Modelling Typical Alphabetic Analogical Reasoning in ACT-R

Judith D.M. Grob (j.grob@ai.rug.nl)
Artificial Intelligence & Cognitive Engineering Institute, University of Groningen,
Grote Kruisstraat 2/1. 9712 TS Groningen, the Netherlands

Sharon Wood(sharonw@cogs.susx.ac.uk)
School of Cognitive and Computing Sciences, University of Sussex,
Falmer, Brighton, BN1 9QH, UK

Introduction

In the Copycat project (Hofstadter & Mitchell, 1995), alphabetic analogical reasoning problems (see Figure 1) were studied to gain a better understanding of the fluid processes underlying analogical reasoning. Human data were gathered on 5 different types of problems (see Table 1) and modelled in the hybrid computational model Copycat. The range of responses Copycat was able to produce to this type of problems was compatible with answers given by human participants (Hofstadter & Mitchell, 1995).

	left-hand-side		*right-hand-side*
source	**ABC**	→	**ABD**
target	**IJK**	→	**?**

Figure 1: Problem example

In their work, Hofstadter and Mitchell (1995) regard answers that are situated at a deeper conceptual level (e.g. answering problem 3 (Table 1) numerically with MRRJJJJ, reflecting 123?124) as more interesting or 'elegant'. However, inspecting their human data, we noticed that these more elegant answers were given only by a small percentage of participants, and didn't seem to be the typical answers of choice. We were interested to see what processes underlie the more commonly given answers, as this would give a better idea of how most people solve analogical reasoning problems.

Table 1: five problem types

	Source	*Target*	*Type*
1	ABC→ABD	IJK→?	Successor
2		IIJJKK→?	Grouped
3		MRRJJJ→?	Numerical
4		KJI→?	Reversed
5		XYZ→?	Boundary

Experimental data

To establish whether more frequently given answers, can be considered as being more typical statistically, a study was conducted. 40 Participants were asked to solve 22 alphabetic analogical reasoning tasks, which were selected from the Copycat work (see Table 3).

Inspecting the answers revealed that all problems but one, were most frequently solved by applying the rule "change the last letter(group) to its successor". For 13 problems this typicality reached statistical significance ($p<0.05$). On top of this, the tasks in cluster 3 showed a typical answer pattern, with three specific answers reaching a combined statistical typicality

To gain further insight in the underlying problem solving mechanism; verbal protocols were recorded for two more participants. All data combined led to a model for typical alphabetic analogical reasoning, which was implemented and tested in ACT-R (Anderson & Lebiere, 1998).

An ACT-R Model of Analogical Reasoning

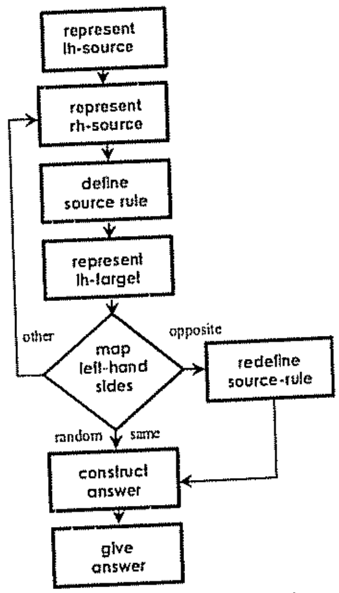

Figure 2: Flowchart of how the model solves a problem

The model starts tackling a problem by representing it (see Figure 2). Individual letters and groups of the same letters are represented on a syntactic level with counters denoting the size of the lettergroups. A semantic representation encodes the relationship between neighbouring items in the syntactic representation, being either 'next' for successive items or 'other' for non-consecutive items. When encoding of the entire string is complete, a higher level semantic representation, labelling the complete string as either a 'successorgroup', or an 'othergroup'; is constructed.

Table 2: Overview of how the model solves the problem "ABC" -> "ABD", "IIJJKK" -> "?"showing the result of each consecutive step.

