

# Deep Transfer: A Markov Logic Approach

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■ Currently the largest gap between human and machine learning is learning algorithms' inability to perform deep transfer, that is, generalize from one domain to another domain containing different objects, classes, properties, and relations. We argue that second-order Markov logic is ideally suited for this purpose and propose an approach based on it. Our algorithm discovers structural regularities in the source domain in the form of Markov logic formulas with predicate variables and instantiates these formulas with predicates from the target domain. Our approach has successfully transferred learned knowledge among molecular biology, web, and social network domains.

People are able to take knowledge learned in one domain and apply it to an entirely different one. For example, Wall Street firms often hire physicists to solve finance problems. Even though these two domains have superficially nothing in common, training as a physicist provides knowledge and skills that are highly applicable in finance (for example, solving differential equations and performing Monte Carlo simulations). Yet standard machine-learning approaches are unable to do this. For example, a model learned on physics data would not be applicable to finance data, because the variables in the two domains are different. Despite the recent interest in transfer learning, most approaches do not address this problem, instead focusing on modeling either a change of distributions over the same variables or minor variations of the same domain (for example, different numbers of objects). We call this *shallow transfer*. Our goal is to perform *deep transfer*, which involves generalizing across different domains (that is, between domains with different objects, classes, properties, and relations). Performing deep transfer requires discovering *structural* regularities that apply to many different domains, irrespective of their superficial descriptions. For example, two domains may be modeled by the same type of equation, and solution techniques learned in one can be applied in the other. The inability to do this is arguably the biggest gap between current learning systems and humans.

We believe that an approach to deep transfer should satisfy three desiderata. First, it should be relational in order to capture properties among different predicates. Second, it should be probabilistic, to handle the uncertainty inherent in transfer in a principled way. Lastly, it should be able to express knowledge in a domain-independent manner to allow for transfer between domains described by different predicates and types. To meet these requirements, we have developed an approach, called deep transfer via Markov logic (DTM), based on a form of second-order Markov logic (Kok and Domingos 2007). It can be viewed as a way to automatically discover important structural regularities in one domain and apply them in another (Davis and Domingos 2009).

Markov logic unifies first-order logic and probability. It softens a logical knowledge base by associating a weight with each formula. Worlds that violate formulas become less likely, but not impossible. The logical formulas capture regularities that hold in the data for a given domain. However, the knowledge that the formulas encode is specific to the types of objects and predicates present in that domain. Deep

transfer attempts to generalize learned knowledge across domains that have different types of objects and predicates. In order to abstract away the superficial domain description, DTM uses second-order Markov logic, where formulas contain predicate variables (Kok and Domingos 2007) to model common structures among first-order formulas. To illustrate the intuition behind DTM, consider the formulas  $Complex(z, y) \wedge SameFunction(x, z) \Rightarrow Complex(x, y)$  and  $Location(z, y) \wedge Interacts(x, z) \Rightarrow Location(x, y)$  from a molecular biology domain. Both are instantiations of  $r(z, y) \wedge s(x, z) \Rightarrow r(x, y)$ , where  $r$  and  $s$  are predicate variables. Introducing predicate variables allows DTM to represent high-level structural regularities in a domain-independent fashion. This knowledge can be transferred to another problem, where the formulas are instantiated with the appropriate predicate names.

DTM works with any learner that induces formulas in first-order logic. Given a set of first-order formulas, DTM converts each formula into second-order logic by replacing all predicate names with predicate variables. It then groups the second-order formulas into cliques. Two second-order formulas are assigned to the same clique if and only if they are over the same set of literals. It is preferable to use second-order cliques as opposed to arbitrary second-order formulas because multiple different formulas over the same predicates can capture the same regularity. A clique groups formulas with related effects into one structure. DTM evaluates which second-order cliques represent regularities whose probability deviates significantly from independence among their subcliques. It

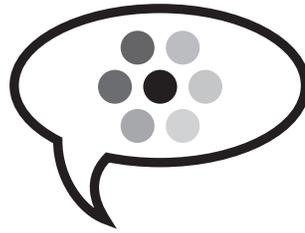
selects the top  $k$  highest-scoring second-order cliques to transfer to the target domain. Finally, the highest-scoring cliques are transferred to the target domain where they guide the structure learner to fruitful parts of the search space.

We have applied DTM to transferring learned knowledge among molecular biology, web, and social network domains. Across a variety of transfer conditions, we found that DTM led to more accurate learned models in the target domain compared to learning from scratch. In addition to improved empirical performance, DTM discovered patterns that include broadly useful properties of predicates, like symmetry and transitivity, and relations among predicates, such as various forms of homophily.

Despite its promise, deep transfer remains an underexplored area of research within the artificial intelligence community. From a practical standpoint, the ability to exploit previously acquired data and knowledge can both lead to more accurate learned models and help mitigate the need to collect large amounts of labeled data for each new task. From a cognitive perspective, transfer can help bring a learning system's capabilities closer to those of humans. Going forward, many crucial research questions must be addressed, including: investigating new structure learning algorithms, deciding the best source domain to transfer from for a given target domain, performing a theoretical analysis of deep transfer, and studying transferring from multiple domains at once. One direction that we find particularly exciting is pursuing approaches that discover regularities beyond simple properties like transitivity. For example, networks have many different structural properties that can be discovered and transferred: rings, hierarchies, cliques, chains, and so on (Kemp, Goodman, and Tenenbaum 2008; Kemp and Tenenbaum 2008). Furthermore, causal relationships are another important type of structure that we would like to uncover. This would allow us to learn a theory of causality in one domain and apply it in others. In fact, Goodman, Ullman, and Tenenbaum (2009) have hypothesized that this is what infants do. Detecting these types of structures may require new approaches to deep transfer. Deep transfer promises to be a source of fascinating problems and significant advances for machine learning for years to come.

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