Extracting Relationships by Multi-Domain Matching

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Motivation & Contribution

1) We study domain adaptation from *multiple* sources. All data share the same labels (i.e. diagnosis), but the underlying reason for the decision (i.e. cause) may be different in each domain.

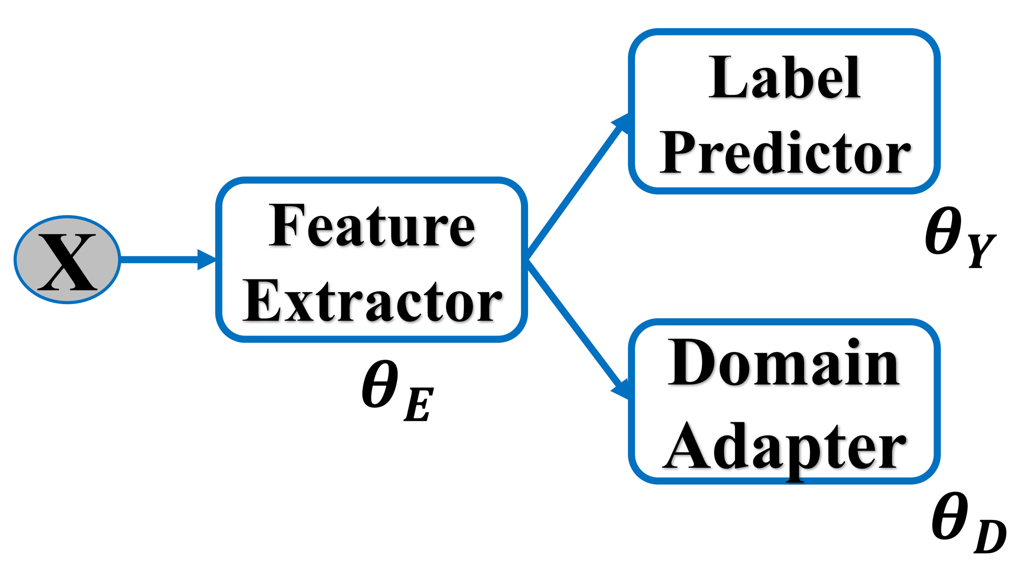
2) The training corpus is constructed from only a multiple sources within a larger population.

3) We hypothesize that each domain should be similar to a few other domains and share statistical strength, while many other domains are irrelevant (i.e different reasons for outcomes).

4) We propose the Multiple Domain Matching Network (MDMN) to perform unsupervised domain adaptation as well as extract these domain relationships.

5) Theoretical results (in paper) bound the target error using source error and the discrepancy between domains.

