Multi-Task Learning (MTL) has been an active research area in machine learning for two decades. By training multiple relevant tasks simultaneously with information shared across tasks, it is possible to improve the generalization performance of each task, compared to training each individual task independently. During the past decade, most MTL research has been based on the Regularization-Loss framework due to its flexibility in specifying various types of information sharing strategies, the opportunity it offers to yield a kernel-based methods and its capability in promoting sparse feature representations.

However, certain limitations exist in both theoretical and practical aspects of Regularization-Loss-based MTL. Theoretically, previous research on generalization bounds in connection to MTL Hypothesis Space (HS)s, where data of all tasks are pre-processed by a (partially) common operator, has been limited in two aspects: First, all previous works assumed linearity of the operator, therefore completely excluding kernel-based MTL HSs, for which the operator is potentially non-linear. Secondly, all previous works, rather unnecessarily, assumed that all the task weights to be constrained within norm-balls, whose radii are equal. The requirement of equal radii leads to significant inflexibility of the relevant HSs, which may cause the generalization performance of the corresponding MTL models to deteriorate. Practically, various algorithms have been developed for kernel-based MTL models, due to different characteristics of the formulations. Most of these algorithms are a burden to develop and end up being quite sophisticated, so that practitioners may face a hard task in interpreting and implementing them, especially when multiple models are involved. This is even more so, when Multi-Task Multiple Kernel Learning (MT-MKL) models are considered.

This research largely resolves the above limitations. Theoretically, a pair of new kernel-based HSs are proposed: one for single-kernel MTL, and another one for MT-MKL. Unlike previous works, we allow each task weight to be constrained within a norm-ball, whose radius is learned during training. By deriving and analyzing the generalization bounds of these two HSs, we show that, indeed, such a flexibility leads to much tighter generalization bounds, which often results to significantly better generalization performance. Based on this observation, a pair of new models is developed, one for each case: single-kernel MTL, and another one for MT-MKL. From a practical perspective, we propose a general MT-MKL framework that covers most of the prominent MT-MKL approaches, including our new MT-MKL formulation. Then, a general purpose algorithm is developed to solve the framework, which can also be employed for training all other models subsumed by this framework. A series of experiments is conducted to assess the merits of the proposed mode when trained by the new algorithm. Certain properties of our HSs and formulations are demonstrated, and the advantage of our model in terms of classification accuracy is shown via these experiments.

Major: Electrical Engineering

Educational Career:
Bachelor's of Electronic Information Engineering, BS, 2009, Tianjin University
Master's of Electrical Engineering, MS, 2014, University of Central Florida

Committee in Charge:
Michael Georgiopoulos, Chair, Electrical Engineering and Computer Science
Georgios C. Anagnostopoulos, Co-Chair, Electrical and Computer Engineering
Haiyan Hu, University of Central Florida
Marshall Tappen, Amazon.com, Inc
Liqiang Ni, University of Central Florida