Transfer Learning by Mapping and Revising Relational Knowledge

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1 Transfer Learning (TL)

Traditional machine learning algorithms operate under the assumption that learning for each new task starts from scratch, thus disregarding knowledge acquired in previous domains. Naturally, if the domains encountered during learning are related, this *tabula rasa* approach wastes both data and computational resources in developing hypotheses that could have potentially been recovered by simply slightly modifying previously acquired knowledge. The field of *transfer learning* (TL), which has witnessed substantial growth in recent years, develops methods that attempt to utilize previously acquired knowledge in a *source* domain in order to improve the efficiency and accuracy of learning in a new, but related, *target* domain [7,6,1].

2 Statistical Relational Learning (SRL)

Traditional machine learning methods also assume that examples are represented by fixed-length feature vectors and are *independently and identically distributed* (i.i.d). *Statistical relational learning* (SRL), studies techniques that combine the strengths of relational learning (e.g. *inductive logic programming*) and probabilistic learning of graphical models (e.g. *Bayesian networks* and *Markov networks*). By combining the power of logic and probability, such methods can perform robust and accurate reasoning and learning about complex relational data [2]. Also, SRL frequently violates the i.i.d. assumption since examples are not independent, in which case, inferences about examples must be made in unison (i.e. collective classification).

3 TL for SRL

Most TL research addresses supervised feature-vector classification or reinforcement learning. In contrast, our research has focussed on developing TL methods for SRL. *Markov logic networks* (MLNs) are an expressive SRL formalism that represents knowledge in the form of a set of weighted clauses in first-order predicate logic [5]. We have developed an initial MLN transfer system, TAMAR, that

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first autonomously maps the predicates in the source MLN to the target domain and then revises the mapped structure to further improve its accuracy [3]. Our results on transfer learning between three real-world data sets demonstrate that our approach successfully reduces the amount of computational time and training data needed to learn an accurate model of a target domain compared to learning from scratch.

We view transferring an MLN to a new domain as consisting of two subtasks: *predicate mapping* and *theory refinement*. In general, the set of predicates used to describe data in the source and target domains may be partially or completely distinct. Therefore, the first transfer task is to establish a mapping from predicates in the source domain to predicates in the target domain. For example, the predicate `Professor` in an academic source domain may map to `Director` in a target movie domain. Tamar searches the space of type-consistent mappings and determines the mapping that results in an MLN that best fits the available data in the target domain. Once a mapping is established, clauses from the source domain are translated to the target domain. However, these clauses may not be completely accurate and may need to be revised, augmented, and re-weighted in order to properly model the target data. This revision step uses methods similar to those developed for theory refinement [4], except the theory to be revised is *learned* in a previous domain rather than manually constructed for the target domain by a human expert.

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