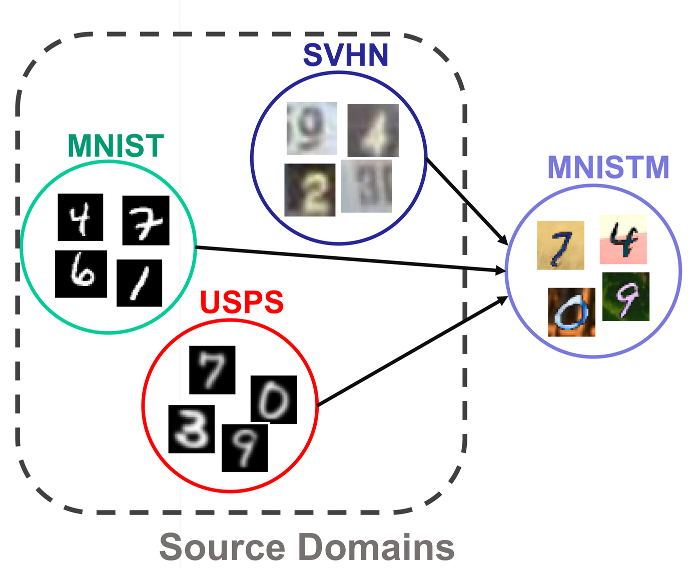
Model Framework



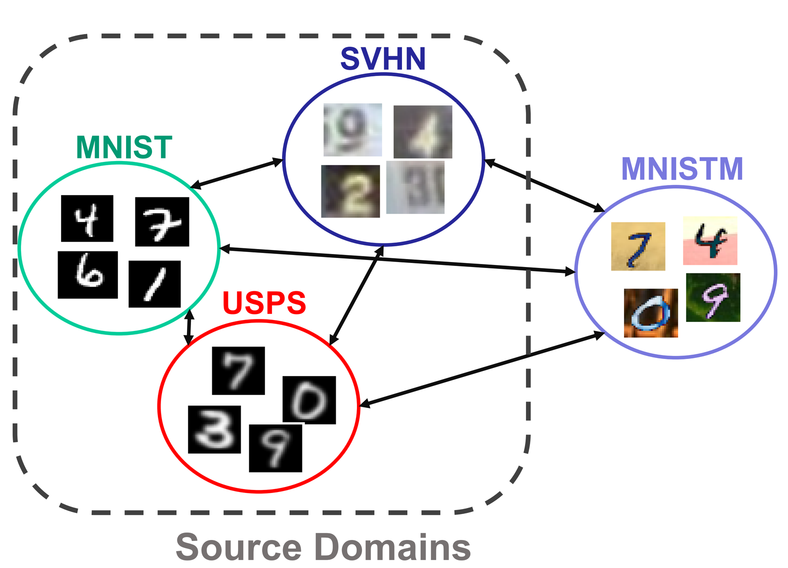
The features should be learned to perform well on label prediction and perform poorly on a domain loss or prediction:

$$min_{\theta_E,\theta_Y} max_{\theta_D} \mathcal{L}_Y - \mathcal{L}_D$$

Model Illustration



Domain Adversarial Networks



Multiple Domain Matching Network

Measure the Difference between Domains

- All domains, including sources and target, are denoted as $\mathcal{D}_s$, for $s = 1, \cdots S$.
- We have feature encoder $E(\cdot;\theta_E)$, and a domain discriminator $f_s(\cdot)$ for each domain $s = 1, \cdots, S$.
- Distance between two domains $\mathcal{D}_s$ and $\mathcal{D}_{s'}$:

$$d(\mathcal{D}_s, \mathcal{D}_{s'}) = \max_{f_s, \|f_s\|_L \leq 1} \mathbb{E}_{x\sim\mathcal{D}_s}[f_s(E(x))] - \mathbb{E}_{x\sim\mathcal{D}_{s'}}[f_s(E(x))]$$

- Distance between domain $\mathcal{D}_s$ and all other domains $\overline{\mathcal{D}}_s$:

$$d(\mathcal{D}_s, \overline{\mathcal{D}}_s) = \max_{f_s, \|f_s\|_L \leq 1} \mathbb{E}_{x\sim\mathcal{D}_s}[f_s(E(x))] - \mathbb{E}_{x\sim\overline{\mathcal{D}}_s}[f_s(E(x))]$$

- $\overline{\mathcal{D}}_s$ comes from the weighted combination of other domains:

$$\overline{\mathcal{D}}_s = \sum_{s'=1}^{S} w_{ss'} \mathcal{D}_{s'} \quad with \quad \|w_s\|_2 = 1 \quad and\ w_{ss} = 0$$

