# AI and Similarity

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As AI moves into the second half of its first century, we certainly have much to cheer about. It has produced a wealth of solid results on many fronts, including machine learning and knowledge representation, for instance. More generally, the field has delivered impressive, reliable, and widely applicable techniques we couldn't have dreamed of 50 years ago: constraint-satisfaction problem solving, probabilistic learning techniques, real-time planning, case-based reasoning, market-based models for societies of agents, and so on. AI has made significant headway on developing techniques, computational models, and systems that advance its synergistic twin goals of modeling cognition and building systems to get the job done. In fact, a lot of AI systems get the job done spectacularly.

*For AI to become truly robust, we must further our understanding of similarity-driven reasoning, analogy, learning, and explanation. Here are some suggested research directions.*

Yet we still have much work to do on some topics. Among these are similarity-driven reasoning, analogy, learning, and explanation, especially as they concern open-textured, ever-changing, and exception-riddled concepts. Although some of these were recognized from its beginning, AI still cannot deal well enough (at least for me) with the inherent messiness that characterizes much of the world that humans and AI artifacts operate in.

There is no way to shrink from this challenge. Even though some subfields, such as my own disciplines of case-based reasoning (CBR) and AI and law, have made significant advances, abundant opportunities exist to push the envelope further. Doing so is necessary both to shed light on cognition and to advance the state of the art of performance systems. In the next half-century, AI can become robust enough not only to cope with our messy world but also to thrive in it. In this essay, I discuss a few aspects of the topics that I believe are important in order to realize truly robust AI.

## The enduring problem of similarity

From its earliest days, AI has been interested in similarity. For instance, in introducing the AI section of *Computers and Thought*,[1] Edward Feigenbaum wrote, "A useful rule of thumb used by human beings in most of their problem-solving is this: Attack a new problem by methods that have solved similar problems in the past. The criteria for 'similarity' may themselves be heuristic." Marvin Minsky also addressed this in his 1961 essay "Steps toward Artificial Intelligence," reprinted in the same collection.[2] In discussing teleology and classification, he wrote that "objects grouped together in the classification should be 'similar' in a useful sense; they should depend on relevant or essential features." Earlier still in his paper for the 1958 Teddington conference, Minsky wrote, "Try methods that are similar 'in an appropriate sense' to those that have been successful in the past. Each problem domain has, of course, its own structure, and its own relevant kinds of similarity."[3] Indeed, yes.

Despite this spotlight on what we might call the CBR heuristic, researchers haven't answered this early call to arms on similarity-based problem solving—or on the very nature of similarity itself—nearly enough. Of course, these aren't small topics: they're fundamentally about analogy, cases, concepts, context, relevance, reuse, and more, and similarity is at the heart of much learning and teaching. And vice versa, since similarity is a Cheshire-cat type of notion that depends on "where you want to get to," particularly in explanation and argument.

Broadly construed, the problem of similarity has been attacked from all quarters over the years—for instance, we can even consider some work on game playing and character recognition in this light.[4,5] Of course, CBR is particularly concerned with reasoning with similar cases and modeling different notions of similarity (see the sidebar "The Case-Based Rea-


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## The Case-Based Reasoning Process

CBR is the process of solving new problems by using old cases. Generally speaking, there are two types of CBR: interpretive CBR, in which a new situation is interpreted in light of past ones; and problem-solving CBR, in which a new problem is solved by adapting an old solution. Classifying or arguing for a particular interpretation of a new fact situation in light of existing legal precedents is an example of the first type, and creating a new design or plan by adapting old ones is an example of the second.

In all types of CBR, the process proceeds as follows:

1. The new problem case is analyzed.
2. Based on the analysis, relevant cases are retrieved from a case base using various sorts of indices.
3. From these relevant cases, the most on-point or most relevant are selected using a method for assessing similarity (a so-called *similarity metric*).
4. The most similar or "best" cases (there might be several) are used to craft a solution for the new case.
5. This proposed solution is vetted in some way (for example, with a simulation, sensitivity analysis, or hypotheticals).
6. The new solution is possibly saved in the case base, and indices and similarity measures are possibly updated.

In some CBR systems, some of these steps (for instance, steps 2 and 3) happen together.[1,2] The CBR process is sometimes described in terms of Rs: for instance, retrieve, reuse, revise, and retain.[3]

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soning Process"). Investigations of analogical reasoning are also on target; while fewer in number, they've given us significant insights.

Although other lines of research also have embedded notions of similarity, they tend not to reason explicitly with individual cases. Rather, they encapsulate similarity in various sorts of generalizations (for example, weights); most throw away the cases and thus mask the similarity-based reasoning involved. In such systems, it is hard to unpack the reasoning to understand how and why similarity was used and so those interested in shedding light on human cognition will find it difficult to learn much about similarity from them.

In contrast, CBR and analogical-reasoning programs explicitly (and mostly symbolically) use individual cases, and the best present the reasoning behind their conclusions. This not only enhances the use of such systems as tools for cognitive studies of similarity, but also makes their output more useful in domains such as law and mathematics where the reasoning is as highly valued as the conclusions.

