More Than Meets The Eye: Semi-supervised Learning Under Non-IID Data

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Motivation and context

Mismatch between distributions P_{I} and P_{u} of labelled data S_{I} and unlabelled data S_{u} in semi-supervised deep learning (SSDL)

Question

Given labelled data S_{l} ...



...which unlabelled data S_u should we choose?



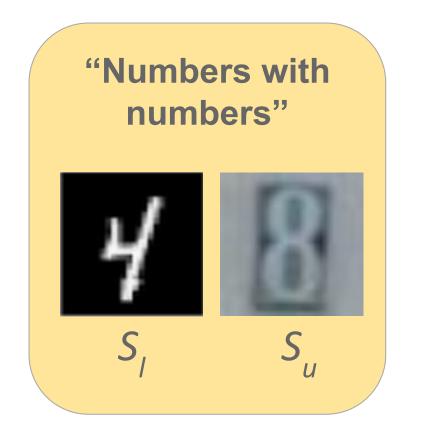


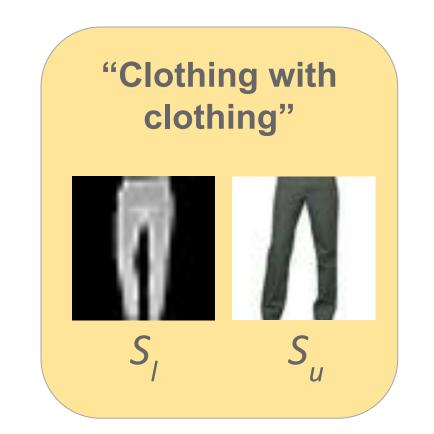
. . .

SVHN?

ImageNet?

In absence of explicit data models, **semantic similarity matching** is often used:





Contributions

- Quantitative impact estimation of distribution
 mismatch for MixMatch SSDL
- Deep data set dissimilarity measures (DeDiMs): a simple and quantitative decision heuristic for S_u selection before SSDL training

Proposed method

Deep data set dissimilarity measure (DeDiM)

$$\widehat{d}_{j} = \sum_{r=1}^{n'} \delta_{g} (p_{r,a}, p_{r,b})$$

 \widehat{d}_j estimated dissimilarity for the sample j $\sum_{r=1}^{n'}$ sum over all n' dimensions in feature space

 δ_{g} distance measure, g=c for cosine distance

 $p_{r,a}$ approximate density functions for feature r of data set a

 $p_{r,b}$ approximate density functions for feature $\it r$ of data set $\it b$

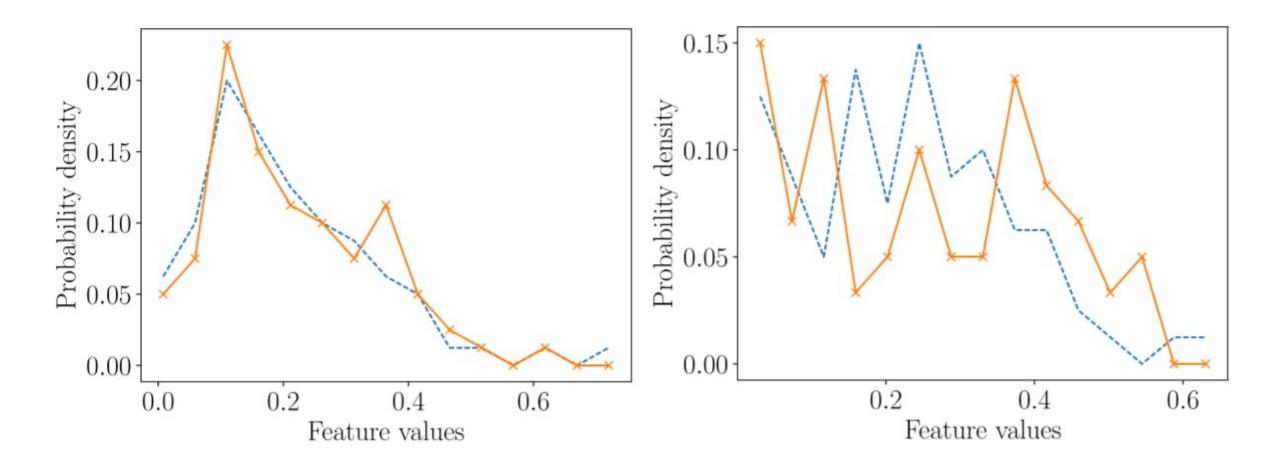


Fig 1. A specific feature density of a model trained with MNIST labelled data (orange and continuos inboth plots), and ImageNet and SVHN unlabelled data (left and right column, respectively, with the blue dashed line in both)

Results

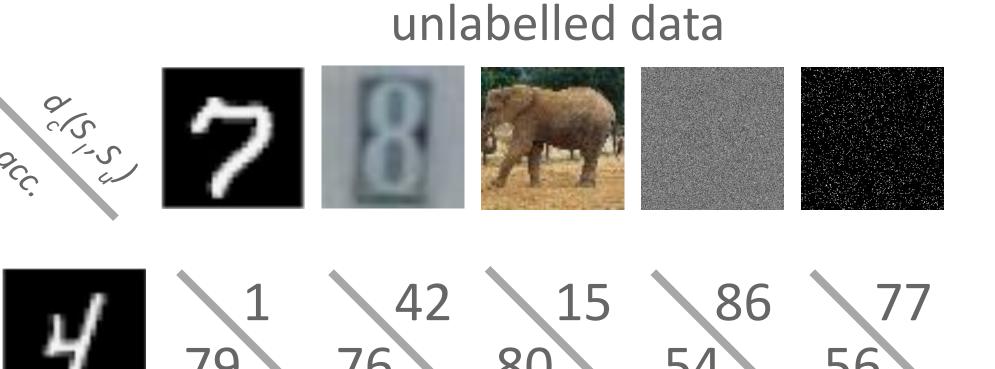


Fig 2. SSDL accuracy (acc.) and cosine deep data set dissimilarity measures between labelled and unlabelled data $(d_c(S_1,S_u))$. Full results on more data sets in the paper.

| $\mathbf{S}_{\mathbf{l}}$ | nı | \mathbf{d}_{ℓ_1} | \mathbf{d}_{ℓ_2} | d_{JS} | $\mathbf{d}_{\mathbf{C}}$ |
|---------------------------|-----|-----------------------|-----------------------|----------|---------------------------|
| MNIST | 60 | -0.876 | -0.898 | -0.969 | -0.944 |
| | 100 | -0.805 | -0.83 | -0.786 | -0.948 |
| | 150 | -0.794 | -0.822 | -0.81 | -0.944 |
| CIFAR-10 | 60 | -0.823 | -0.853 | -0.944 | -0.921 |
| | 100 | -0.826 | -0.878 | -0.966 | -0.947 |
| | 150 | -0.808 | -0.838 | -0.952 | -0.927 |
| FashionMNIST | 60 | -0.2 | -0.268 | -0.735 | -0.789 |
| | 100 | -0.264 | -0.326 | -0.781 | -0.824 |
| | 150 | -0.286 | -0.347 | -0.785 | -0.827 |

Tab 1. Correlation results for the dissimilarity measures between S_l and S_u with OOD contamination and SSDL accuracy

Conclusions

- Semantic similarity matching between labelled and unlabelled data is not a reliable recipe for successful SSDL
- Deep data set dissimilarity measures (DeDiMs)
 offer a simple, quantitative and practical decision
 heuristic for S_i, selection before SSDL training

Code https://github.com/luisoala/non-iid-ssdl



