Training With Less Data: Adapting Unsupervised Domain Adaptation Methods to Scaled Down Datasets for Visual Recognition Tasks

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Overview

Problem Statement:

- Large datasets of images, are used to train AI models for visual recognition tasks but are difficult to create.

- In general, the larger the dataset, the better the performance will be.

- More recently the privacy of training data has also become a concern.

Overview

Domain Adaptation – use two different but related datasets to improve the performance.

- Source domain – a dataset used as a starting point for training
- Target domain – the dataset that is similar to the source domain, but is specifically made for the task at hand

Source Domain

Target Domain

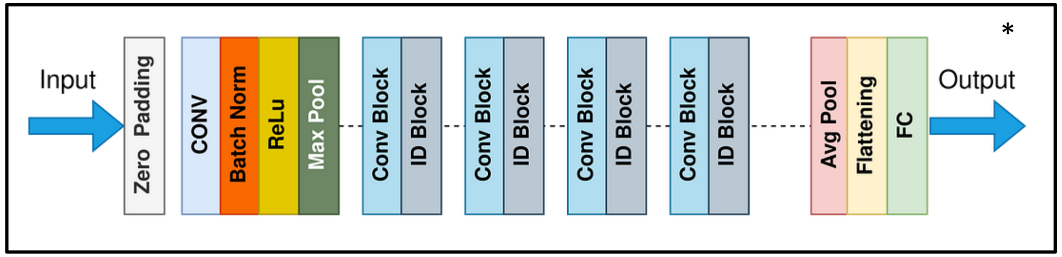
Overview

Proposed Method – ‘UDA Boost’

- Combines multiple existing methods with new ideas to create a design that can provide more reliable results as the size of the training dataset decreases.
- Data-side improvements: MixMatch algorithm, Data augmentations
- Network-side improvements: Target adapter block, Source Hypothesis Optimiser

Background - Convolutional Neural Networks (CNNs)

- A type of AI used for classifying objects within images
- Takes a large dataset of images with known classes as input
- Trained network known a model



"Scissors"

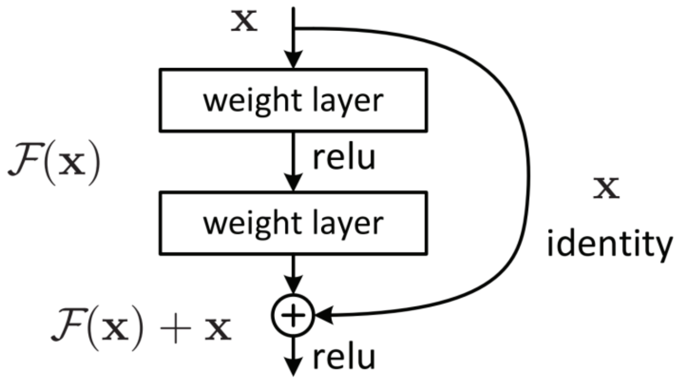
Example Classification of image (from Office Dataset)

* ResNet34/ResNet50 architecture shown [He et al., 2015]

Background - ResNet (He et al., 2015)

- A powerful CNN design based on the idea that deeper networks should be able to perform just as well as shallower ones.

- Skip-connections allow for information from earlier layers to bypass layers.



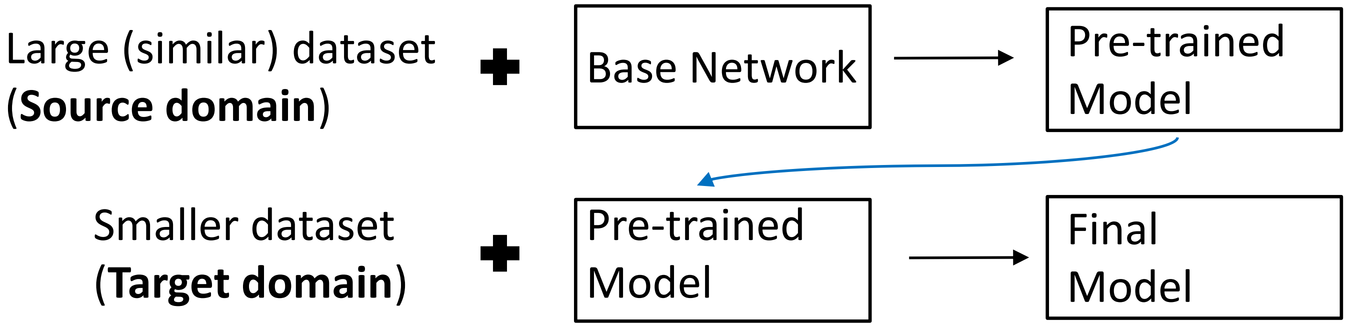
A typical ResNet 'residual block' of layers with a skip-connection (He et al., 2015)