Despite AI's advances, we need more insight and techniques for performing similarity-based reasoning. We must also understand different types and uses of similarity and the concepts and contexts for which they are useful or appropriate, and the relationship of similarity to explanation and learning, and by implication with a host of other core AI topics. These include methods for knowledge representation and techniques for dealing with concepts, context, and purpose.

## The persistent need for explanations

A key requirement for intelligent systems is that the reasoning they do should not be opaque. For instance, just classifying an instance isn't enough. We—humans and AI systems—should be able to provide an explanation to back up the classification. Announcing an answer to a problem without an explanation, even if it is based on the best practices of the inference technique involved, isn't enough. At present, while a host of methods can perform concept learning and classification, for instance, fewer can provide explanations, say, via analogies with past exemplars. Fewer still can explain the model of similarity used to reach a conclusion and why it's the appropriate one to use in the given problem-solving context.

Explanation often involves the CBR heuristic—that is, reasoning about similar relevant cases. That's especially so in domains such as law and mathematics where a black-box or "because I say so" approach isn't acceptable. Although these two domains are at opposite ends of the messy–neat spectrum, both place a high premium on explanation. Examples and cases play a key role in explanations in both of them. This is obviously the case with Anglo-American law, which is based on precedent. However, even in mathematics, where the standard for justification is logical proof, examples can play a key role in explaining a proof and illustrating its nuances, coming up with conjectures and plans for proving them, reminding us of the importance of a theory's elements and the connections among them, and so on.[6,7]

Explanation involving exemplars can foster concept learning in a wide variety of learners, from toddlers to graduate students. For instance, Dedre Gentner and her colleagues have shown that when young children engage in explicit comparison of exemplars from a concept class during categorization, their learning is deeper in the sense that they move away from perceptual features (such as shape) to deeper, more conceptual ones (such as functional roles).[8] They are also more able to ignore perceptually seductive features in favor of relational ones. In a study of business school students, researchers found that students who explicitly compared negotiation scenarios were more apt to use the appropriate strategy in actual problem scenarios than those who read the same two cases but didn't compare them.[9]

Explanation and argument are at the heart of the case method used in many professional schools. Introduced in 1870 by the Dean of Harvard Law School, Christopher Columbus Langdell, it is now also established practice in business schools and to some degree in medical schools (teaching rounds can be considered akin to a CBR experience). The case method focuses on close readings of cases, often presents conflicting cases and principles, engages students in pointed Socratic dialogue, and makes strong use of hypotheticals. In essence, it focuses on hard, borderline cases. As Elizabeth Warren, a Harvard law professor, says, "You know the difference between daylight and dark? Well, we spend all of our time at the Law School on dawn and dusk."[10] And, I might add, all the umbral shades in between.

The need for explanation is especially critical when the conclusion will be used in making decisions, giving advice, or other contexts with potentially significant impact. Situations involving health, finances, or legal issues come to mind. For instance, consider the slippery concept of creditworthiness and the task of classifying a consumer as creditworthy. No one—neither credit applicant nor banker—should be satisfied with a system that doesn't explain its conclusions.

Imagine that you've just been classified as not creditworthy. An "explanation" that is only a raw score would be particularly unsatisfying, especially if this decision matters to you—for instance, if it means you won't be approved for an important loan or mortgage.

To understand why, you'd probably want a detailed explanation. You might want to know how the score was computed, what the theory behind that computation is, where the theory came from, and what alternative theories and thus scores and outcomes there might be. You might want to know what data of yours was used and its provenance. You might want to know what training data gave rise to the theory, or the theory's biases and track record.

You might benefit from a contrast-and-compare analysis with relevant past exemplars, both positive and negative. Illustrative examples might make the decision more understandable. You might want to know how you could improve your situation or imperil it further. That is, you might want to consider hypotheticals that shed light on your situation. You might like advice on what to do and perhaps a comparison of the courses of action open to you. You certainly wouldn't want to pursue a course of action that would make things worse. In short, you might want a highly reasoned explanation complete with actual precedents and illustrative hypothetical examples, and a bit of well-laid-out guidance. Of course, you might not want all of this at once, but you should be able to get it if and when you want it—in the manner of *explanation on demand*. I know I would.

The same comments apply for those making the decisions. In arenas with more earth-shaking implications such as international relations, this should be part of decision-making best practices. Comparisons of courses of action (I call them CoCoAs) involving precedents and hypotheticals aren't just a nicety; they're essential for making good decisions. Ignoring them can lead to spectacularly awful decisions.[11]

To provide informative explanations requires more research on CBR, analogy, and hypothetical reasoning. We must know more about what constitutes a good explanation and about the art of explaining and advice-giving.

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## Messy concepts

What we might call "messy" concepts make excellent subjects for studying similarity, explanation, examples, argument, analogy, and so on. Conversely, these methods are key ways—perhaps the best, or only ways—of dealing with messy concepts.

Most real-world concepts are messy, so dealing with them is unavoidable. Only in the world of mathematics do we have the luxury of fixed concepts with crisp, black-and-white boundaries. Even these aren't so neat and clean when they're evolving.