Step	Result
Represent left source	ls-syntactic = A(1)-B(1)-C(1) ls-semantic = "successorgroup" (next-next)
Represent right source	rs-syntactic = A(1)-B(1)-D(1) rs-semantic = "othergroup" (next-other)
Infer source-rule	source-rule = body(same)-last(next)
Represent left target	lt-syntactic = I(2)-J(2)-K(2) lt-semantic = "successorgroup" (next-next)
Map left sides	"successorgroup"="successorgroup" => same
Construct Answer	lt-syntactic source-rule application I(2)- Body(same) I-I- J(2)- J-J- K(2) Last(next) L-L
Give Answer	Output = I-I-J-J-L-L

Table 2 shows how the model goes from representing to solving an example problem. In this example, there is a perfect mapping between the left side of the target and source. Therefore, the source rule, which describes how the left hand side should be changed to construct the answer, can easily be applied. For items with a reversed alphabetic flow (cluster 3) the model backtracks and re-represents the left hand target as a 'predecessorgroup', leading to a source rule that captures the fact that source and target are each others' opposites. If the alphabetic boundary is encountered (cluster 5), a circular notion of the alphabet ("A" being the successor of "Z") is conceived and applied.[1]

Evaluation

The model was run on the 22 problems shown in Table 3. Goodness of fit of the model was defined as the percentage of answers that the model could give that were the same as the data to which it was compared. The model shows a 100% goodness of fit, on the tasks for which typical answers had been identified.

Of course many more alphabetic analogical reasoning tasks can be imagined, and further research is needed to identify more precisely what the present model can and cannot handle, and why. Ultimately, the computational model should not only be able to describe typical answers, but predict them as well.

Discussion and Future Work

The presented work suggests that most people solve alphabetic analogical reasoning problems at an intermediate level, taking letter groups and reversed alphabetic flow into account, but ignoring deeper conceptual levels (e.g. numerical). Given this observed typicality, the question arises, why some people give non-typical answers. Do they, for instance, generate typical solutions like everyone else, but ignore them in the quest for more interesting solutions, or are these non-typical solutions their first best guesses?

Finally, Hofstadter and Mitchell (1995) suggest that answers based on a higher level of representation, are more 'creative'. It would be interesting to see whether a positive relationship between giving more elegant answers on the alphabetic analogical reasoning task and some general measure of creativity, does indeed exist. By extending the computational model to produce such 'elegant' solutions, we might become better placed to understand what constitutes 'creativity' of this kind.

Table 3: Most frequent answers given by participants and model to 22 alphabetic analogical reasoning problems with source ABC?ABD. "T" denotes statistical typicality and "Same" correspondence between model and human data.

Type	*N*	*Item*	*Most Frequent*	*T*	*Model*	*Same*
cluster 1	1	IJK	IJL	+	IJL	+
	2	XLG	XLH	+	XLH	+
	3	XCG	XCH	+	XCH	+
	4	ABCD	ABCE	+	ABCE	+
	5	CDE	CDF	+	CDF	+
	6	CAB	CAC	-	CAC	+
	7	CMG	CMH	+	CMH	+
cluster 2	8	IIJJKK	IIJJLL	+	IIJJLL	+
	9	HHWWQQ	HHWWRR	+	HHWWRR	+
	10	LMFGOP	LMFGOQ	-	LMFGOQ	+
	11	MNFGHOPQ	LMNFGHOPR	+	LMNFGHOPR	+
cluster 3	12	KJI*	KJH	-	KJH	+
			LJI	-	LJI	+
			KJJ	-	-	--
	13	EDC*	EDB	-	EDB	+
			FDC	-	FDC	+
			EDD	-	-	-
	14	CBA*	CBZ	-	CBZ	+
			DBA	-	DBA	+
			CBB	-	-	-
cluster 4	15	MRRJJJ	MRRKKK	-	MRRKKK	+
	16	MRR	MRS	-	MSS	-
	17	MMRRRJJJJ	MMRRRKKKK	-	MMRRRKKKK	+
	18	RSSTTT	RSSUUU	+	RSSUUU	+
	19	XPQDEF	XPQDEG	-	XPQDEG	+
cluster 5	20	XYZ	XYA	+	XYA	+
	21	GLZ	GLA	+	GLA	+
	22	CMZ	CMA	+	CMA	+

References

Anderson, J. and Lebiere, C. (1998). *The atomic components of thought*. Erlbaum, Mahwah, Nj.

Grob, J.D.M. (2002). *Modelling alphabetic analogical reasoning in ACT-R*. Unpublished Masters Thesis. University of Sussex, Falmer. http://www.ai.rug.nl/~judith/dissertation.ps

Hofstadter, D.R. and Mitchell, M. (1995) Perspectives on Copycat. In D.R. Hofstadter and FARG(Eds.) *Fluid Concepts and creative analogies. Computer models of the fundamental mechanisms of thought*. Basic Books, New York.

[1] See Grob (2002) for an extensive explanation of the workings of the model.