clear, but we imagine, for some distant future, an online lexical resource, which we can refer to as a “frame-based” dictionary, which will be adequate to our aims. In such a dictionary (housed on a workstation with multiple windowing capabilities), individual word senses, relationships among the senses of polysemous words, and relationships between (senses of) semantically related words will be linked with the cognitive structures (or “frames”), knowledge of which is presupposed for the concepts encoded by the words. A user’s keying in of a word to be looked up will cause a window to appear that will display relationships between particular lexical meanings and specific lexico-syntactic patterns. Each of these lexico-syntactic patterns will have its components indexed with specific parts or aspects of the associated frame. The language used in the description of this indexing will contain category names founded on the characteristics of the relevant underlying frames. Accompanying each such description will be provided the means for giving the user access to descriptions of the associated conceptual frames, allowing the user who wishes to be reminded of the properties of the frames associated with a given word to open an additional window that presents information about it, and which identi-

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1 The main product of that larger work is Fillmore and Atkins (forthcoming). The authors are indebted to the computational facilities of the Institute of Cognitive Studies at the University of California, Berkeley; to IBM, Hawthorne, for providing the concordance lines, and the American Publishing House for the Blind for the use of the APHB corpus.