A Simple Domain Shifting Network for Generating Low Quality Images

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Problem Definition

Goal: Learn a classification model that generalizes to low quality target images (e.g. captured by cozmo robot camera) leveraging high quality labeled data.

- Networks trained on high quality images perform poorly on low quality images.
- Specific low quality training data is not always available.

Standard: 1.0 dog
Adapted: 1.0 dog
a) High quality

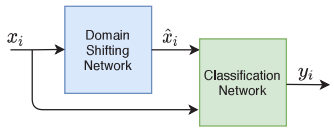
Standard: 0.007 dog
Adapted: 1.0 dog
b) Cozmo recorded

Standard: 0.038 dog
Adapted: 1.0 dog
c) Generated low quality

Our Solution: A simple, effective domain adaptation approach using a "Domain Shifting Network" (DSN) that operates without task specific low quality training data.

Our Approach

- Train a DSN with unlabeled high quality and low quality image pairs.
- Use the trained DSN to map the new labeled source domain (high quality) data x_i to the target domain (low quality) $\hat{x}_i$.
- Train a classification network with both x_i and $\hat{x}_i$ to learn domain invariant features.



- Can be used for any-shot Domain Adaptation (DA).

Zero-shot DA:

- Target domain data relevant to classification task unavailable.
- DSN trained on unlabeled data that excludes images relevant to classification task.

Unsupervised DA:

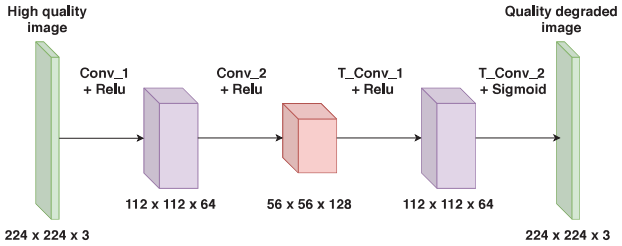
- Some unlabeled target domain data relevant to classification task is available.
- DSN trained on unlabeled data that also include a small subset of images from the relevant categories.

Domain shifting Network

Recording Training Data:

- High quality images are displayed on a screen, captured by low-cost robot camera.
- Generated training set with high quality and low quality image pairs.

Network Architecture:



$$C^3_{3\to 64}\downarrow_2 \to C^3_{64\to 128}\downarrow_2 \to C^2_{128\to 64}\uparrow_2 \to C^2_{64\to 3}\uparrow_2$$

Training:

- Objective is to degrade input high quality images to mimic their low quality versions.
- Training loss: Reconstruction error between output and corresponding low quality image.

Synthetic low-quality generated images:

a) Standard

b) Cozmo recorded

c) Network output

Experimental setting and Evaluation

MobileNet-V2, a light weight network for classification.

Baselines:

Source Supervised - Classifier trained on source domain high quality images.

Cozmo Supervised - Oracle classifier trained on target domain low quality images captured by Cozmo robot.

Our Approach: Classifier trained on source domain+synthetic target domain images from DSN.

- ▷ **Ours Zero-shot** uses DSN trained on unlabeled data that excludes images relevant to classification task.
- ▷ **Ours Unsupervised** uses DSN trained on unlabeled data with a small subset of images from the relevant categories.

Evaluation:

Classification accuracy of standard high quality and cozmo captured test data for

- ▷ 2-way classification.
- ▷ 5-way classification.

Additional evaluation with limited number of images captured under varying illuminations, distances and orientations known as “Cozmo in wild” for 2-way classification.

Example images "Cozmo in Wild":

Quantitative Results & Conclusion

Performance comparison for 2-way classification:

Approach	Standard	Cozmo	Cozmo in wild
Source Supervised	97.86%	86.97%	90.13%
Ours Unsupervised	98.76%	94.67%	91.27%
Ours zero-shot	98.60%	94.24%	95.28 %
Cozmo Supervised (Oracle)	97.40%	95.00%	92.27%

Performance comparison for 5-way classification:

Approach	Standard	Cozmo
Source Supervised	92.87%	73.49%
Ours Unsupervised	91.66%	77.56%
Ours zero-shot	92.09%	76.39%
Cozmo Supervised (Oracle)	84.88%	80.15%

Assumption:

- Requires initial unlabeled high quality and low quality image pairs for training the domain shifting network.

Observations:

- Training with high quality images yields poor accuracy on low quality images.
- Adding low quality images generated from DSN to high quality images:
  - Increases accuracy on low quality images.
  - Retains accuracy on high quality images.

Conclusions:

- Proposed a simple practical solution for real-world domain adaptation problems for robotic cameras
- The domain shifting network can be used to generate low quality images even from previously unseen categories.
- Our approach achieves improved accuracy on the target domain at no sacrifice of source domain accuracy.