

# Efficient Modeling of Analogy

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**Abstract.** Analogical modeling (AM) is a memory based model with a documented performance comparable to other types of memory based learning. Known algorithms implementing AM have a computational complexity of  $O(2^n)$ . We formulate a representation theorem on analogical modeling which is used for implementing a range of approximations to AM with a complexity starting as low as  $O(n)$ .

## 1 Introduction

The algorithm for Analogical Modeling (AM) was first published in 1989 [1], and has since remained unchanged with the exception for some minor corrections [1, 2]. Known implementations of AM [2] suffer from having an exponential time complexity  $O(n)$  where  $n$  is the number of features used to describe a particular example.

AM is a memory based model and constructs a classifier on the basis of a set of examples  $\mathcal{D}$ . The key computation for the analogical classifier is the construction of the analogical set  $\mathcal{A}$  (defined below) associated with an exemplar  $\tau$  in conjunction with  $\mathcal{D}$ . We will show that the effect of the analogical classifier is obtained by constructing a generally smaller set  $\mathcal{M}$ , which, together with a set of parameters  $C$ , has the same effect as the original. The aim of this article is to prove that there exists a simpler, yet (roughly) equivalent function to build an analogical classifier, which avoids building the full lattice  $\mathcal{L}$  of the original model. The new function uses the set  $\mathcal{M}$  and a set of parameters to compute a close approximation. Different parameter sets correspond to different approximations.

## 2 Background on AM

AM has been used as a simulation model of cognitive psycholinguistics, and it compares well with connectionist models [3, 4]. AM does not suffer from the problems associated with the delta-rule of connectionist learning [3, pp.62 ff], and at the same time it accounts for significant phenomena such as ‘perceptual learning, latent inhibition, and extinction [...] within a single mechanism’ (ibid. p.62). In fact, there are very few assumptions in AM; there are, for example, no assumption on the distribution of exemplars, nor are global weights calculated.