Background - Domain Alignment

- Main idea – utilise the source and target domains by training the network using ‘domain invariant’ information.
- Shallow methods such as CORrelation ALignment (CORAL) modify the data of both domains to make them more similar to each other (Sun et al., 2016).
- Deep methods such as ’Domain-Adversarial Neural Network’ (DANN) learn how to identify the domain of a given example and use that to determine the domain invariant information (Ganin et al., 2016).
- A key focus is on determining which information will lead to more reliable classification performance.

Background - Hypothesis Transfer Learning (HTL)

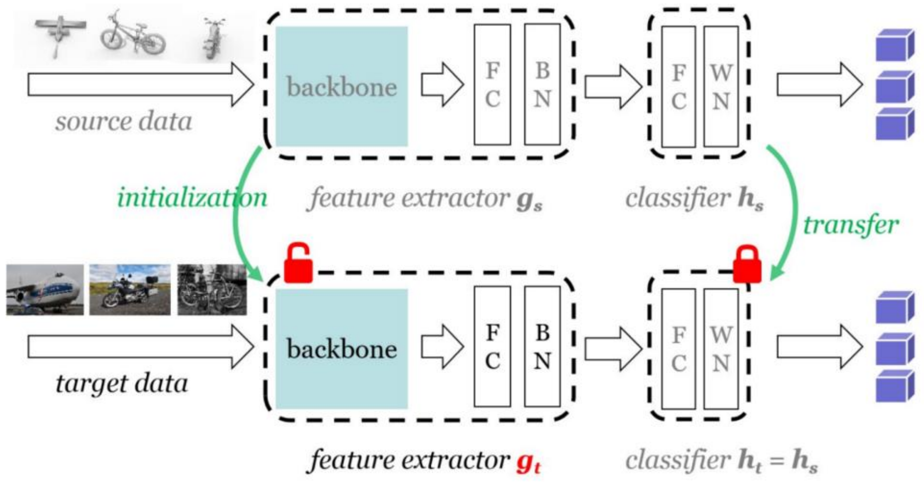
- Train on the source domain first, then train on the target domain.
- Only requires access to one domain at a time, which preserves the privacy of the source domain



Background -Source Hypothesis Transfer (SHOT/SHOT++) (Liang et al., 2021)

- A HTL method for Domain Adaptation that trains different parts of the network differently to adapt to the target domain.

- Was the first to achieve state-of-the-art results using HTL for Domain Adaptation.

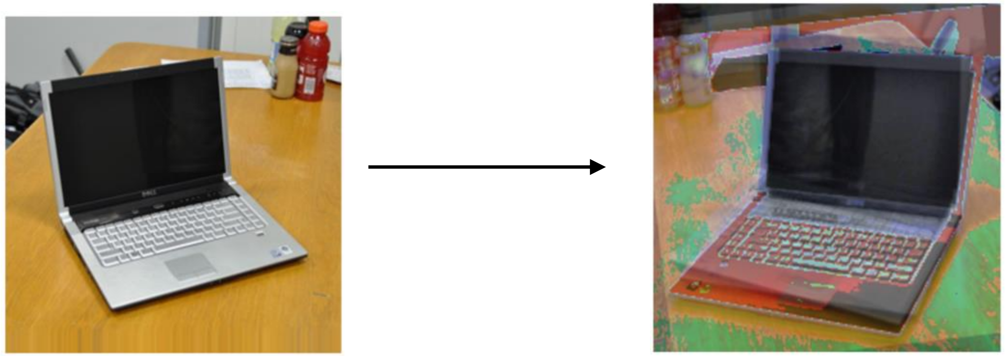


SHOT training pipeline(Liang et al., 2021)

Background – Adapting to Scaled Down Datasets

- MixMatch (Berthelot et al., 2019) – use a partially trained network to produce a set of predictions for each example, split the examples into two groups based on how hard they were to classify. For the examples that were easier to classify, use their prediction as their label and train using mixed groups of unlabelled and pseudo-labelled examples.

