TDAAN: Target Data Agnostic Adversarial Network for Domain Adaptation

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Abstract

The abstract goes here.

1. Introduction

2. Related Work

Place filler

3. Domain Adaptation

Imagine a standard classification problem of mapping a datapoint x ($x \in \mathbb{R}^D$) to its label y from the label set C_T, where x is an instance of domain T and is drawn from an unknown distribution p_T. The task becomes conceivable and, correspondingly, a supervised classification framework can be learnt if we have access to a labelled dataset $D_T = \{(x_i, y_i)\}_{i=1}^{n_T}$, with x_i ($x_i \in \mathbb{R}^D$) drawn from p_T and $y_i \in C_T$. However, the problem turns out to be more challenging if the learning task is thwarted by making D_T unavailable during training, i.e., the only information present during designing the classification model is the label set C_T. In such a scenario, relevant information can be acquired by looking into:

- a labelled dataset D_S comprising of samples from a different domain S ($S \neq T$), where $D_S = \{(x_j, y_j)\}_{j=1}^{n_S}$, x_j ($x_j \in \mathbb{R}^D$) is drawn from a distribution p_S ($p_S \neq p_T$), $y_j \in C_S$ and $C_T \subseteq C_S$.

- an unlabelled dataset $D_T^x = \{x_k\}_{k=1}^{n'_T}$, with x_k ($x_j \in \mathbb{R}^D$) drawn from p_T with no prior information about the label types present in the dataset.

3.1. Neural Network

4. Experiments

4.1. Setup

4.2. Results

4.3. Analysis

5. Conclusion

6. Acknowledgements

References