In discussing concepts, a useful metaphor is that of a *set* of instances residing in a *space* of instances or examples. (The notion of *what space* to use is a complex one depending on context, available features, and so on. Given the space, *what topology* or *metric* to endow it with depends critically on what sort of similarity one wants to emphasize. These are not small issues.) Instances in the set's interior are "in" the concept class (that is, positive exemplars), and those that are "outside" aren't (negative exemplars). As in mathematics, sets are often imagined or pictured as roundish areas sitting in a 2D plane. Of course, few concepts reside in such a low-dimensional space, and fewer still have such simple (for example, connected) topology. Nonetheless, the picture is useful because it facilitates metaphorically borrowing ideas such as boundary, interior, and the like from mathematics.

Messy concepts have three characteristics: they have gray areas of interpretation, they change, and they have exceptions. In other words, they are *open textured*, *nonstationary*, and *nonconvex*.

### Open-textured concepts

Open-textured concepts cannot be defined by universally valid, necessary and sufficient conditions. They don't have hard boundaries offering black-and-white distinctions between positive and negative instances. They are more like open sets in that their boundaries are soft and gray and always allow a bit of wiggle room.

The world is full of such concepts. For instance, if a regulation forbids taking a "vehicle" into a public park, what counts as a vehicle? A bicycle, kiddie-car, motorized wheelchair, park department work truck? A Segway? A rickshaw, pedicab, or palanquin? In discussing such concepts, the legal philosopher H.L.A. Hart introduced the "penumbra-core" distinction:

> [T]hen the general words we use—like "vehicle" in the case I consider—must have some standard instance in which no doubts are felt about its application. There must be a core of settled meaning, but there will be, as well, a penumbra of debatable cases in which words are neither obviously applicable nor obviously ruled out. These cases will each have some features in common with the standard case; they will lack others or be accompanied by features not present in the standard case.[12]

While instances clearly situated in the interior region—the core—might be easy to classify, those in the boundary region—the *penumbra*—aren't. In the penumbra, there are often good reasons to call an instance "in" and equally good ones to call it "out."

### Nonstationary concepts

Nonstationary concepts change over time. The change might be gradual ("normal science" or "concept drift") or abrupt (a "paradigm change or shift").[13] Furthermore, change is ubiquitous. Sometimes concepts begin to change as soon as they come into being; at other times, they occur after a long period of dormancy or settledness. Changes are often provoked by some anomaly or other disturbing example or circumstance that calls into question the concept's meaning or scope. Sometimes the catalyst comes from new data, and sometimes from new ways of looking at old data.

Real-world concepts can exhibit tremendous change. The legal domain provides numerous examples. A few familiar ones from American constitutional law are privacy, protected speech, due process, obscenity, and taxable income.

Even long-settled legal concepts can become unglued and undergo change so intense that the exceptions cause a complete flip in the rule. For example, the legal scholar Edward Levi described how the rise of the "inherently dangerous" exception and manufacturer liability in contract and commercial law reversed the once-supreme rule of privity of contract.[14] (Up until the mid-1800s, the privity rule required that to be compensated for a defect in a product, you had to be in a direct relationship with the manufacturer and not a "third party" or "remote purchaser." In a nutshell: "No privity, no liability.") Some concepts, such as "separate but equal," can even die.

The situation with mathematical and scientific concepts is similar. Change is often triggered by examples of a particularly unsettling nature: counterexamples. The history of mathematics is full of change in fundamental concepts (for example, natural numbers, irrational numbers, and functions).[15]

In his wonderful book *Proofs and Refutations*,[16] Imre Lakatos recounts how during the mathematical history of Euler's formula, changes in key concepts such as face, edge, and polyhedron were triggered by pesky examples (Kepler's "urchin," for example). He describes how such "monsters" catalyzed attempts to rejigger definitions in order to bar certain exceptional cases. He goes on to describe the push and pull between (counter)examples and (re)definition and the dialectic of refutation, reformulation, and rejustification. George Pólya called this ubiquitous dialectic the "alternating process."[6]

## Nonconvex concepts

Concepts can have "holes"—that is, negative examples residing in the concept's interior where (only) positive examples ought to be, and vice versa—and thus can fail to be convex. Holes often arise from exceptional cases that come to light after a concept has been initially formulated.

Nonconvexity is intimately bound up with conceptual change involving counterexamples and methods of monster barring. Sometimes, a hole is caused by nothing more than a one-time anomaly; at other times, it's more sizable and contains a bevy of counterexamples. Sometimes the hole can be patched—for instance, by fixing an aspect of the concept's definition, monster barring, narrowing the discussion's setting, or redefining the instance space—and sometimes it can't. Often, the hole simply grows larger and larger in the face of a stream of challenging examples. Many areas of the law have bodies of exceptions that have grown over time, sometimes to the point of "swallowing the rule."

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Nonstationary, nonconvex, open-textured concept can thus be likened to a pliable slice of Swiss cheese with blurry holes and morphing boundaries. While concepts more akin to well-machined designs cut into sheet metal are important, I think they're less interesting, even though the process of *how* they get hammered out so that they are clear-cut, fixed, and convex is exceedingly interesting. Perhaps more to the point for AI, the study of flexible, slippery concepts has great potential for shedding light on how we think and how to build robust systems capable of dealing with the evolving, messy world we and our systems need to thrive in.

AI has had a long, abiding interest in many aspects of messy concepts (see the sidebar "AI's Abiding Interest in Messy Concepts"). Core research in AI has contributed to our understanding of many foundational issues: commonsense concepts, default reasoning, exceptional cases, case memory, analogy, and classification, to name just a few.