- AugMix (Hendrycks et al., 2020) – generate new synthetic data by augmenting examples and adding them to the training dataset.



An example of data augmentation using AugMix

Methodologies

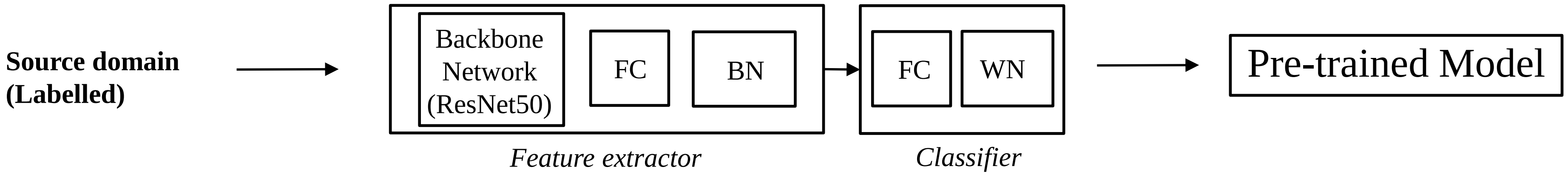
- Three main steps:

1. Train on the full, labelled source domain
2. Train on the unlabelled target domain but do not train the last section of the network

3. Benchmark System – Use the MixMatch algorithm and train the whole network

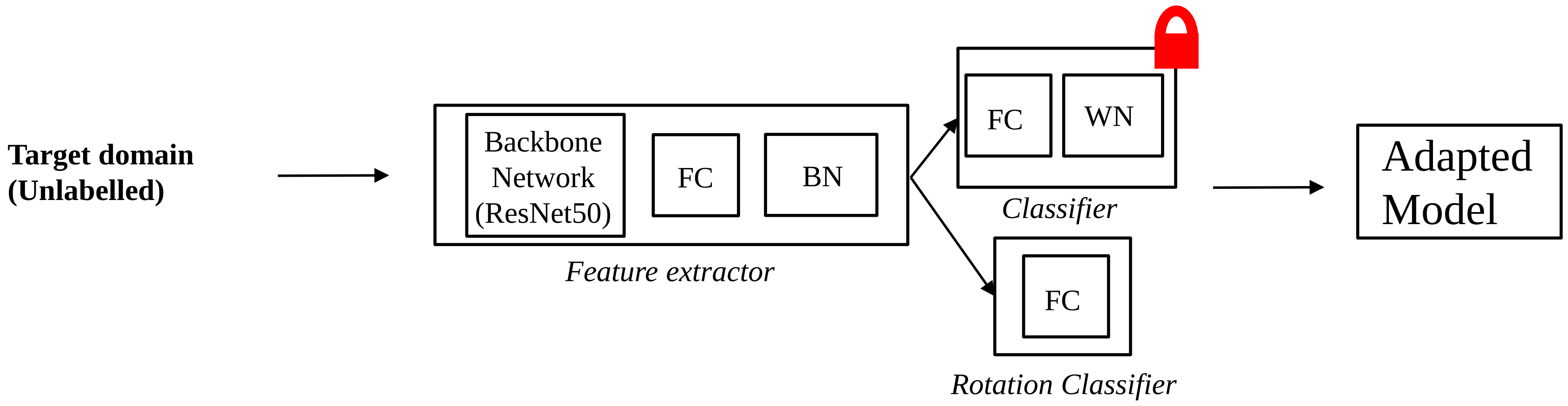
3. UDA Boost – Apply the UDA Boost method including the MixMatch algorithm, data augmentations, added layers and a new optimisation method

Methodologies – Step 1 ‘Source’



*Steps 1 & 2 adapted from SHOT/SHOT++ [Liang et al., 2021]

Methodologies – Step 2 ‘Target’