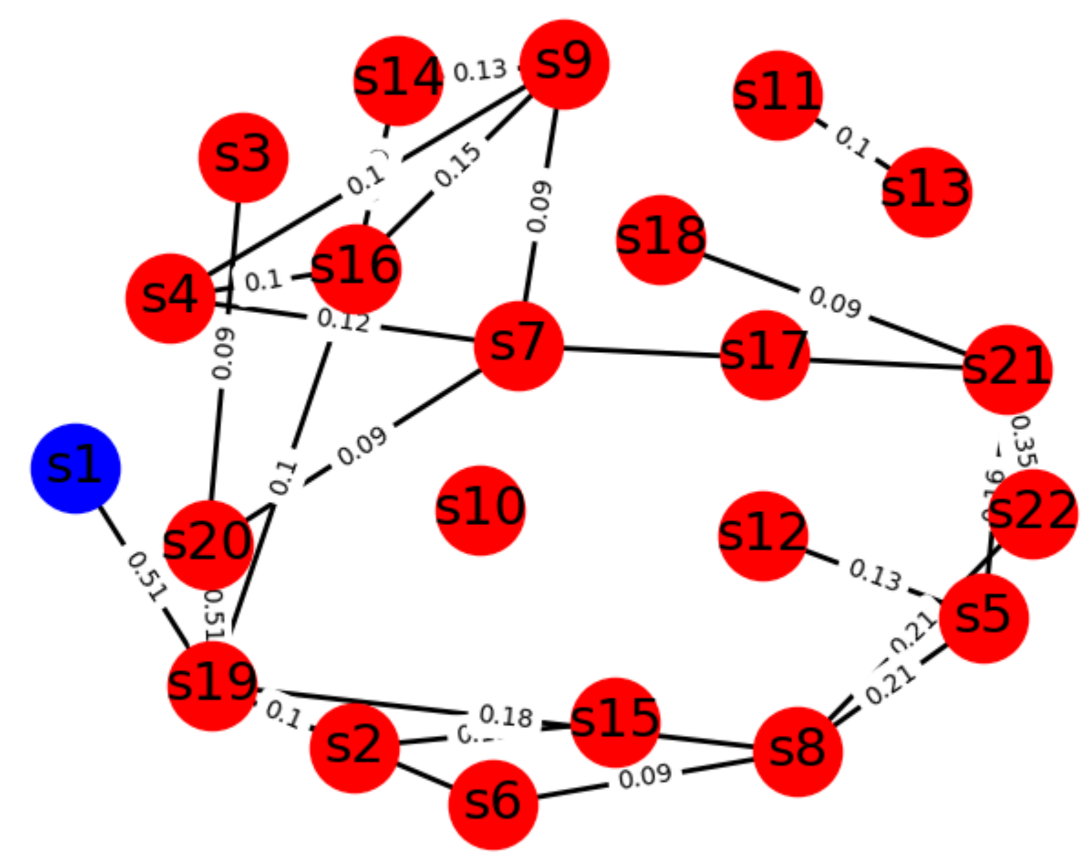
- The total domain loss function minimizes this pair-wise domain distance with λ_s as domain weights (target domain is upweighted)

$$\mathcal{L}_D = -\sum_{s=1}^{S} \lambda_s d(\mathcal{D}_s, \overline{\mathcal{D}}_s)$$

Calculating Domain Weights

- Domain weights $w_s = [w_{s1}, w_{s2}, \cdots, w_{sS}]$ denotes the similarity between domain $\mathcal{D}_s$ and all other domains.
- First, calculate $d(\mathcal{D}_s, \mathcal{D}_{s'})$ for every two domains in the set, including the target. Note that $d'_{ss} = d(\mathcal{D}_s, \mathcal{D}_s) = 0$.
- Second, compute $w_s = \text{softmax}([d_{s1}, \cdots, d_{sS}])$.
- Can set a temperature variable in the softmax if desired
- w_s and parameters of the networks are updated iteratively.

