



Foreword: special issue for the journal track of the 12th Asian conference on machine learning (ACML 2020)

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We welcome you to this special issue of Machine Learning Journal (MLJ), comprising of papers accepted to the journal track of the 12th Asian Conference on Machine Learning (ACML 2020), held virtually from 18 to 20 November 2020 (<https://www.acml-conf.org/2020/>). The ACML conference runs a dedicated journal track alongside the usual conference proceedings track. We are delighted to share the contributions with you.

This year's ACML journal track received a total of 38 submissions and 6 papers have been accepted for this special issue, after two rigorous rounds of reviews. Promising papers that did not quite meet the expected standard were allowed to be resubmitted after improvement, following the reviewing policy of this journal. The program committee members of ACML made bids on the papers for review assignment while ensuring that there were no conflicts of interest. The senior program committee members of ACML also followed the same process, acting as meta-reviewers for the papers. The senior program committee members who contributed to the reviewing process are:

Aditya Menon (Google, USA).
Alice Oh (KAIST, Korea).
Dinh Phung (Monash University, Australia).
Gang Niu (RIKEN AIP, Japan).
Jaegul Choo (KAIST, Korea).
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Qibin Zhao (RIKEN AIP, Japan).
Seungjin Choi (BARO AI, Korea).

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Takayuki Osogami (IBM Research—Tokyo, Japan).
Tao Qin (Microsoft Research Asia, China).
Vincent Zheng (WeBank, China).
Wei Lu (Singapore University of Technology and Design, Singapore).
Wittawat Jitkrittum (Google Research, Germany).
Yang Yu (Nanjing University, China).
Yasuo Tabei (RIKEN AIP, Japan).
Yung-Kyun Noh (Seoul National University, Korea).
Zhouchen Lin (Peking University, China).

The paper 'Learning with Mitigating Random Consistency from the Accuracy Measure' by Yuhua Qian, Jieting Wang and Feijiang Li presents a new evaluation metric, called Pure Accuracy (PA), which seeks to offset the performance of random consistency from the traditional accuracy metric. The authors show that PA is insensitive to the class distribution of the classifier and is more fair to majority and minority classes, as well as provide novel generalization bounds on PA. The paper shows that a plug-in rule introduced to maximize PA performs statistically better than logistic regression on twenty benchmark data sets.

The paper 'Robust High Dimensional Expectation Maximization Algorithm via Trimmed Hard Thresholding' by Di Wang, Xiangyu Guo, Shi Li and Jinhui Xu presents a new method called Trimmed (Gradient) Expectation Maximization to address the problem of estimating latent variable models with arbitrarily corrupted samples in high dimensional spaces where the underlying parameter is assumed to be sparse. This method, which adds a trimming gradients step and a hard thresholding step to the Expectation step (E-step) and the Maximization step (M-step), is shown to be corruption-proof under some mild assumptions and with an appropriate initialization. The theory is supported through numerical results on three canonical models: mixture of Gaussians, mixture of regressions and linear regression with missing covariates.

The paper 'Boost Image Captioning with Knowledge Reasoning' by Zhixin Li, Feicheng Huang, Haiyang Wei, Canlong Zhang and Huifang Ma presents an approach to improve image captioning performance by injecting external knowledge extracted from knowledge graphs into an encoder-decoder framework to facilitate meaningful captioning. The work also leverages word-level attention to improve the correctness of visual attention when generating sequential descriptions word-by-word, and shows promising results on well-known image captioning benchmarks: Microsoft COCO and Flickr30k datasets.

The paper 'Fast and Accurate Pseudoinverse with Sparse Matrix Reordering and Incremental Approach' by Jinhong Jung and Lee Sael presents FastPI, a new incremental singular value decomposition (SVD) based pseudo-inverse method for sparse matrices. FastPI reorders and divides the feature matrix and incrementally computes low-rank SVD from the divided components. Through extensive experiments on real-world multi-label linear regression problems, the paper demonstrates that FastPI, without loss of accuracy, computes the pseudoinverse up to 496% faster than other approximate methods and uses much less memory compared to full-rank SVD-based approaches.

The paper 'Spanning attack: reinforce black-box attacks with unlabeled data' by Lu Wang, Huan Zhang, Jinfeng Yi, Cho-Jui Hsieh and Yuan Jiang presents a method called

spanning attack to improve the query efficiency of adversarial black-box attacks which are widely used to evaluate the robustness of pre-trained models. By constraining adversarial perturbations in a low-dimensional subspace via spanning an auxiliary unlabeled dataset, the spanning attack significantly improves the query efficiency of black-box attacks. Extensive experiments show that the proposed method works favorably in both soft-label and hard-label black-box attacks.

The paper 'Binary classification with ambiguous training data' by Naoya Otani, Yosuke Otsubo, Tetsuya Koike and Masashi Sugiyama presents a new method to handle binary classification in the presence of ambiguous samples that are difficult to label even by domain experts. The proposed method extends binary classification with a reject option, which trains a classifier and a rejector simultaneously using P and N samples based on the $0-1-c$ loss with rejection cost c . A convex upper bound of the $0-1-c-d$ loss is used for efficiently training a classifier, whose performance is validated on numerical experiments that show how the method can successfully utilize additional information brought by such ambiguous training data.

We would like to acknowledge the contribution from many people which made this special issue possible. We would like to thank the senior program committee and the program committee of ACML for their time and effort in reviewing papers and the authors for their contributing articles. We also would like to thank Peter Flach and Hendrik Blockeel, past and present editor-in-chiefs for MLJ, Dragos Margineantu, editor of special issues for MLJ, as well as the ACML Steering Committee for their guidance and support. Our gratitude also goes to Katherine Moretti and Sarvagnan Subramanian from the Springer editorial office for the help in ensuring that the process ran smoothly.