# Multi-Source Domain Adaptation

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## Objectives

In this project, our goal is to learn an image classification model where training data come from 3 distinct domains, and testing data is another novel domain.

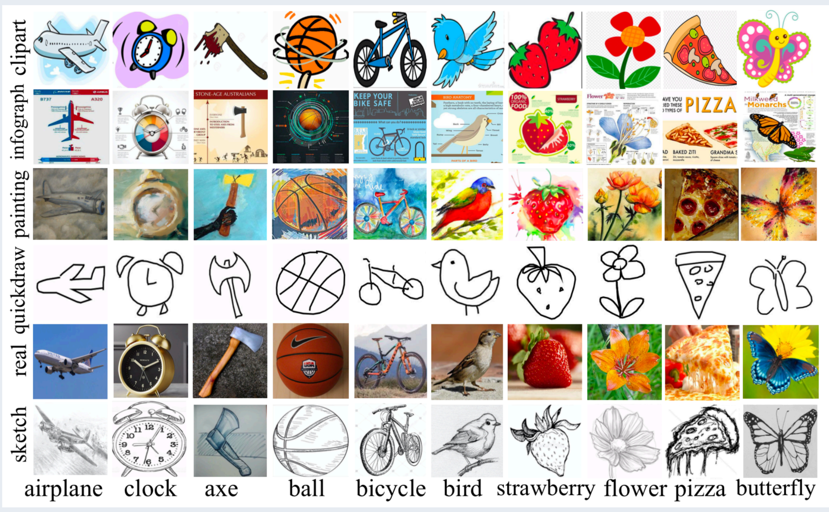


Figure 1: Multi-source Domain Samples

## Baseline

We conduct extensive experiments on scenarios from single to multiple source domains following standard image classification procedure. We fine-tune a feature extractor $f_\theta$ with ImageNet pre-trained weights and the classifier $C$. We investigate the relationship between the provided 4 domains(infograph, quickdraw, sketch, real) through observing the performance of each others.

| Domains | inf,qdr,rel→ *skt* | inf,rel,skt→ *qdr* | qdr,rel,skt→ *inf* | inf,qdr,skt→ *rel* |
|---|---|---|---|---|
| Resnet50 | - | - | - | 47.7 |
| Resnet101 | 44.0 | 13.4 | 21.4 | 52.5 |
| Resnet152 | 45.3 | **13.9** | 22.5 | **55.2** |
| Inception v3 | **46.46** | 11.11 | **22.6** | 53.9 |

Table 1: Accuracy(%) with different feature extractors.

In Kaggle competition, our focus is the scenario of "inf+qdr+skt→real". We train individual models on each source domain and directly make predictions on target domain. Results are shown in Table 2.

| Domain | infograph | quickdraw | sketch |
|---|---|---|---|
| its own testing set | 35.37 | 68.27 | 66.29 |
| training set on real | 42.45 | 6.45 | 46.93 |

Table 2: Accuracy(%) of fine-tuning on single domain.

As we can see, transfer learning from quickdraw to real domain has poor performance. Assumption is that quickdraw shares little information with real images in common.

We draw several t-SNE to show the distribution of encoded features in the colors of differrent domains and classes.

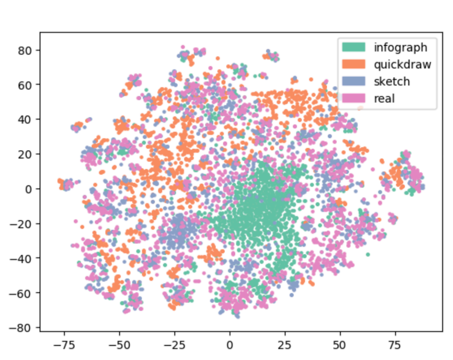

Figure 2: t-SNE visualization on all domains.

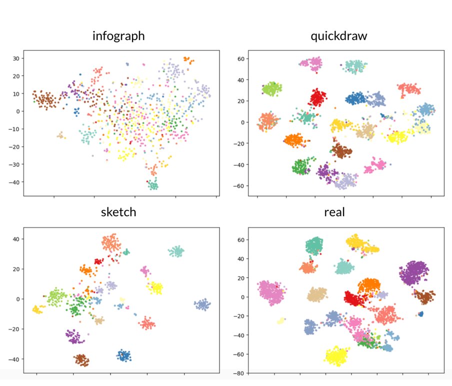


Figure 3: t-SNE visualizations with randomly picked 20 classes.

We demonstrate that our baseline model trained with source-combined domains can still classify images from novel domain with an acceptable performance.

## DANN

By proposed new gradient reversal layer[1], domain adaptation can be achieved in using almost any feed-forward model.

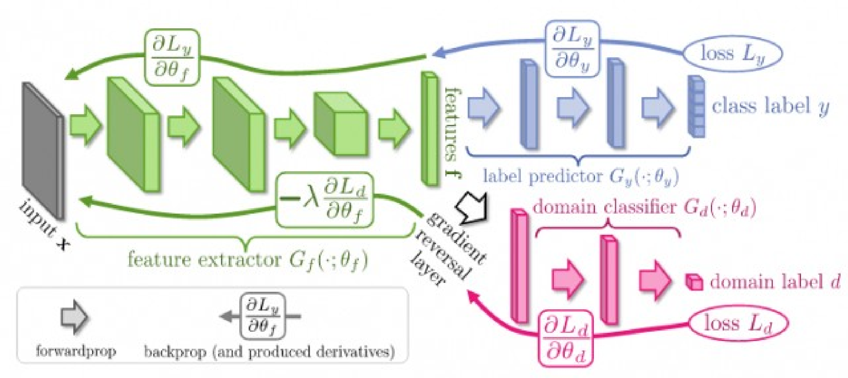

Figure 4: The framework of Unsupervised Domain Adaptation by Backpropagation.

