Self-Rule to Adapt: Learning Generalized Features from Sparsely-Labeled Data Using Unsupervised Domain Adaptation for Colorectal Cancer Tissue Phenotyping

EPFL

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LTS5

Motivations

- **Save** annotation **time** for pathologists.
- Benefit from the **widely available data** in the institute to learn proper features representation.
- Use **self-supervised** learning to perform unsupervised **domain adaptation.**

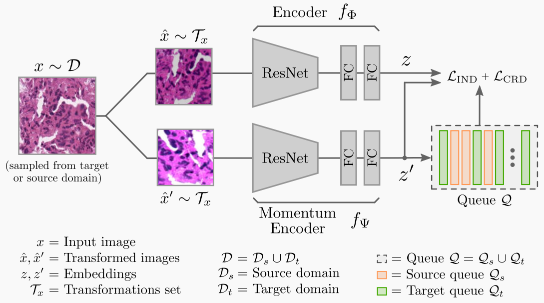
Contributions

- We present a new label **transferring approach** from a partially labeled source domain to an unlabeled target domain.
- We perform **progressive** entropy **minimization** based on the similarity distribution among the unlabeled target and source domain samples.
- We show that our method can discover the **relevant semantic** information even in the presence of few labeled source samples and yields a **better generalization** on target domain.

Proposed Approach

Architecture

The proposed Self-Rule to Adapt (SRA) architecture.



The model optimizes the contribution of the in-domain and the cross-domain loss term.

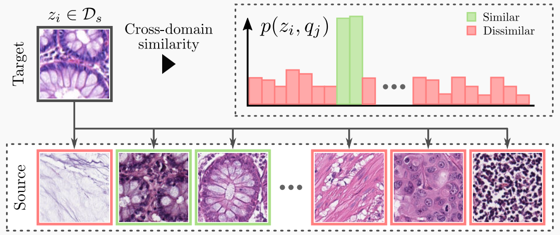
$$\mathcal{L}_{\text{SRA}} = \mathcal{L}_{\text{IND}} + \mathcal{L}_{\text{CRD}}$$

In-domain

Individually optimize the representation of the source and target sets to create robust sets embedding.

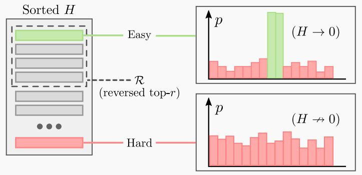
Cross-domain

The model tries to find good candidates using cosine similarity. Here is a case of low entropy when matching target to the source domain.



Easy-to-hard

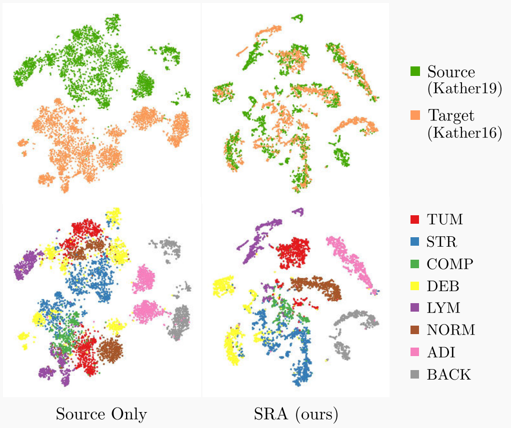
Progressively match samples based on the entropy of similarities.



Experiments

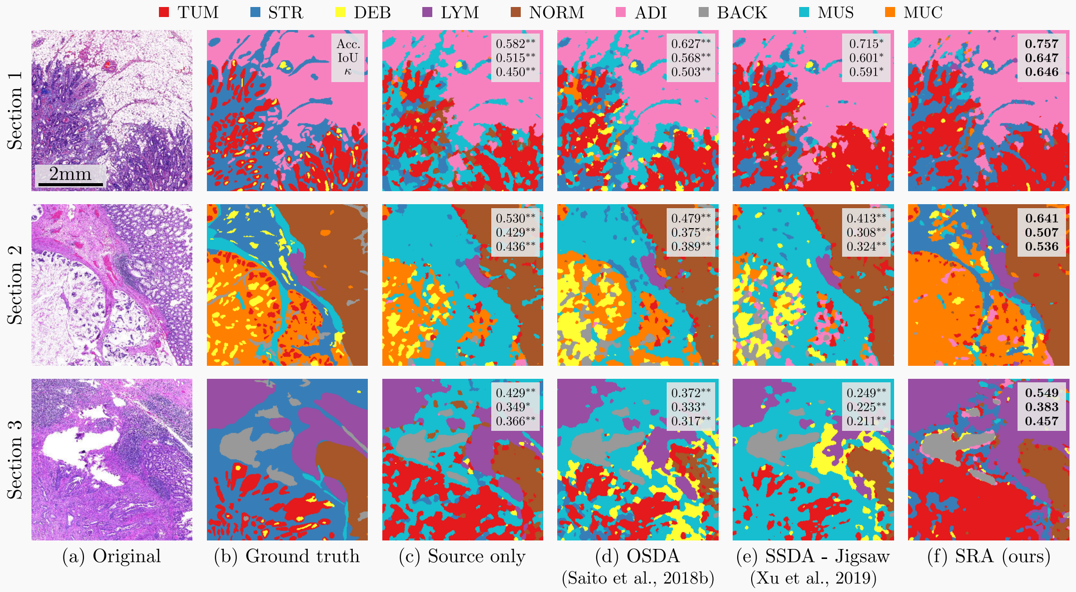
Features Alignment

The t-SNE projection comparison with and without SRA.



WSIs Segementation

Segmentation of whole slide images over multiples classes. We compare the performance of our SRA algorithm to other baselines. We report the pixel-wise accuracy, the weighted intersection over union, and the pixel-wise Cohen's kappa.



$^{+}$ $p \geq 0.05$; $^{*}p < 0.05$; $^{**}p < 0.001$; unpaired t-test with respect to the top result.

Benefits of Easy-to-hard

Effects on similarity distribution and confidence score with and without easy-to-hard learning.