## Synergies

The study of messy concepts isn't the sole province of AI, of course. It has been of long-standing interest in other disciplines such as philosophy, psychology, and law, and we ought to borrow more liberally from their insights. It was Ludwig Wittgenstein, for instance, who coined the term *family resemblance* and provided the famous example of a "game"; it's a classic example of an open-textured concept. Linguists and philosophers have long pursued natural concepts and their meaning.[17,18] Ethnographic studies—for instance, of concepts used by the Itzaj Maya of Guatemala and other cultures—have given us insights about concept formation far beyond those from our usual subject base (typically undergraduate psychology majors).[19,20]

Much of legal reasoning—whether in common, statutory, or constitutional law—focuses on formation and change in the meanings of concepts.[14] For instance, the problem of statutory interpretation focuses on the meaning of words in statutes and regulations.[21,22] In Anglo-American law, the doctrine of *stare decisis*—the very heart of our jurisprudence—is all about similarity: it dictates that similar cases should be decided similarly (even though similarity itself isn't spelled out in much detail). Basically it is reasoning by example.

Psychologists such as Eleanor Rosch,[23,24] Douglas Medin[25–27] and Gentner[8,28] have given us fundamental insights about such notions as family resemblance, typicality, basic categories, and analogy by structure mapping. Some have studied differences in novices and experts.[29] This foundational research is summarized in Gregory Murphy's *Big Book of Concepts*.[30]

Psychology has long since abandoned the view that concepts are defined by universally valid, necessary and sufficient features (the so-called *classical* or *definitional* view), replacing it with new paradigms (the *exemplar*, *prototype*, and *knowledge* views). In the prototype paradigm, categories have a graded structure, with some instances being more "typical" than others in that they share many features common in the category and share few features common to other categories. In some versions of this paradigm, a prototype is a maximally typical actual example; in others, it's more of a summary representation or ideal of what a most typical example would be. In either view, typical examples are closer to the prototype, and atypical examples and borderline examples—penumbral examples

## AI's Abiding Interest in Messy Concepts

AI has addressed fundamental questions about how to represent real-world concepts. Note, for instance, Marvin Minsky's well-known seminal work on frames and common sense and subsequent discussion about them.[1,2] CBR has addressed similarity issues head on. Roger Schank and his students have led the way on explanation and similarity-based problem solving.[3–5] Closely related work has explored example-based approaches.[6–8]

The subfield of AI and law has developed models of case-based argument, explanation, and hypothetical reasoning.[9–11] Projects have delved into how cases, examples, and explanations are intertwined;[12,13] how to represent complex concepts such as "ownership";[14] and the role of examples—hypothetical, prototypical, and real—in systems that do legal reasoning.[15–18]

From AI's earliest days to the present, researchers have studied analogy.[19–23] Thomas Evans' Analogy program, one of AI's earliest projects, dealt with it explicitly, and Patrick Winston's Arch program was one of the earliest to tackle learning and analogy together. Karl Branting's legal-reasoning system GREBE (Generator of Exemplar-Based Explanations)[12] adopted the structure-mapping approach developed by Dedre Gentner and Ken Forbus.[24,25] Manuela Veloso combined CBR and Jaime Carbonell's derivational analogy.[26] Recently Forbus and his group revisited the geometric analogy problems Evans studied, and developed a two-level analogical-processing scheme (involving first structure mapping and then reasoning with differences) that can produce human-like performance.[23]

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in Hart's sense—are much further away. In the exemplar paradigm, categories are represented in toto by the known positive examples of the category; it is a completely extensional representation. The knowledge view captures information such as commonsense knowledge and the purposes of the category. While there isn't universal agreement concerning views, there's no going back to the simplistic classical view.

Our allies in other fields have much to offer us, and we them. For instance, while similarity is indeed the keystone of precedent-based reasoning, what jurisprudence has to say about similarity is nowhere concrete enough for AI purposes. When we build AI programs that reason with precedents, we cannot avoid taking a computational stance on what similarity means, and this can't help but inform jurisprudential ideas about it.

Likewise for psychology, while ideas about similarity are central to much work on categories, they're sometimes woefully vague or limited, especially in the exemplar view. In the prototype view, the similarity measure, while sufficiently defined, is rather simplistic: it's essentially a threshold for a linear evaluation function. In both views, there's too little discussion of what constitutes an example, and how to index, retrieve, and (partially) match them. By comparison, CBR has offered some detailed investigations of these issues. Work on knowledge representation—for instance, on frames and common sense—can inform the prototype and knowledge views. A case in point is Michael Pazzani's research[31] on how prior expectations and background knowledge can enhance category learning. Veloso's current work situates ideas about concepts in a robot environment.[32]

Disappointingly, the categories examined in psychology experiments are often—natural categories aside—overly simple and impoverished. Furthermore, the context aspired to in psychology experiments can be pristine to the point of being empty, and subjects can be viewed as *tabulae rasae*. These approaches aren't, in my view, the way forward. Psychology seems reluctant to explore or espouse hybrid approaches—such as a mixture of prototype and exemplar views—even though evidence exists for them.[30] By contrast, AI has made significant use of hybrids, and researchers are currently even more inclined to do so.