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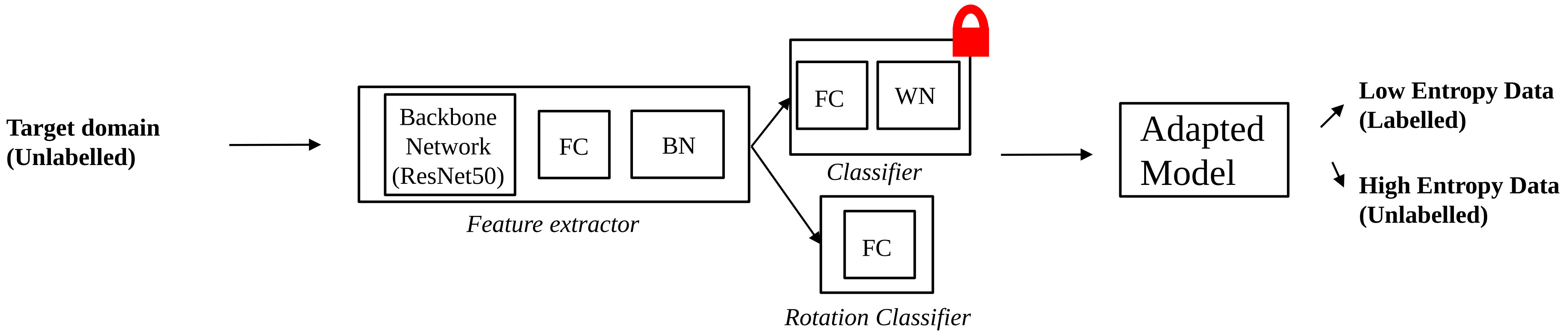
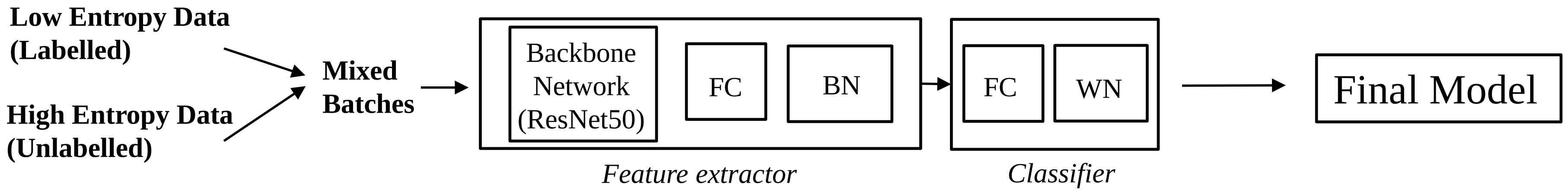
Methodologies – Step 2 ‘Target’



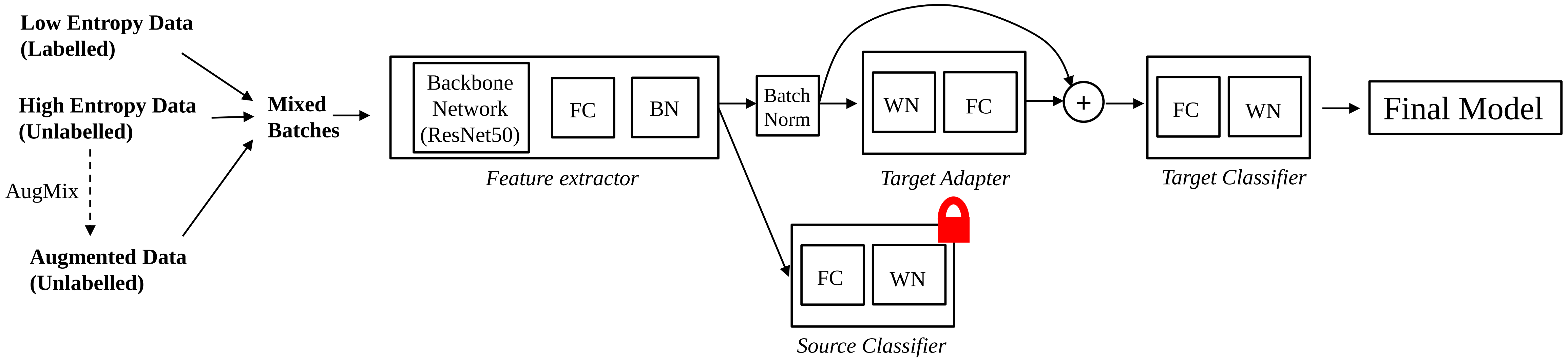
*Steps 1 & 2 adapted from SHOT/SHOT++ [Liang et al., 2021]