Learned Graph from Domain Weights

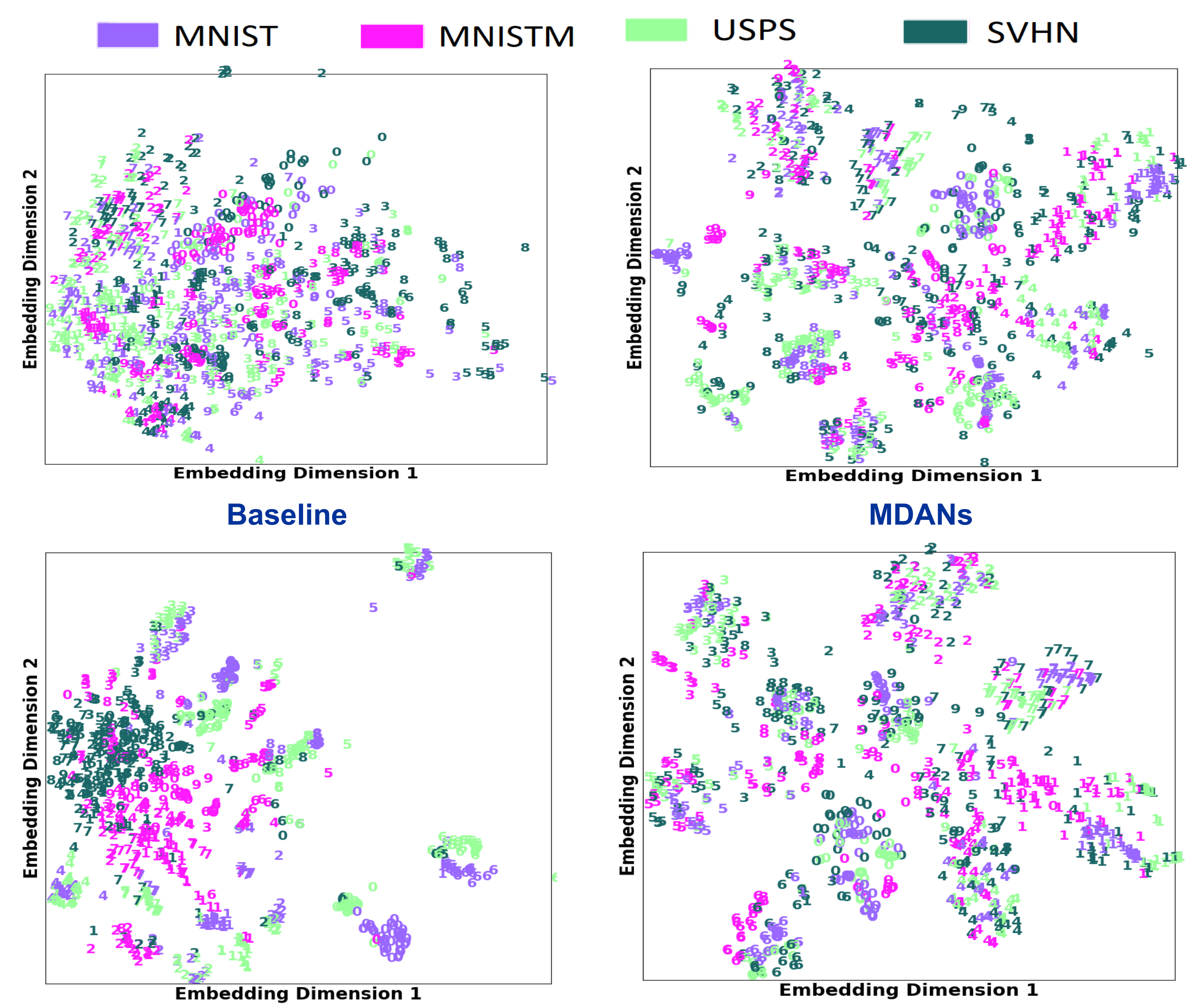


Learned Subject Relationship from Autism Spectral Disorder Dataset

Experiments on Digit Dataset

- We use MNIST, MNIST-M, SVHN and USPS datasets.

- Treat MNIST-M as target and the other three as training.



Baseline MDANs DANN MDMN

Experiments on EEG Dataset

- Classification Accuracy

Dataset	SEED	ASD
SyncNet	49.29	62.06
TCA	39.70	55.65
SA	53.90	62.53
ITL	45.27	54.62
DAN	50.28	61.88
DANN	55.87	63.81
MDANs	56.65	63.38
MDMN	**60.59**	**67.78**