**From:** **KR 2022** kr2022@easychair.org
**Subject:** KR 2022 notification for paper 106
**Date:** 15 April 2022 at 14:14
**To:** Alessandra Russo a.russo@imperial.ac.uk

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Dear Alessandra,

We are pleased to inform you that your submission

106: Embed2Sym - Scalable Neuro-Symbolic Reasoning via Clustered Embeddings

has been accepted for the technical program of KR2022 as a full paper. Congratulations!

We received 218 paper submissions (180 full, 38 short) to the conference, of which 58 submissions (26.6%, 51 full, 7 short) were accepted (or conditionally accepted) for the technical program (consisting of the Main track, the Applications & Systems track, and the Special Sessions on KR & Machine Learning and KR & Robotics). We received a large number of high-quality submissions, the decisions were not easy, and the threshold for acceptance was high. You can be proud of the success of your paper!

The KR 2022 Program Committee worked hard to provide a careful evaluation of the submitted papers. All papers received at least three reviews. Following the author response period, the reviewers and the area/track chairs discussed (sometimes extensively) the overall merits of papers, in several cases, when required by the discussion, with the help of additional reviewers.

Please note:

1. The camera-ready copy of a full paper is restricted to 10 pages including references. Please address any comments or concerns raised by the program committee in the final version of your paper.

The final, hard deadline for submissions of the camera-ready version of your paper and all source files, along with a signed copyright form, is

** Saturday, May 7, 2022 (AoE). **

The accepted full papers and short papers will be published by IJCAI Inc. in the KR 2022 proceedings.

2. Regarding the camera-ready copy submission, you will receive a separate email with an invitation link and instructions to submit your final version. Please stay tuned.

3. At least one author must register and attend the conference for the paper to be included in the proceedings (but of course we hope that all authors will attend KR 2022). The registration page will open soon.

4. In addition to publication of your paper in the KR 2022 proceedings, you will be given an oral presentation slot at the conference. The details will be provided in a separate email later on.

We'd like to bring to your attention the upcoming deadlines for other components of the KR program, as well as related events:

* 35th International Workshop on Description Logics (deadline: April 23): https://dai.fmph.uniba.sk/events/dl2022/
* 20th International Workshop on Non-Monotonic Reasoning (deadline: April 23): https://sites.google.com/view/nmr2022/home-page
* KR 2022 Doctoral Consortium (deadline: April 30): https://kr2022.cs.tu-dortmund.de/call_for_doctoral_consortium_applications.php
* KR 2022 Workshops (paper submission deadline: May 10): https://www.floc2022.org/workshops

Please consider submitting to these events yourself and/or encouraging your colleagues and students to do so.

At present, KR 2022 is intended to be a fully in-person event (not a hybrid event). The final decision on whether to go ahead with an in-person event will be made on May 1. Information about this decision, as well as details about registration and the conference program, will be posted on the conference website as they become available.

We thank you for submitting to KR 2022.

Regards,

Gabriele Kern-Isberner and Tommie Meyer
KR 2022 Program Chairs

SUBMISSION: 106
TITLE: Embed2Sym - Scalable Neuro-Symbolic Reasoning via Clustered Embeddings

------------------------ METAREVIEW ------------------------
There was complete agreement among the reviewers that this is an interesting and valuable paper worth being accepted at KR 2022. I fully agree and recommend acceptance.

----------------------- REVIEW 1 ---------------------
SUBMISSION: 106
TITLE: Embed2Sym - Scalable Neuro-Symbolic Reasoning via Clustered Embeddings
AUTHORS: Yaniv Aspis, Alessandra Russo, Krysia Broda and Jorge Lobo

----------- Overall evaluation -----------
SCORE: 2 (accept)
----------- Reviewer's confidence -----------
SCORE: 3 (medium)
----------- Relevance of the paper to KR -----------
SCORE: 4 (good)
----------- Novelty -----------
SCORE: 3 (fair)
----------- Significance -----------
SCORE: 4 (good)
----------- Technical quality -----------
SCORE: 4 (good)
----------- Discussion of related work -----------
SCORE: 4 (good)
----------- Quality of the presentation -----------
SCORE: 4 (good)
----------- Review -----------
After rebuttal: Thank you for the response to the questions that I pointed out in the review. I would like to suggest that the points that arouse some misunderstanding are clarified in the final version.

The paper contributes with a learning algorithm in the category of neuro-symbolic reasoning systems. The paper aims at reducing the training time of other learning algorithms in this same category by augmenting the neural network components and making the symbolic part responsible for automatically labeling latent concepts discovered by the neural components. The output of the neural components in the form of embeddings first feeds a clustering procedure, and an ASP-based solver labels the clusters.