All these allied fields have much work to do. None addresses well enough the fact that notions of similarity are not static. Nonetheless, there's synergy to be exploited among such scientifically allied fields, and analogies across them might suggest new questions and new approaches. At the very least, both psychology and AI should broaden their investigations to include more research on messy concepts, and each should look to the other for cross-fertilization.

## Representing messy concepts

Representation of messy concepts clearly presents challenges. For instance, it's difficult, if not impossible, to represent them in the paradigm of mathematical logic with a fixed set of features or predicates and restrictions to sound inference rules. Probabilistic methods aren't the answer either. Although they can deal with some aspects of uncertainty and classification, they're not particularly well suited for providing explanations, analogies, comparisons, contrasts, and so on.

For the most part, AI has focused more on working around messy concepts rather than on accepting them at face value. Researchers seldom exploit open-texture or conceptual change or, dare I say, rejoice in it. AI for the most part treats such characteristics as difficulties. I feel quite the opposite: they're features, not bugs. They permit a degree of flexibility that is an immeasurably valuable asset in domains such as law where concepts hardened in cement would be unacceptably brittle. By the way, it's not for lack of trying or diligence that fields such as law can't tame the open-textured, nonstationary, nonconvex nature of their concepts; rather, I believe it is in their very nature. Instead of trying to cure them, perhaps we should simply embrace the fact that they're open-textured "all the way down," so to speak—that the one constant is change, and exceptions aren't exceptional.

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One way to deal with messy concepts is to take an extensional approach: use examples and cases. Obviously, one can use an extensional approach in concert with others, such as logic, prototypes, frames, or statistics. We can sum up the example-based approach with Oliver Wendell Holmes's well-known aphorism that "the life of the law has not been logic: it has been experience." Adding experience—that is, examples—to the mix, in my mind, can only help.

Even in mathematics, it is exceedingly difficult to make progress on hard problems without the aid of examples and cases. Working mathematicians need them for checking conjectures and for coming up with them in the first place.[6] They play a key role in developing understanding. Mathematical reasoning involves a highly interconnected network of many types of knowledge, including theorems, definitions, proofs, heuristics, and examples, and there are many types of each—particularly examples.[7]

A problem for most of us with the extensional approach is that the only examples we've ever encountered are typical ones (in the core); we've never had to grapple with strange examples (in the penumbra). Intuitively—to paraphrase Justice Potter Stewart—we might know what to do with an easy example when we see one, but we really don't know how to deal with hard ones. Much of professional education in disciplines such as mathematics and law is about penumbral examples. The examples we use for induction often come from the core; only later on, when we begin to explore our ideas' ramifications, do we tackle penumbral examples. We've also been given contradictory messages about examples: Use examples to perform induction, but be wary of them because no example ever proves a rule (recall what your high school geometry teacher told you).

In the probabilistic sense, we tend not to be well acquainted with the rare instances in the tails of distributions. This paucity of examples often forces us to create hypotheticals or otherwise populate the little-encountered parts of the instance space to give us added experience with atypical situations. Instances and concepts are inevitably intertwined in the continuing cycle of conceptualization, testing, and refinement.

In putting together a hybrid approach, we can take a lead from the core-penumbra metaphor and, for instance, use rules, prototypes, or models for the core and cases or examples for the penumbra. We can view examples as annotations on the rules or models. Instead of a rule and its constituent predicates needing to be revised at every turn, cases can serve as updates to their meaning and scope. They are extensional patches. When (and if) the rules are revised, the cases can be taken into consideration. Over the years, various CBR systems have successfully used rule-case hybrids.[33–35] Cases have also been used to extensionally define principles in ethics.[36]

Another hybrid approach would be to use probabilistic approaches in concert with symbolic ones—for instance, statistical methods to propose concepts and classifications, and symbolic methods to provide precedent-based explanations and hypotheticals to test them out. Perhaps a three-way approach using cases and examples, rules and prototypes, and probabilistic methods would combine the best of many worlds.

To get a toehold on representation, we often make hefty assumptions that really don't hold with real-world concepts. One is that the features, predicates, or descriptors in which a concept is couched don't change. Another is that features aren't open-textured or hard to evaluate. In reality, features often change while the concept is changing, and they can be as tricky to identify and work with as the concept they represent.

As Murphy says, "category learning itself may be needed to identify features." Robert Collins and I discussed this same problem in the context of Levi's well-known legal example using a version space approach.[37] It's a central problem in statutory law, where rules tend to change in the same time frame as their ingredient terms do. For instance, in American personal (Chapter 13) bankruptcy law, the concept of a "good plan" changed at the same time that the underlying predicate of "good faith" (and, in turn, its underlying feature of "disposable income") changed. In the Lakatos example, the substrate of concepts about faces, edges, and so on changed at the same time that the concept of Eulerian polyhedra did.

Such issues have implications for all manner of human and machine learning, in that the representational framework in which the learning is supposed to take place often changes simultaneously with the concepts, generalizations, rules, prototypes, and so on being learned. Although pragmatically we need to "live" in some space to get something started, we'll need to revisit these deep problems. We can't sweep them under the rug forever.

