



Bachelorarbeit

A Comparison of Synthetic-to-Real Domain Adaptation Techniques

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Peter Trost (Matrikelnummer 4039682), June 10, 2019

Abstract

Template

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If you have someone to Acknowledge ;)

Contents

1. Introduction	11
1.1. Problem Statement	11
2. Related Work	13
2.1. Adapting Visual Category Models to New Domains	13
2.1.1. Abstract	13
2.1.2. Introduction	13
2.1.3. Domain Adaptation Using Regularized Cross-Domain Trans- forms	14
2.2. Adversarial Discriminative Domain Adaptation	14
2.3. Adversarial Dropout Regularization	14
2.4. Adversarial Feature Learning	15
2.5. Adversarially Learned Inference	15
2.6. CyCADA	15
3. Datasets	17
4. Domain Adaptation Techniques	19
5. Conclusion	21
A. Blub	23

1. Introduction

What is this all about?

Cite like this: [GPAM⁺14]

1.1. Problem Statement

TODO: what you have to do here :)

2. Related Work

2.1. Adapting Visual Category Models to New Domains

see [SKFD10]

Notes while reading:

2.1.1. Abstract

- one of the first studies of domain shift in context of object recognition
- method that adapts object models acquired in a particular visual domain to new imaging conditions by learning a transformation that minimizes the effect of domain-induced changes in the feature distribution **TODO: is copy paste, rephrase this!**
- supervised learning
- no labeled examples in the new domain needed
- could also be applied to non-image data
- authors also contribute a freely available multi-domain object database

2.1.2. Introduction

- kernel-based, nearest-neighbor classifiers (**TODO: look these up**) often fail on other visual domains than the one trained on
- often want to label *target* visual domain that doesn't have labels yet while having access to *source* domain that has labeled examples
- insufficient using object classifiers trained on source domain **TODO: include Figure 1, look up SVM[-bow] and NBNN**
- domain shift can affect feature distribution and cause the classifier to fail its prediction
- causes of visual domain shift include changes in camera, image resolution, lighting, background, viewpoint, post-processing **TODO: rephrase!**

- introduce domain adaptation technique based on cross-domain transformations
- key idea: regularized non-linear transformation that maps points in the source domain (green) closer to those in the target domain (blue) using supervised data from both domains. The input consists of labeled pairs of inter-domain examples that are known to be either similar (black lines) or dissimilar (red lines). The output is the learned transformation, which can be applied to previously unseen test data points. **TODO: include Figure 2, rephrase!**
- **TODO: look up '[theoretic] metric learning'**

2.1.3. Domain Adaptation Using Regularized Cross-Domain Transforms

general domain adaptation model in linear setting:

let source domain be \mathcal{A} and target domain \mathcal{B} . Vectors $\mathbf{x} \in \mathcal{A}$, $\mathbf{y} \in \mathcal{B}$. Learn transformation W from \mathcal{B} to \mathcal{A} (and W^T from \mathcal{A} to \mathcal{B}). Let dimensionality of \mathbf{x} be d_A and of \mathbf{y} be d_B then the transformation matrix W is $d_A \times d_B$. Resulting inner product similarity function between \mathbf{x} and the transformed \mathbf{y} as

$$\text{sim}_W(\mathbf{x}, \mathbf{y}) = \mathbf{x}^T W \mathbf{y}$$

to avoid overfitting use regularization function for W denoted as $r(W)$.

TODO: lookup Mahalanobis metric learning method, information theoretic metric learning (ITML)

($\|W\|$: square root of sum of squares of elements)

2.2. Adversarial Discriminative Domain Adaptation

see [THSD17]

TODO: Look up cross entropy loss

2.3. Adversarial Dropout Regularization

see [SUHS17]

experiments on p4d dataset and VisDA-classification

TODO: read this again for the benchmarks and comparison of domain adaptation techniques

2.4. Adversarial Feature Learning

see [DKD16]

TODO: look up jensen-shannon divergence

2.5. Adversarially Learned Inference

see [DBP⁺16]

2.6. CyCADA: Cycle Consistent Adversarial Domain Adaptation

see [HTP⁺17]

3. Datasets

4. Domain Adaptation Techniques

5. Conclusion

To conclude...

A. Blub

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