In DANN, we let domain classifier to predict exact 4 domains for gradient reversal. Experiments about the choice of distinguishing just novel domain or all domains are conducted. We find out that the latter is better.

## M3SDA

M3SDA proposed moment matching component and weighted classifiers to achieve domain adaptation[3]. The prediction of target domain instance would be the weighted output of separately trained classifiers on source domains.

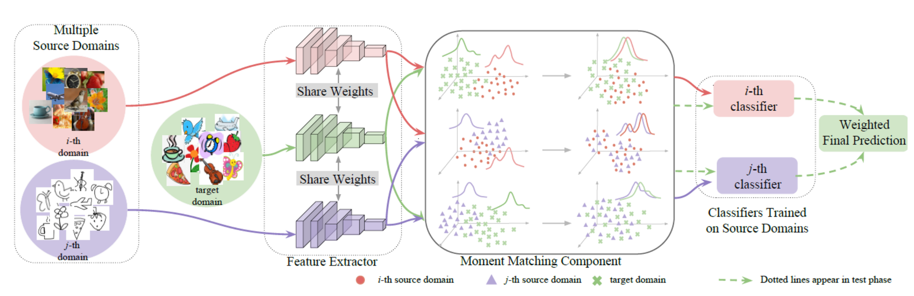

Figure 5: The framework of Moment Matching for Multi-source Domain Adaptation.

| Domains | inf,qdr,rel→ *skt* | inf,rel,skt→ *qdr* | qdr,rel,skt→ *inf* | inf,qdr,skt→ *rel* |
|---|---|---|---|---|
| M$^3SDA$ | 38.5 | 12.3 | 18.1 | **45.5** |

Table 3: Accuracy(%) with Resnet101 backbone.

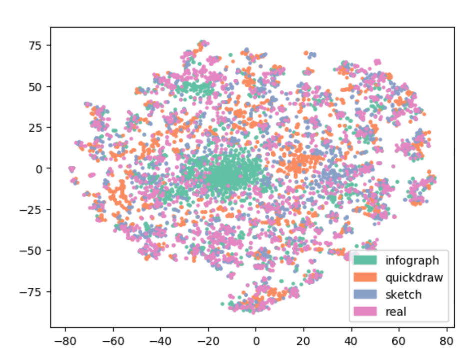

Figure 6: t-SNE visualization encoded by M3SDA.

## MDAN

A feature extractor, a task classifier and multiple domain classifiers are integrated in training process. Domain adaptation can be accomplished by adopting 'Hard version' or 'Soft version' of gradient reversal[5].

In the experiment, we choose the 'Soft version' of gradient reversal since it performs better than 'Hard version' in most cases[5].

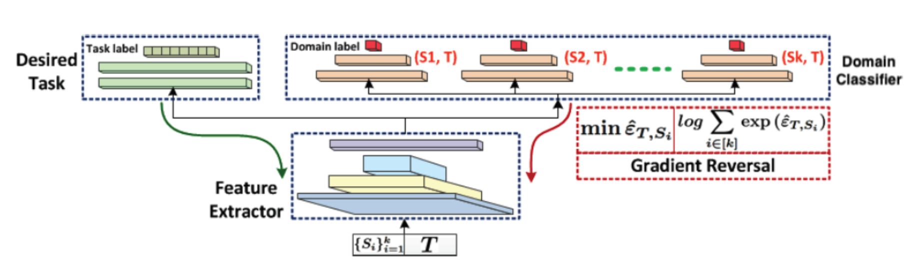

Figure 7: The framework of Multisource Domain Adversarial Networks Network.

## Experiments

| Domains | inf,qdr,rel→ *skt* | inf,rel,skt→ *qdr* | qdr,rel,skt→ *inf* | inf,qdr,skt→ *rel* |
|---|---|---|---|---|
| DANN | 48.2 | 11.8 | **26.1** | 56.7 |
| M$^3SDA$ | 48.5 | 16.6 | 24.5 | **57.7** |
| MDAN | **50.1** | **17.4** | 24.0 | 57.0 |

Table 4: Accuracy(%) using fine-tuned Resnet152.

DANN achieves the highest accuracy 26.1% when the target domain is *infograph*; however, when target domain is *quickdraw*, it performs worse than source-only baseline, which indicates negative transfer in this case.

M3SDA achieves the highest accuracy in the target domains *infograph* and *real*. In addition, it performs better in every case than source-only baseline.

MDAN achieves the highest accuracy in the target domains *sketch* and *quickdraw*, and performs better in every case than source-only baseline, too.

These models still show limited capability of boosting the accuracy although they improved the prediction on target domain. The performance is dominated by the fine-tuned model.

## Conclusion

In this project, we implemented three different unsupervised domain adaptation methods on four domains.

Despite all state-of-the-art models try to make the distribution of target domain to be consistent with source domains, there is no guarantee that the distribution of each class will be aligned too. We think that is the reason why these models cannot improve too much and baseline model becomes crucial for the overall performance.

## References

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