## Example-based probing

The part of a concept that often requires the most interesting reasoning is in the penumbra, or penumbras—the boundary zones where classification of instances isn't clear. One way to probe the penumbra is through hypotheticals—that is, made-up instances. (See the sidebar "An Example from Law.") In the penumbra, actual experience can be sparse (otherwise, the issues would probably have been fleshed out), and hypotheticals enrich the store of experience.

There are two aspects of probing with hypotheticals or examples:

1. *Specification*—deciding, out of a vast instance space, what (few) artful examples to use.
2. *Generation*—producing examples that satisfy the specifications. I call this *constrained example generation*, or CEG.

The constraints for probing examples come from the reasoning context. For instance, in mathematics, if you suspect that a conjecture (say A => B) is false and want to disprove it, you need a counterexample—that is, an instance having property A and not property B. If you believe the conjecture is true, you want a supportive, positive example—that is, an example having both properties. Teachers often put a lot of care into specifying examples to motivate, illustrate, refine, and limit the concepts they're teaching. They take into account not only domain-specific specifications but also those specific to their students and their own tastes, capabilities, and so on. Examples and hypotheticals are often used sequentially.[7,38] For adults, children, and machine learners, the examples' order can be important.[39–41]

The part of a concept that often requires the most interesting reasoning is in the penumbra, or penumbras—the boundary zones where classification of instances isn't clear.

To explore the limits of a line of reasoning, an appellate judge or law school professor might pose a hypothetical that is more extreme than the case at hand in order to press the advocate or student about whether the proffered line of reasoning should extend to the part of the instance space exemplified by the hypothetical. A series of hypotheticals might be constructed in the manner of a "slippery slope" sequence. Hypotheticals can include facts that support two conflicting lines of reasoning (for example, a house on wheels). Many argument strategies and tactics involve hypotheticals.[42]

CEG uses a retrieval-plus-modify strategy: satisfy as many constraints as possible through retrieval from a corpus of examples and then modify the best candidates with domain-specific methods to try to satisfy the other constraints.[43–45] This is essentially a case-based approach, so CEG can be considered an early CBR precursor.

The HYPO project, which grew out of CEG, initially set out to model the creation of hypotheticals in law. It culminated, in Kevin Ashley's 1987 doctoral dissertation, in a full-scale computational model for case-based legal argument encompassing point-counterpoint thrusts and parries, methods to compare cases, and methods for creating hypotheticals.[46–48] HYPO was one of the earliest "interpretive" CBR systems: its goal was to interpret a new fact situation in light of existing precedents. HYPO has since had many progeny, including a mixed-paradigm cases-and-rules system called CABARET (for *ca*se-*ba*sed *re*asoning *t*ool) for the income tax law domain[33] and a case-based tutoring system called CATO to help law school students learn how to argue.[49,50]

A key mechanism in HYPO-style systems is a *dimension*.[46,48,51] Dimensions capture the knowledge that different ways exist to argue about an issue. They're an intermediate level of representation that encodes the knowledge that certain sets of facts enable a legal dispute to be approached in a particular way, and that changes in these facts tend to strengthen or weaken the argument of one side or the other. Dimensions focus attention on important aspects of cases. For instance, in HYPO's domain of misappropriation of trade secrets, the dimension called "secrets voluntarily disclosed" captures the idea that the more disclosures you (the plaintiff) have made of your putative secret, the less convincing is your argument that a particular party (the defendant) is responsible for letting the cat out of the bag (the secret). Dimensions are a hallmark of HYPO-style systems. There are several ways to use dimensions to generate hypotheticals, including making a case weaker or stronger, making a case extreme, enabling a near-miss, disabling a near-hit, and making a conflict hypothetical.[52] HYPO used such heuristics to generate hypotheticals in the context of an argument.[48]

Of course, there are other ways to generate hypotheticals that don't rely on dimensions. For instance, if you have metricized the instance space, you can create an instance lying midway between the centers of clusters of positive and negative examples, between the center of the core and the nearest unlike neighbor, between a particular case

## An Example from Law

The sort of reasoning done in Anglo-American appellate law provides good examples of what we (and our colleagues in psychology) should consider in future forays into similarity-based reasoning, explanation, analogy, learning, and teaching with nonstationary, nonconvex, open-textured concepts (see main article for more details). The law is rife with such examples.

This example is taken from the body of Fourth Amendment law concerning the warrant requirement. The Fourth Amendment states: "The right of the people to be secure in their persons, houses, papers, and effects, against unreasonable searches and seizures, shall not be violated and no Warrants shall issue, but upon probable cause, supported by Oath or affirmation, and particularly describing the place to be searched, and the persons or things to be seized." The US Supreme Court has interpreted this to mean that to execute a search the police must have a warrant except in a few circumstances (for example, incident to an arrest). With respect to a person's home, there's a longstanding reluctance to allow exceptions to the warrant requirement—"a man's home is his castle" sums up the default position. One of the primary rationales for this doctrine is that people have an *expectation of privacy* in their homes, hotel rooms, and similar places.

