SEMI-SUPERVISED LEARNING FOR DEEP LEARNING IN MEDICAL IMAGING

Training period: 4-6 months in 2020 (March-August).

Salary: ≈ 550 euros/month, funded by SysNum Cluster, IdEX Bordeaux

Expected skills: Computer Vision, Machine Learning, python

Supervisors:

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Magnetic resonance (MR) imaging plays a crucial role in the detection of pathologies, the study of brain organization and clinical research. Every day, a vast amount of MR data is produced in clinical settings and this number is increasing rapidly, which prevents the use of manual analysis approaches. As a result, the development of reliable segmentation techniques for the automatic extraction of anatomical structures is becoming an important field of quantitative MR analysis.

Deep Learning (DL) is a fast-growing field in computer vision that has recently obtained many successes. DL methods are now considered as the state of the art in numerous applications. Moreover, inference time of DL method is really low compared to previous methods thanks to GPU implementations. Therefore, there is no doubt that DL methods will soon be a major tool for fast quantitative MRI analysis [2]. However, so far, results obtained by DL for brain MRI segmentation are not as good as expected compared to performance of DL on other computer vision problems. The current limited performance of DL in neuroimaging mainly results from the limited number of training MRI available. In this project we propose to tackle this issue by using semi-supervised learning (SSL).

SSL approaches are designed to learn a model from a small set of examples. Current SSL methods based on DL still require a huge amount of annotated data ($\approx 10^5$) for general classification tasks in computer vision [6]. On the other hand, SSL methods dedicated to classical segmentation methods have the potential to solve efficiently a specific task on brain MRI data, from a limited set ($\approx 10^2$) of examples [5]. The objective of the project is to fill in the gap and propose SSL strategies, build on top of deep network architectures, that can be trained from an extremely small set of annotated data. The candidate will namely investigate the use of manifold learning [34] and label propagation [1,3,7] methods in order to address the current limit of DL in medical imaging.

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[2] Coupé, P., Mansencal, B., Clément, M., Giraud, R., de Senneville, B. D., Ta, V. T., Lepetit, V.& Manjon, J. V. (2019). AssemblyNet: A Novel Deep Decision-Making Process for Whole Brain MRI Segmentation. In MICCAI.

[3] Iscen, A., Tolias, G., Avrithis, Y., & Chum, O. (2019). Label propagation for deep semi-supervised learning. In IEEE CVPR, pp. 5070-5079.

[4] McInnes, L., Healy, J., & Melville, J. (2018). Umap: Uniform manifold approximation and projection for dimension reduction. arXiv preprint arXiv:1802.03426.

[5] Wolz, R., Aljabar, P., Hajnal, J. V., Hammers, A., Rueckert, D., & Alzheimer's Disease Neuroimaging Initiative. (2010). LEAP: learning embeddings for atlas propagation. NeuroImage, 49(2), 1316-1325.

[6] Yalniz, I. Z., Jégou, H., Chen, K., Paluri, M., & Mahajan, D. (2019). Billion-scale semi-supervised learning for image classification. arXiv preprint arXiv:1905.00546.

[7] Zhuang, C., Ding, X., Murli, D., & Yamins, D. (2019). Local Label Propagation for Large-Scale Semi-Supervised Learning. arXiv preprint arXiv:1905.11581.