The proposed method is successful compared to NEURASP and DeepProblog in terms of accuracy and training time in three tasks: MNIST addiction, CIFAR-10 addiction, and the Member task. Although the paper does a good job of introducing examples and algorithms to guide the explanation of the inner workings of the proposed method, there are a few points that require clarification. First, the meaning of 'h in its symbolic form' is not clear, as 'h' is a typical neural network so far in the paper. Although the paper includes the ASP-solver in a logical program, it is unclear how the rules account for the score and misclassified data points. It is also unclear how dependent the method is on background knowledge. As some problems may require difficult-to-code BK, it is unclear what would happen in cases where the BK is unavailable. The paper mentions that learning such rules is a matter of future work, but it should be more explicit if the BK stands for constraints of the problem only
or if they should hold more knowledge essential to solving the tasks.

The paper states that Tables 1, 2, and 3 include training and testing results concerning the experiments. As Tables 1 and 2 exhibit accuracy, it is not clear if those accuracies are only the predictive ones. Also, the paper states that the reasoning component was not trained efficiently for the MNIST task, and it is unclear what this means. Several previous works also combine neural and symbolic components to solve tasks such as link prediction, question answering, and classification in relational problems, such as knowledge graphs. One may wonder how this system would behave on such kinds of problems. It is not clear if the method's input should always be in the form of multimodal data (image, text, symbolic data). Finally, the paper should compare their results with DeepStochLog, as it is much faster than DeepProbLog, and the central claim of the current paper is scalability.

----------------------- REVIEW 2 ---------------------
SUBMISSION: 106
TITLE: Embed2Sym - Scalable Neuro-Symbolic Reasoning via Clustered Embeddings
AUTHORS: Yaniv Aspis, Alessandra Russo, Krysia Broda and Jorge Lobo

----------- Overall evaluation -----------
SCORE: 1 (weak accept)
----------- Reviewer's confidence -----------
SCORE: 3 (medium)
----------- Relevance of the paper to KR -----------
SCORE: 4 (good)
----------- Novelty -----------
SCORE: 3 (fair)
----------- Significance -----------
SCORE: 3 (fair)
----------- Technical quality -----------
SCORE: 3 (fair)
----------- Discussion of related work -----------
SCORE: 3 (fair)
----------- Quality of the presentation -----------
SCORE: 3 (fair)

SCORE: 3 (fair)
----------- Review -----------
The paper discusses a neuro-symbolic system that consists of a two-stage neural network
architecture for solving a downstream task end to end with a symbolic optimization method for extracting learned latent concepts. The trained perception network generates clusters in embedding space that are identified and labeled using symbolic knowledge and a symbolic solver.

In the related work, the authors should draw clear comparisons as to what is missing in existing approaches and what they are targeting. Moreover, a clearer comparison to the baseline methods such as DeepProbLog and NeurASP should be given.

Section 3 should present a pictorial representation of the overall framework/architecture proposed by the authors, this will provide more structure to the paper.

Tables 1 and 2 should highlight the best results since the proposed approach does not always outperform the existing system. The accuracy should also be reported over the iterations as presented in the original papers of the baselines.

The authors should also discuss the other tasks as discussed in the original paper [1] such as "Learning how to solve sudoku" or "learning the shortest path". If it is possible or not and if not why not.

[1] https://www.ijcai.org/proceedings/2020/0243.pdf

---------------------- REVIEW 3 --------------------
SUBMISSION: 106
TITLE: Embed2Sym - Scalable Neuro-Symbolic Reasoning via Clustered Embeddings
AUTHORS: Yaniv Aspis, Alessandra Russo, Krysia Broda and Jorge Lobo

----------- Overall evaluation -----------
SCORE: 2 (accept)
----------- Reviewer's confidence -----------
SCORE: 4 (high)
----------- Relevance of the paper to KR -----------
SCORE: 5 (excellent)
----------- Novelty -----------
SCORE: 4 (good)
----------- Significance -----------
SCORE: 4 (good)
----------- Technical quality -----------
SCORE: 5 (excellent)
----------- Discussion of related work -----------
SCORE: 4 (good)
----------- Quality of the presentation -----------
SCORE: 4 (good)
----------- Review -----------
The Embed2Sym paper introduces a new neuro-symbolic approach based on clustering information in encoded space for the perceptional model that takes inputs (images, in all given examples), and using a clever cluster label assignment strategy to connect a symbolic solver.

My review can be kept short: I liked the paper, because it is well-written, tackles a relevant and interesting topic, the authors clearly know the relevant related work, and the key idea of the paper is simple to grasp and seems to work.
The introduction is well-written and informative (beyond only the scope of the presented model), the method is clearly described, and the experiments are well formulated, and seem to be correctly executed and compared to DeepPropLog and NeurASP, with clear advantages in training efficiency.

The only point of criticism is the fact that all experimental results rely on latent image classification (MNIST / CIFAR), which can be expected to induce clear clusters in image representation space.  In that respect, the comparison to DeepProbLog and NeurASP is somewhat one-sided. To me the CIFAR-10 addition task could have been described more shortly, leaving space for an additional task.
For example, would the proposed idea work for the forth_sort task (from the 2021 version of the DeepProbLog paper)?  Not only cluster id's would be important, but also an ordering of clusters in representation space. Looking forward to seeing more work in this direction in the future.