### *Carroll* and the rise of "The Automobile Exception"

On the other hand, the US Supreme Court has held that a person's car is not nearly as sacrosanct. Quite the contrary—it established the "automobile exception" to the warrant requirement in the prohibition-era case of *Carroll v. United States*.[1] This case involved a warrantless search on a public highway of a bootlegger's car, which the police suspected of transporting whiskey. The police did find 68 bottles of bootleg whiskey, but not before they ripped apart the back seat.

In *Carroll*, the Supreme Court held that when the police have probable cause to believe that a moving or temporarily stationed vehicle contains the fruits or instrumentalities of a crime, they may search it without a warrant. To justify the exception, the *Carroll* opinion relied in part on the long tradition of warrantless search of ships, especially for smuggled or contraband goods. It reasoned that a vehicle's mobility creates such an *exigent* situation that an exception to the warrant requirement is constitutionally valid. It recognized

> *a necessary difference between search of a store, dwelling house or other structure in respect of which a proper official warrant readily may be obtained, and a search of a ship, motor boat, wagon, or automobile, for contraband goods, where it is not practicable to secure a warrant because the vehicle can be quickly moved out of the locality or jurisdiction in which the warrant must be sought. (p. 153)*

However, it also wrote:

> *In cases where the securing of a warrant is reasonably practicable, it must be used.*

In carving out the automobile exception, the *Carroll* case triggered a stunning conceptual change.

### From *Carroll* to *Carney*

In the years following *Carroll*, the vehicle exception was considered many times. For the most part, the dichotomy in the class of places for Fourth Amendment purposes remained neatly cleaved into "homes" and "vehicles." In some cases, the Court questioned the exigency rationale of *Carroll* and used a competing rationale based on a *lesser expectation of privacy*—for instance, in *Cardwell v. Lewis*, it wrote:

> *One has a lesser expectation of privacy in a motor vehicle because its function is transportation and it seldom serves as one's residence or as the repository of personal effects. A car has little capacity for escaping public scrutiny. It travels public thoroughfares where both its occupants and its contents are in plain view.[2] (p. 590)*

The Court also tried to keep the exception in check. For instance, in *Coolidge v. New Hampshire*, it remarked that

> *The word "automobile" is not a talisman in whose presence the Fourth Amendment fades away and disappears.[3]*

Nonetheless, the vehicle exception became well-settled doctrine with a comfortable bifurcation—houses and cars—and two distinct ways of looking at the problem—exigency and privacy—with each having a gradation of circumstances. Situations with low expectation of privacy or high exigency (cars) are candidates for constitutionally valid warrantless searches, while those with high expectation of privacy and low exigency (houses) enjoy the warrant requirement's full protection. Although what happens otherwise—say, high expectation and high exigency—is arguable, at least what obtains in these prototypical cases appears clear.

Another way to picture the situation is to think of the concept of valid Fourth Amendment searches and seizures as an open set sitting in some (high-dimensional) instance space. A house is in the settled core. A hole exists in this set owing to *Carroll*, and a car is clearly a typical case in the core of this hole. An (interior) penumbral case—in the boundary of the *Carroll* hole—would be a Winnebago. An (exterior) penumbral case would be a camper's tent or a homeless person's cardboard box shelter.

Over the years, the search issue in the automobile context has been revisited again and again. There have been innumerable cases about searching containers (for example, suitcases and packages) in cars searched without a warrant. The Court created and even closed up exceptions. In a 1979 case (*Arkansas v. Sanders*), the Court held that an unlocked suitcase in a cab's trunk could not be searched without a warrant.[4] This created a hole in the hole of the automobile exception. Then in 1982 (*United States v. Ross*), it partially closed up the hole when it held that "if probable cause justifies the search of a lawfully stopped vehicle, it justifies search of every part of the vehicle and its contents."[5] In 1991, the Supreme Court completely overturned *Sanders* in *California v. Acevedo*.[6]

Thus, we don't have just a stoma in the concept, we have islands (of positive examples) within it, and holes within these. Visually, this is akin to a coral atoll with interior islands or even whole archipelagos within them. There are exceptions in the "main" home-as-castle part of the concept as well.

### *Carney*

Difficulties with the automobile exception were brought to the fore in *Carney v. California*, a perfect storm of a case.[7] *Carney* involved a warrantless search of a motor home for drugs.

A sequence posed to the attorney for the State of California:

**J**: Well, what if the vehicle is in one of these mobile home parks and hooked up to water and electricity but still has its wheels on?
**A**: If it still has its wheels and it still has its engine, it is capable of movement … very quickly.
**J**: Even though the people are living in it as a home, are paying rent for the trailer space, and so forth?
**J**: Well, there are places where people can plug into water, and electricity, and do … where people go and spend the winter in a mobile home. And do you think there would be no expectation of privacy in such circumstances?
**A**: Well, I am not suggesting that there is no expectation …
**J**: May I inquire, just so I understand your position? Is it that the vehicle have wheels? Could a trailer without a tractor in front of it qualify?
**A**: No. I don't think it would … if the officer looks … and determines that it has the objective indicia of mobility …
**J**: It has to be self-propelled?
**J**: But then what about a self-propelled vehicle that's plugged into the plumbing and the electricity?
**J**: And … even if it had been parked there three months or so …
**J**: What about a camper's tent, if the camper takes his things out of the motor home and pitches a tent next to it?
**A**: The motor home would be subject to search … Not the tent …
**J**: Why wouldn't the tent be just as mobile as a self-propelled vehicle? I gather you can pull it down pretty fast –
**J**: It doesn't have wheels, right?