Methodologies – Step 3 'Benchmark'

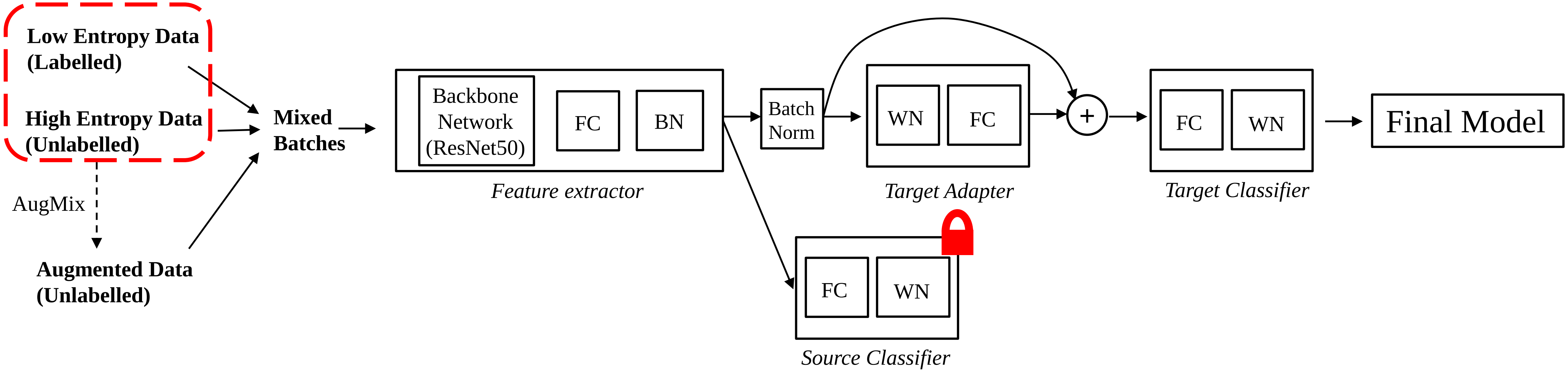


*Benchmark step based on SHOT++ [Liang et al., 2021]

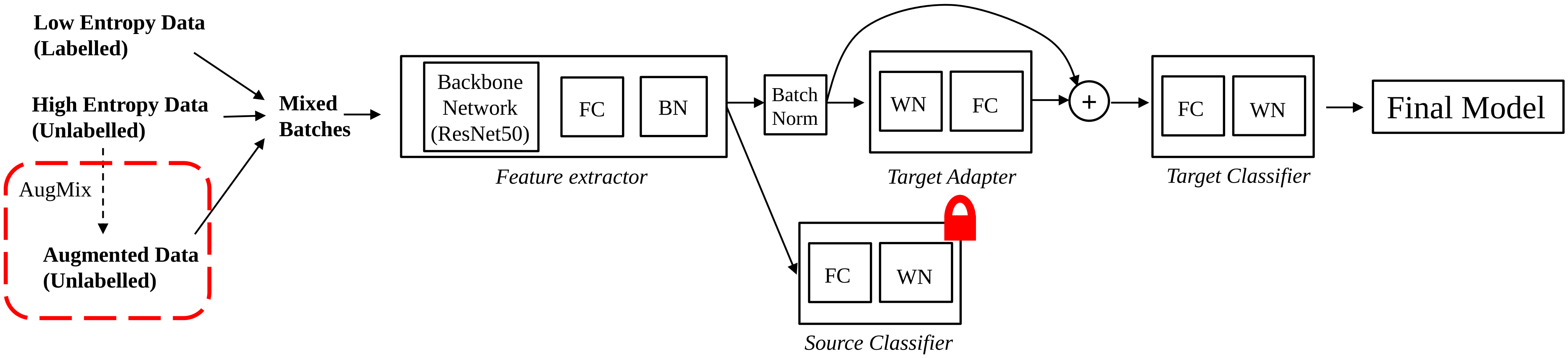
Methodologies – Step 3 'UDA Boost'



