MVA Internship at CVN

Proposal

Equipe de coordination Antonio SILVETI-FALLS (antonio.silveti-falls@centralesupelec.fr), Jean-Christophe PESQUET.

Titre en français Optimisation robuste pour la segmentation avec des annotations incertaines

Mots clés Optimisation Robuste, apprentissage automatique, segmentation, étiquettes bruitées

English title Robust Optimization for Segmentation with Uncertain Labelling

Keywords Machine learning, robust optimization, segmentation, noisy labels

Project Summary Often in machine learning, one deals with imperfect datasets that are affected by errors in the form of incorrectly applied labels. This has downstream consequences for classifiers or generative models whose parameters are selected by solving optimization problems based heavily on these datasets. Robust optimization provides a framework that allows one to account for and overcome these errors by modeling uncertainty in the data in a probabilistic way and optimizing over the expected worst-case. There are several ways to incorporate these uncertainties that have been explored recently; by estimating the label distributions jointly during the optimization process [7], by optimizing over all label distributions that are close to the observed labels in the sense of the Wasserstein metric or other divergences between probability distributions [5], or by adding an entropic regularizer to the initial optimization problem to select the most robust solution with respect to the observed data [1].
We propose to revisit these approaches in the context of image segmentation problems, where recent works [6] have shown high sensitivity to perturbations. First, we propose to study the problem of extending standard supervised classifiers, e.g. logistic regression or SVM, to segmentation problems. Using bilevel optimization formulations to set hyperparameters (e.g., regularization parameters) we can optimally balance robustness and data fidelity, even for nonsmooth models. This will be accompanied by rigorous convergence guarantees using recent advances in nonsmooth implicit differentiation [2, 3] and nonsmooth unrolling [4]. We envision also exploring extending these approaches to deep neural networks, leveraging the compatibility of these advances [2, 3, 4] with automatic differentiation and backpropagation. In particular, networks obtained by unrolling optimization algorithms or with implicitly defined optimization layers [2] will be investigated.

Thématique Science des données

Domaine Vision par ordinateur

Objectifs Proposer des algorithmes robustes et rapides pour la segmentation d'images en présence d'annotations erronées, en utilisant les modèles non-lisse mais compatible avec autodiff.

Contexte Le problème ici traité se rencontre fréquemment en analyse d'images médicales, qui constitue une large part de l'activité du laboratoire d'accueil (équipe Inria OPIS).

Méthode Le sujet repose sur l'expertise de l'équipe d'encadrement sur les méthodes d'optimisation en grande dimension et en apprentissage profond. Il constitue un prolongement de certains des travaux menés récemment dans cette équipe.

Résultats attendus Résultats nouveaux tant en optimisation qu'en vision par ordinateur. Développement de logiciels en PyTorch/JAX/TensorFlow.

Caractère confidentiel des travaux Non

Candidature

Profil et compétences recherchées Le candidat recherché doit avoir une bonne formation en traitement d'images, en particulier en segmentation et optimisation d'images. Une expérience et une familiarité avec la programmation Python, en particulier avec les environnements dédiés aux réseaux de neurones profonds (PyTorch, JAX ou TensorFlow), seront nécessaires.

Profile and skills required The desired candidate should have experience with image processing, in particular image segmentation, and optimization. Experience and familiarity with Python programming, in particular with the common deep learning libraries (PyTorch, JAX, or TensorFlow), will be necessary.

Références bibliographiques

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[3] Jérôme Bolte, Edouard Pauwels, and Antonio Silveti-Falls. Differentiating nonsmooth solutions to parametric monotone inclusion problems. *To appear in SIOPT*.

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[7] K. Yi and J. Wu. Probabilistic end-to-end noise correction for learning with noisy labels. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*, pages 7017–7025. IEEE Computer Society, 2019.