Some hypotheticals posed to Carney's attorney:

**J**: We're getting closer to your case. Suppose somebody drives a great big stretch Cadillac down and puts it in a parking lot, and pulls all the curtains around it, including the one over the windshield and around all the rest …
**A**: It does come closer to a home …
**J**: Well it has everything in the back of it that your [house] has …
**A**: Does it have a bed?
**J**: Yes, yes.
…
**J**: [W]hat about a van. You see thousands of them on the road.
**A**: A van ordinarily would not be subject to the motor home exception.
**J**: Well, I've seen some with all the chairs, all the upholstered chairs in them.
**J**: So you would say that if there is a car parked alongside the motor home … they could enter the car but not the motor home?

**Figure A. Excerpts from the oral arguments in the US Supreme Court case *Carney v. California*. "J" indicates a hypothetical question from a Justice, and "A" indicates a reply by an advocate, either Carney's or the one for the State of California.**

The motor home was parked in a public parking lot, just a few blocks from the courthouse. A drug enforcement agent and others had it under surveillance for over an hour. They questioned a youth who had emerged from the motor home, and he told them that he had received marijuana in exchange for sex. The police then knocked on Carney's door. Carney stepped outside, and without his express consent or a warrant, the police entered and spotted marijuana. This led to his conviction on drug charges.

*Carney* presents a head-on clash between a citizen's expectation of privacy and the desires of the police to investigate unfettered where there is exigency. In the oral argument, the Justices probed with many hypotheticals (figure A offers some excerpts). As for the case's outcome, despite a strong dissent by Justices Stevens, Brennan, and Marshall, the Court reasoned that because Carney's motor home was "readily mobile," was parked in a public place "not regularly used for residential purposes," and was subject to many motor vehicle state regulations, it had a lesser expectation of privacy.

## Lessons learned

The *Carney* oral-argument example in figure A illustrates how hypotheticals can be used to probe a concept's penumbral regions. This extended example also illustrates how difficult it would be to craft a definition for a concept like constitutionally valid warrantless search. Heuristic rules of thumb do exist, but they're not hard and fast. Even if we could feed the corpus of Supreme Court cases into a concept-formation engine and then use the induced rule (or prototype) to classify a new case, this still would not be a useful model of legal reasoning. In particular, judicial reasoning requires consideration of precedents—both pro and con—to justify a decision. Giving a high probability or a nice hyperplane isn't sufficient.

The *Carroll-Carney* example also illustrates the role of exceptional cases in concept change. One critical issue about concept change is identification of episodes of change, particularly their onset. While the beginning of a change that's provoked by a single, stunning example such as *Carroll* isn't that hard to spot, gradual change is usually harder to identify other than in retrospect, because a court might initially dismiss an early harbinger case as an anomaly or even wrongly decided.

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6. *California v. Acevedo*, 500 U.S. 565 (1991).
7. *Carney v. California*, 471 U.S. 386 (1985).

and its nearest like neighbor, and so on.[53] You could use hypotheticals on either side of a boundary—say, close pairs of like and unlike neighbors that straddle a known flip in classification.

In the next few years, I hope we pay more attention to dealing with the problems of concepts and problems of analogy and explanation. Concepts must be dealt with in their own right, particularly those that are open-textured, changing, and exception ridden. Our systems must learn to keep their versions up-to-date and responsive to changes in their application and their contexts.

We must understand better how one entity—human or not—can instruct, show, teach, advise, or argue with another. We must know more about explanation and justification—for instance, how one agent can convince or dissuade others about an interpretation or a course of action. We must better understand how explanation, learning, and concept change are inextricably intertwined.

In summary:

- Our systems must be able to deal with messy concepts, including learning their changes and detecting exceptions and anomalies. At the beginning, of course, we'll have to program in such dealings, but they must be widely alterable and adaptable at all levels.
- A key process is to be able to work with similarities (and differences) in the system's experiences, often at many levels at once. That is vital for handling analogies, so that lessons learned can be explained and applied suitably.
- Work on CBR, example-based reasoning, and explanation can help us break through current boundaries to give AI a vaster arsenal of methods for similarity-based problem solving. We need more of it.
- As our systems work through different experiences, they should learn to discover new similarity measures and new techniques.

Right after discussing the CBR heuristic in *Computers and Thought*, Feigenbaum and Feldman suggest that one problem "ripe for attack" is the learning of heuristics, particularly those dealing with concepts. Perhaps in the next few decades, AI systems will be able to discover new approaches to similarity and new, powerful reasoning methods for analogy. Perhaps one day, as the great mathematician Stefan Banach was said to remark, they'll even be able to "see analogies between analogies."[54]


## Acknowledgments

I thank Jake Beal, Paul Cohen, Ken Forbus, Dedre Gentner, Jim Hendler, Roger Hurwitz, David Waltz, Patrick Winston, and especially Oliver Selfridge for all their critical discussions and generous feedback on this article. I acknowledge the support of the US National Science Foundation in preparing this article. Any opinions, findings, conclusions, or recommendations expressed in this material are my own and do not necessarily reflect the views of the NSF.


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