INSPECTION AND SELECTION OF REPRESENTATIONS

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OVERVIEW

Motivation

How to describe representations?

How to select representations?

Conclusions and work in progress

Motivation

People change representation to get to information

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We aim to build a tool that can help choose a suitable representation for a given problem for a particular person





Bayesian approach: represent problem in formal conditional probability.



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Bayesian approach: represent problem in formal conditional probability.

Assume: $\Pr(b) = \frac{1}{4}$, $\Pr(f \mid b) = \frac{2}{3}$, $\Pr(b \mid f) = \frac{1}{2}$. Calculate: $\Pr(\bar{b} \cap \bar{f})$

SOLUTION UNDER BAYESIAN APPROACH

Notice the following facts:

$$\Pr(\bar{b}) = \Pr(\bar{b} \cap \bar{f}) + \Pr(\bar{b} \cap f) \tag{1}$$

$$\Pr(f) = \Pr(b \cap f) + \Pr(\bar{b} \cap f) \tag{2}$$

$$\Pr(\bar{b} \cap f) = \Pr(\bar{b} \mid f) \Pr(f) = \frac{1}{2} \Pr(f).$$
(3)

From (2) and (3) we can show that $Pr(\bar{b} \cap f) = \frac{1}{2} Pr(b \cap f) + \frac{1}{2} Pr(\bar{b} \cap f)$, from which we obtain

$$\Pr(\bar{b} \cap f) = \Pr(b \cap f). \tag{4}$$

Thus, we have the following:

$$Pr(\bar{b} \cap \bar{f}) = Pr(\bar{b}) - Pr(\bar{b} \cap f) \qquad \text{from (1)}$$

$$= Pr(\bar{b}) - Pr(b \cap f) \qquad \text{from (4)}$$

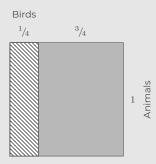
$$= (1 - Pr(b)) - Pr(f \mid b) Pr(b) \qquad \text{from probability axioms}$$

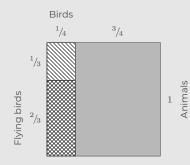
$$= \frac{3}{4} - \left(\frac{2}{3}\right) \left(\frac{1}{4}\right) = \frac{7}{12}. \qquad \text{from assumptions} \qquad \Box$$

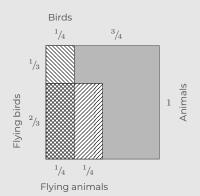
One quarter of all animals are birds. Two thirds of all birds can fly. Half of all flying animals are birds. Birds have feathers. If X is an animal, what is the probability that it's not a bird and it cannot fly?

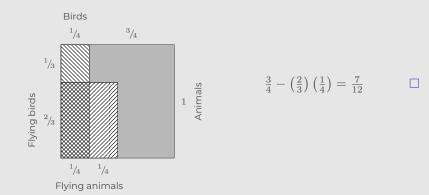
Animals











Assume: $Pr(b) = \frac{1}{4}$, $Pr(f|b) = \frac{2}{3}$, $Pr(b|f) = \frac{1}{2}$. Calculate: $Pr(\overline{b} \cap \overline{f})$

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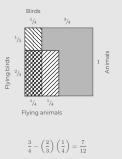
$Pr(\overline{b}) = Pr(\overline{b} \cap \overline{f}) + Pr(\overline{b} \cap f)$	(1)
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$\operatorname{Pr}(\overline{b} \cap f) = \operatorname{Pr}(\overline{b} f) \operatorname{Pr}(f) = \frac{1}{2} \operatorname{Pr}(f).$	(3)

From (2) and (3) we can show that $\Pr(\bar{b}\cap f)=\frac{1}{2}\Pr(b\cap f)+\frac{1}{2}\Pr(\bar{b}\cap f),$ from which we obtain

$$Pr(\overline{b} \cap f) = Pr(b \cap f).$$
 (4)

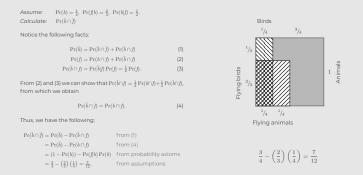
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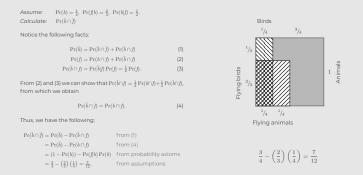


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Thus, we have the following:		1/4 1/4 Flying animals
$Pr(\overline{b} \cap \overline{f}) = Pr(\overline{b}) - Pr(\overline{b} \cap f)$ from (1)		
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How to describe representations?

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By the *symbols* they use, the *inferences* that can be done, and the *knowledge* they encode.

