ILP14 Reviews

----------------------- REVIEW 1 ---------------------  
PAPER: 22  
TITLE: Fast Learning of Relational Dependency Networks  
AUTHORS: Oliver Schulte, Zhensong Qian and Arthur E. Kirkpatrick  
  
OVERALL EVALUATION: 4 (extended version in LNCS)  
REVIEWER'S CONFIDENCE: 3 (medium)  
  
----------- REVIEW -----------  
This paper presents  an approach to compute a relational dependency network  by first learning a  Bayesian network and then transforming it into a relational dependency network. Experiments investigate both accuracy and scalability of the proposed approach compared to benchmark competitors  
  
Some suggestions to improve this manuscript are listed below:  
1) A theoretical study of the time **complexity** of the presented approach should be reported in Section  3.  
2) The **pseudo code** of the several steps shown in the program flow of Figure 2 should be included in the paper. Some examples can be used to describe these steps.  
3) A **statistical analysis** (e.g. the pairwise Wilcoxon test) of the results reported in Tables 3-4 should be added to the paper, in order to determine the statistical significance of the reported comparisons.  
  
  
----------------------- REVIEW 2 ---------------------  
PAPER: 22  
TITLE: Fast Learning of Relational Dependency Networks  
AUTHORS: Oliver Schulte, Zhensong Qian and Arthur E. Kirkpatrick  
  
OVERALL EVALUATION: 4 (extended version in LNCS)  
REVIEWER'S CONFIDENCE: 4 (high)  
  
----------- REVIEW -----------  
The paper illustrate how to make use of relational Bayesian network learning for learning relational dependency networks.   
  
  
A rather technical question, in the original work on dependency networks Heckerman et al. actually spend quite some space on **consistency**, say that not every DN is consistent.

Now, given you start with learning a BN, does that mean that the induced DNs are always consistent? This may also explain the different performances across the different benchmarks.   
  
Furthermore, the text uses relational models and propositional models in an interchangeable way. It think it would be better to carefully say exactly which type of model is meant in each situation. Why?  
Well, while I agree that a BN can easily turned into a DN, I am not so sure about relational BNs. This very much depends on the semantics.   
For instance, if you allow for existentially quantified variables or equality constraints, then we cannot just link nodes. We have to ground it. And actually Section 4 is all about this.   
  
Finally, and maybe a potential downside is the missing discussion of why the proposed **learning method is performing so well**. Is it the bias of the used relational BN learner? Is it the specific formula explained in Section 4? It appears to me that this implements  
a form of regularization that may explain the better predictive performance on some benchmarks. Or, is it because of a more efficient implementation?  
I mean how much is the slower running time of the boosting approaches due to its implementation? How many iterations does it take actually? Could we stop early?  
  
Anyhow, these are never-ending questions and I like the empirical observation that transformations of different relational models can actually „boost“ performance. This is an interesting take-away story.   
Still, I would like to encourage the authors to spend more space on a discussion trying to explain the difference. In the end, you have **only one large dataset** and here I can imagine that Hoeffding trees could actually speed up the boosting approaches a lot.   
  
<http://ilp11.doc.ic.ac.uk/short_papers/ilp2011_submission_33_old.pdf>  
  
This may in a boosting context even have a regularization effect as we do not „memorize all the training cases“ as explained in the above extended abstract. I think the authors should really touch upon an explanation.  
  
To summarize, an interesting idea that shows some benefit. Unfortunately, only one larger dataset has been used so that we do not understand the scaling behavior well. And the "why" is not discussed.  
  
  
----------------------- REVIEW 3 ---------------------  
PAPER: 22  
TITLE: Fast Learning of Relational Dependency Networks  
AUTHORS: Oliver Schulte, Zhensong Qian and Arthur E. Kirkpatrick  
  
OVERALL EVALUATION: 3 (weak accept in LNCS)  
REVIEWER'S CONFIDENCE: 3 (medium)  
  
----------- REVIEW -----------  
The paper presents an approach for computing RDN from large dataset by using a two-step process of generating first a Bayesian network structure with parameters and then transforming this structure into a RDN. The novel contribution is the transformation of BN parameters into DN parameters. The proposed method uses the notion of Markov blanket.   
  
The approach has been applied to benchmarking large databases of difference sizes including the MovieLens dataset containing 1M records. It is shown that the predictive accuracy compares well with that of existing state-of-the-art function gradient boosting methods but it is can scale up to larger datasets.   
  
The paper clearly provides a valuable contribution to the area of Machine Learning, although in the experimental evaluation section it is not clear what it is learned. The paper is generally well written although it lacks of explanations of the notations used.   
  
- For example, in Figure 1it Is not clear why some functors are have capital initial and others don’t.   
- It is not clear what the dashed arrows mean in the transformation of BN to Dn. The authors should explain this further.   
- In Section 4 Definition 1 provides the main technical contribution of this work: i.e. **how to generate the DN parameters from given BN parameters**. It is therefore important that provide detailed explanation so to allow readers with limited technical background in this area to have a good understanding of the benefits of this method for computing parameters. An example should be given that exemplifies the notion here defined, and instantiate all the notations used.  
  
Minor typos:    
1)        page 6, last line: “new new”  
2)        page 7: include the www link in the references.  
3)        page 11: “learning a Bayesian network learning”