CSE 513T Theory of Artificial Intelligence & Machine Learning October 27, 2016

Lecture 16

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Today′s topics :

- "Common Sense" knowledge and reasoning
- Non-monotonic reasoning and reasoning with examples

Two types of knowledge

1. Acquired knowledge : Deduced/Declarative and Inductively learned (from personal experience or a knowledge that everyone knows), and
2. Innate knowledge

Common Sense
"Common sense" is a variety of tacitly shared knowledge that we rely on in an action or communication. Common sense ≈ Innate knowledge + Inductively learned knowledge that everyone knows.

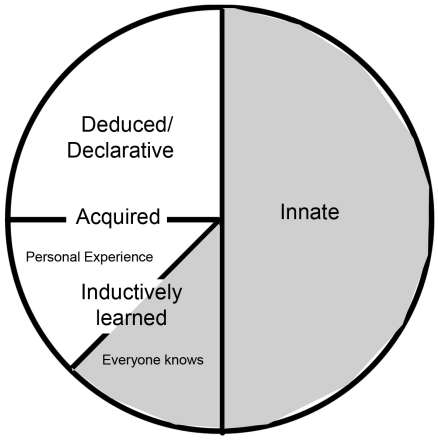

Figure 1: *Types of knowledge with common sense represented in the shaded region.*

Some questions that we do not know answers to:

- How much of what we know is innate?
- What knowledge is innate?

Cognitive psychology has identified several domains that seem to be innate:

- Space & Objects e.g. ideas about "persistence","identity", etc.
- Naive physics
- Naive psychology (intentions and emotions, etc)
- Quantitative reasoning (more vs less, small numbers arithmetic, etc.)

Innate domains are not generally present at birth but are developed according to a fixed schedule. It seems unlikely that some of these could be learned. For example, the relatively complex models of naive psychology. In other cases, for example naive physics, it seems that perhaps simulation or other "non-logical" method are useful to answer such questions.

Non – monotonic Reasoning
In common sense reasoning, it is important to be able to "leap to conclusions". For example, if I place a book in my bag, then in the absence of the evidence to the contrary, I "know" (presume) my book is still there. If I open the bag and the book is not there - maybe it fell out, maybe someone took it out, etc. then I am forced to "retract" that the book is in the bag.

Contrast this with classical logic: As I learn more i.e. add representations to my knowledge base KB, only more representations become valid for the KB, desirable from the KB and so on. In this sense, classical logic is monotonic, but common sense reasoning is not.

Some key questions:

- Which conclusions that aren't entailed should we reach?
  (The common sense's "Law of inertia" i.e. "everything is presumed to remain in the state in which it is" is a good candidate. What else?)
- How do I reach them efficiently?

Many of the properties we wish to assert are similar to the kinds of rules we considered in agnostic learning. For example, birds fly, games are won or lost, etc. Reasoning with examples using "filtering" mechanism captures at least some of the behavior for learned knowledge.

Lets suppose we had some examples drawn from a distribution D, and we "filtered" out the examples where $bird(x) \neq 1$. This has the affect of simulating draws from the conditional distribution $D/bird$ if $bird(x) = 1, and 0$ otherwise. Here, $D/bird(x) = D(x)/Pr(bird)$.

bird	fly	has-beak	red	purple	penguin
1	1	1	0	0	0
1	1	1	1	0	0
1	0	1	0	0	1
1	1	1	0	0	0
1	0	1	0	0	1
1	1	1	1	0	0
1	1	1	0	0	0

Table 1: Sample truth table for $bird(x)$ with example attributes such as fly, has-beak etc.

Suppose we are willing to tolerate $\epsilon = 1/3$ error. Do we conclude that "fly" is $1 - \epsilon$ valid?
$= \frac{1}{7}\sum_{i=i}^{7} fly(x^{(i)}) = \frac{5}{7} \geq \frac{2}{3}$, hence valid.

How about $bird \wedge red$?
$= \frac{1}{7}\sum_{i=i}^{7} fly(x^{(i)}) = 1 \geq \frac{2}{3}$, so red birds fly.

How about $bird \wedge penguins$?
$= \frac{1}{7}\sum_{i=i}^{7} fly(x^{(i)}) = 0 < \frac{2}{3}$, so cannot conclude "fly". But actually, $\frac{1}{7}\sum_{i=i}^{7} \neg fly(x^{(i)}) = 1 \geq \frac{2}{3}$, so birds

that are penguins conclude "do not fly".

If we consider $bird \wedge penguin \wedge has\ beak$, still $\neg fly$ holds.

What about purple penguins?
Here, we have no example. Hence, we are unclear how to decide. If $Pr[\ penguin \wedge purple\ ] = 0$, then the conditional distribution $D/purple\ penguin$ is not well-defined. Hence, we shouldn't come to any conclusions.

Common issues in common sense representations

1. **Qualification problem** :
   It is impossible to list out all of the conditions that are necessary for some "natural concept" to be true.

   For example, take "birds fly". To account for penguins, we might assert that "birds that are not penguins fly". How about dead birds?. To accommodate this we may say "Birds that are not dead and are not penguins fly". However, how about birds in other planets with high gravity? and so on...

   We avoided this problem in PAC semantics by allowing the rule to fail $w.p.\ \epsilon$ for some unexpected reason.

2. **Ramification Problem** :
   Especially when we reason about action and change, one small change or a piece of information can have many consequences. For example, if we are loading a crate on to a boat and the boat sails away. Then the crate goes with the boat along with everything inside the crate.

   We need to efficiently derive the many conclusions about things changing while respecting the law of inertia. On reasoning with examples, at least the attributes that are represented are "automatically" updated when we filter.

3. **Elaboration tolerance** :
   When we do discover a new exception to a rule, we'd like to be able to incorporate the knowledge of this exception without needing to modify every rule in the KB i.e. the updates should be "efficient". In reasoning with examples we simply add exceptional example to a list and reason as usual with the larger list.

Classical approach to common sense

Produce a KB containing all common sense knowledge. Estimates of the size of this KB run on the order of $0.5 - 3.4\ Gb\text{s} \approx 10^7 - 10^8$ "elements" of knowledge. Curating such a KB manually is daunting. Most prominent effort still only contains 7M assertions with about 3M terms in 3 years.

- Automated Collection (For example. from the web)
  KNEXT mined 10^8 "factoids" from Wikipedia and blogs. But we are after really mundane knowledge such as "water needs a container",etc. which is rare to find in web.

- Crowd sourcing
  Open Mind Common Sense (OMCS) project grew from 4.5×10^5 facts to $> 1M$ in 2014. Still may take > 100 years with this rate.

How do we acquire so much knowledge so quickly?
How can we use such a KB so efficiently?

Reasoning with examples by contrast may "implicitly" encode the answers to (exponentially) many queries in relatively few examples.
Main problem is that the method relies heavily on complete information.

Next time, we will extend reasoning with examples to work with complete information.