SOUTENANCE DE THÈSE

M. Xuhong Li

Soutiendra sa thèse de **Doctorat** sur le sujet :

Regularization Schemes for Transfer Learning with Convolutional Neural Networks

Dans l'Unité de Recherche **:**

HEUDIASYC UMR CNRS 7253

Mardi 10 septembre 2019 à 9h30

à l'UTC, bâtiment Blaise Pascal, salle GI042

devant le jury composé de :

M. Gilles Gasso, professeur des universités, INSA de Rouen
M. Nicolas Thome, professeur des universités, CNAM, Paris
M[me] **Véronique Cherfaoui**, professeure des universités, université de technologie de Compiègne
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Transfer learning with deep convolutional neural networks substantially shortens the training process and boosts the performance of the target task, compared to training from scratch. However, transfer learning with a deep network may cause the model to forget the knowledge learned from the source, leading to the known catastrophic forgetting. Since the efficiency of transfer learning derives from the learned knowledge in the source task, the knowledge should be preserved during transfer learning. This thesis copes with this forgetting problem, and proposes two regularization schemes for preserving the knowledge during transfer learning. First we investigate several parameter regularization forms that all explicitly promote the similarity of the final solution with the initial model, based on the L^2, L^2-SP, and Group-Lasso penalties. We also propose the variants that use the Fisher information as a metric for measuring the importance of parameters. We validate these parameter regularization approaches on various tasks. The second regularization scheme is based on the optimal transport theory that can estimate the dissimilarity between distributions. We benefit from optimal transport to penalize the deviations of the output activations on the target task, with the same objective of preserving the knowledge during transfer learning. With a mild increase in computation time for the training, this novel regularization approach improves the performance of the target tasks, and yields higher accuracy on image classification tasks than parameter regularization approaches.