Grammatical & Inferential

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- ► tokens: atomic symbols
- **types**: classes of tokens and expressions
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For each RS, encode this into a table. This is our knowledge of the RS.

Bayesian

kind	value
types	real, event
tokens	$\begin{split} &\Omega, \emptyset, 0, 1, =, +, -, *, \div, \cup, \\ &\cap, \backslash, , \mathrm{Pr}, \end{split}$
patterns	_:real = _:real, Pr(_ _) = _,
facts	Bayes' theorem, law of total probability, non-negative probability,
tactics	rewrite, arithmetic calculation

Geometric

kind	value
types	point, segment, region,
	real, string
tokens	\$point, \$segment,
	\$shade
patterns	\$rectangle, \$contained,
facts	scale-independence of
	ratio, non-negative
	area, area additivity,
tactics	draw point, draw
	segment, delete, join,
	compare sizes





Presented in some RS (natural language in this case). Its table must look a bit like a sub-table of RS, BUT...



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Not everything is equally important!

PROBLEMS AND THEIR IMPORTANCE HIERARCHY

	kind	value
importance →	error allowed	0
	answer type	ratio
	tokens	probability, and, not
	types	ratio, class
	patterns	_: ratio of _: class are _: class,
	facts	Bayes' theorem, law of total probability,
	tactics	deduction, calculation
	tokens	one, quarter, all, animal, birds, two, thirds, can, fly, half, flying,
		X, cannot
	related tokens	times, divided_by, plus, minus, equals, or, union, intersection,
	# of tokens	67
	# of distinct	31
	tokens	
noise	tokens	feathers
no	related tokens	beast, animate, creature,

How to select representations?

A *correspondence* is a reason why one RS is suitable for a problem.

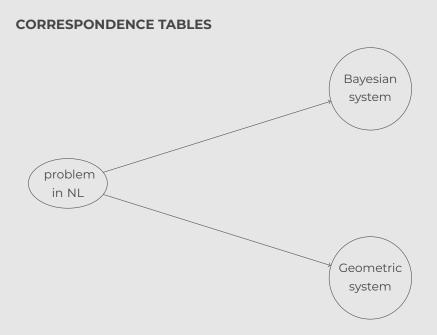
A *correspondence* is a reason why one RS is suitable for a problem.

Mostly analogical representational matches between tokens, types, patterns, tactics, facts etc.

Problem in NL	Bayesian RS	Geometric RS
is about <i>classes</i>	represents events	represents regions
is about	represents Pr	represents area
probability		(size)
is about <i>ratios</i>	represents <i>real</i>	represents <i>real</i>
	numbers	numbers
law of total	law of total	additivity of areas
probability is	probability is a fact	is a fact
useful		
no error allowed	is rigorous	is rigorous

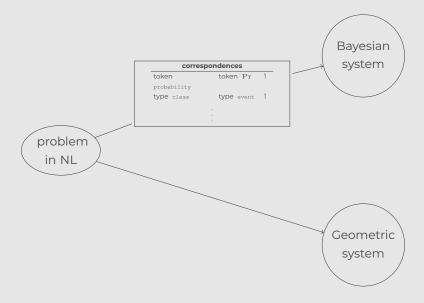
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In practice, we build correspondence tables to relate pairs of properties with a *score* (how good a reason is it?)

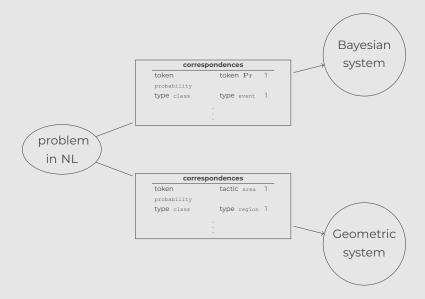


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- Add up correspondence scores (i.e., count reasons why S is good)?
- But reasons are not equally important,
- ▶ and reasons may not be independent from each other!

Thus we weight the score by the importance relative to the problem, and we encode correspondences with a simple logic.

MAKING A RECOMMENDATION

Bayesian	9.3
Geometric	7.2
Natural Language	6.9
Contingency	5.4
Euler	1.5

Conclusions and work in progress

A framework for representing representations

A proof-of-concept algorithm for suitability

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Main limitation is reliance on a human analyst for:

- describing RSs and problems (including importance)
- finding correspondences (including logical dependencies and scores)

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- finding correspondences (including logical dependencies and scores)

Can we automate this?

How can we evaluate this?

WHAT ARE WE WORKING ON NOW?

How to formalise the concept of correspondence.

- The probability of observing certain property in a solution in some candidate RS, given some observed properties in a problem.
- ▶ If so, how to infer correspondence scores, and how to use them?

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How to formalise the concept of correspondence.

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Cognitive properties of representations.

- Figuring out what how to calculate cognitive costs
- How to work the user into the calculations?

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