

Guest Editorial

Special Issue on Recent Advances in Theory, Methodology and Applications of Imbalanced Learning

Imbalanced learning is a challenging task in machine learning, faced by practitioners, and intensively investigated by researchers from a wide range of communities. However, as pointed out in the book entitled "Imbalanced Learning: Foundations, Algorithms, and Applications" and collectively authored by experts in the field, many if not most of the approaches to imbalanced learning are heuristic and ad hoc in nature, hence leaving many questions unanswered. To fill this gap, the aim of this special issue is to collect recent research works that focus on the theory, methodology, and applications of imbalanced learning. After carefully reviewing a large number of submissions, we selected 15 works to be included in this special issue. These works can be roughly categorized into three types: deep-learning based methods (6), methods based on other machine-learning paradigms (7), and empirical comparative studies (2).

The first group of articles includes the following six studies that propose new deep-learning based methods for imbalanced learning:

1. *Learning Deep Landmarks for Imbalanced Classification*: Bao *et al.* propose a deep imbalanced learning framework called DELTA, which introduces the new concept of rebalancing samples in a deeply-transformed latent space. DELTA conducts feature learning, sample rebalancing and discriminative learning in a joint and end-to-end manner, providing the possibility to conduct imbalanced learning with structured feature extraction.
2. *Learning Multi-Level Density Maps for Crowd Counting*: Jiang *et al.* develop a multilevel convolutional-neural network (MLCNN) model to accurately estimate the crowd count from a given scene with imbalanced people distribution. They also introduce a new loss function called balanced loss and a new dataset of more than 1K images with about 50K head annotations.
3. *Objective Video Quality Assessment Combining Transfer Learning with CNN*: Zhang *et al.* propose a full-reference (FR) video quality assessment (VQA) metric integrating transfer learning with a convolutional neural network (CNN) to address the issues encountered in small-scale video quality databases with imbalanced samples and low-level feature representations for distorted videos. Transfer learning is used to enrich the distorted samples, and a CNN is used to extract high-level spatiotemporal features from the distorted videos.
4. *RecSys-DAN: Discriminative Adversarial Networks for Cross-Domain Recommender Systems*: Wang *et al.* address the issues of data sparsity and data imbalance in cross-domain recommender systems by leveraging the concepts from representation learning, adversarial learning and transfer learning (particularly, domain adaptation). Unlike existing approaches, the proposed RecSys-DAN transfers the latent representations from a source domain to a target domain in an adversarial way, and it is flexible to both unimodal and multimodal scenarios, hence relatively robust to the cold-start recommendation.
5. *Siamese Neural Networks for User Identity Linkage Through Web Browsing*: Qiao *et al.* first propose a Siamese neural network architecture-based User Identity Linkage (SAUIL) model to learn the highest-level feature representation of input web-browsing

behaviours for User Identity Linkage (UIL) through the Internet. Then, to address the imbalanced matching and nonmatching pairs in UIL data sets, they further propose a cost-sensitive SAUIL (C-SAUIL) model, which assumes higher costs for misclassifying the minority class.

6. *Deep Least Squares Fisher Discriminant Analysis*: Díaz-Vico and Dorronsoro propose deep Fisher discriminant analysis (DFDA), a straightforward nonlinear extension of least squares FDA by taking advantages of deep neural networks. For large-sample class-imbalanced data, DFDA has classification performance similar to regularized kernel FDA, but it is considerably faster in model building.

The second group of articles contains the following seven articles that introduce methods based on other machine learning paradigms for imbalanced learning:

1. *Adaptive Chunk-Based Dynamic Weighted Majority for Imbalanced Data Streams with Concept Drift*: Lu *et al.* propose a chunk-based incremental learning method called adaptive chunk-based dynamic weighted majority (ACDWM) to deal with imbalanced streaming data containing concept drift. ACDWM uses a dynamically weighted ensemble to address concept drift and uses statistical hypothesis tests to adaptively select the chunk size and ensure the stability of ensemble classifiers for imbalanced data streams.
2. *Discriminative Fast Hierarchical Learning for Multiclass Image Classification*: Zheng *et al.* develop a discriminative fast hierarchical learning algorithm for supporting multiclass image classification. There, a visual tree is integrated with multitask learning to achieve fast training of the tree classifier hierarchically, by handling the data imbalance and identifying the interrelated learning tasks automatically.
3. *Fast Matrix Factorization with Nonuniform Weights on Missing Data*: He *et al.* develop a fast matrix factorization algorithm to address the imbalanced learning problem to predict large-scale missing entries in a high-dimensional sparse data matrix, by weighting the missing entries non-uniformly and using elementwise alternating least squares.
4. *Iterative Privileged Learning*: Li *et al.* investigate iterative privileged learning within the context of gradient boosted decision trees (GBDTs). Unlike conventional static manipulations of privileged information, during the learning phase of the GBDT method, new decision trees are discovered to iteratively update the comments generated from the privileged information to accurately assess and coach the up-to-date model.
5. *Radial-Based Oversampling for Multiclass Imbalanced Data Classification*: Krawczyk *et al.* propose multiclass radial-based oversampling (MC-RBO) for multiclass imbalanced learning problems. MC-RBO uses potential functions and information coming from all of the classes, for generating artificial instances, guided by the exploration of areas where the value of the mutual class distribution is very small.
6. *Self-Paced Balance Learning for Clinical Skin Disease Recognition*: Yang *et al.* propose a self-paced balance learning (SPBL) algorithm to address not only the imbalanced sizes but also the imbalanced-recognition difficulties of multiple classes. They introduce a comprehensive metric termed the complexity of image category that is a combination of both sample number and recognition difficulty, and update the complexity by using the self-paced learning paradigm, accomplishing iterative learning of discriminative representations via balancing the complexity in each pace.

7. Sparse Supervised Representation-Based Classifier for Uncontrolled and Imbalanced Classification: Shu *et al.* propose a model called Sparse Supervised Representation Classifier (SSRC) to address the fact that SRC cannot obtain satisfactory results on uncontrolled and imbalanced data sets. In SSRC, a class weight learning model is proposed to address the class-imbalance problem.

The third group includes the following two articles that present empirical comparative studies for imbalanced learning:

1. Deep Neural Architectures for Highly Imbalanced Data in Bioinformatics: Bugnon *et al.* provide a comparative assessment of recent deep neural architectures for dealing with the large imbalanced data issue in the classification of pre-miRNAs, along with a new graphical way for comparing classifiers' performance in the context of high class imbalances.
2. On the Dynamics of Classification Measures for Imbalanced and Streaming Data: Brzezinski *et al.* study the dynamics of eight classification measures for imbalanced and streaming data, by analysing changes in measure values, distributions and gradients with diverging class proportions. Their results show that the effect the class proportions have on each measure is different and should be taken into account when evaluating classifiers. They also show a direct connection between class ratio changes and certain types of concept drift.

It is our hope that the 15 articles selected for this special issue can push the research and promote many more excellent works in the field of imbalanced learning. To conclude this editorial, we would like to thank all the authors who submitted their work to this special issue, all the reviewers for their great efforts in ensuring the quality of the selected papers, and, last but not least, the Editor-in-Chief and the editorial office for their consistent support.

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