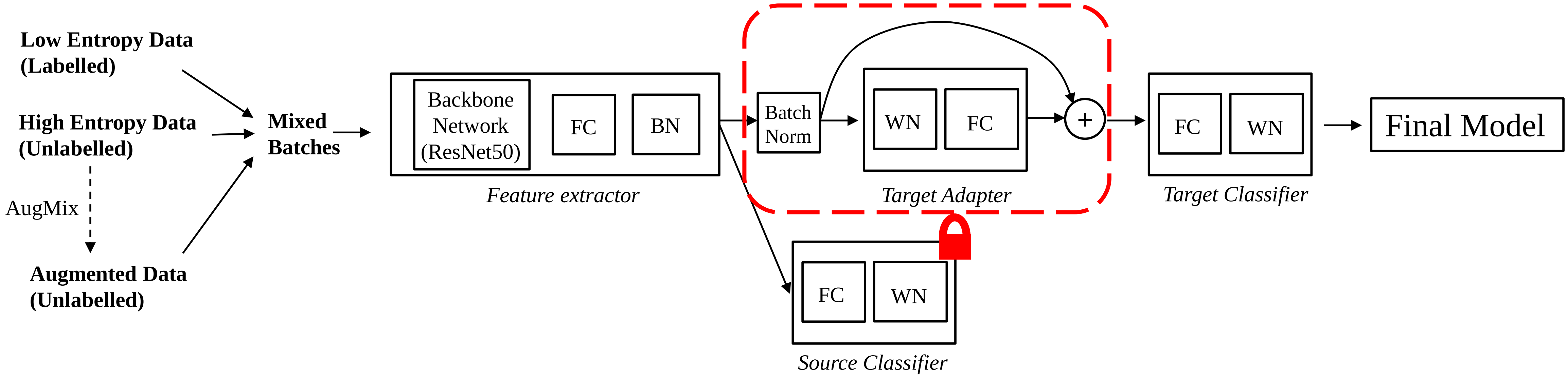
Methodologies – Step 3 'UDA Boost'



Methodologies – Step 3 'UDA Boost'



Methodologies – Step 3 ‘UDA Boost’



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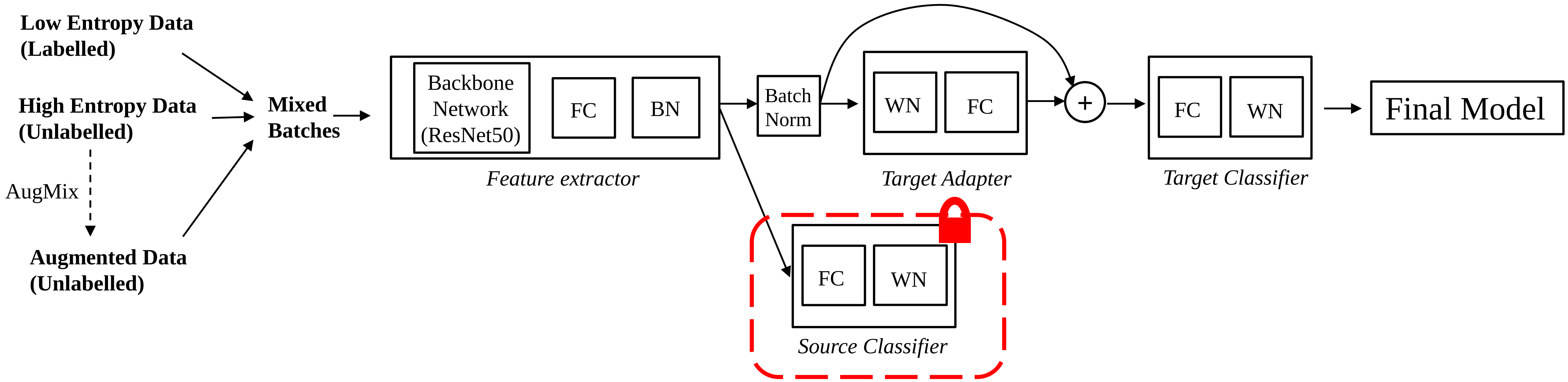
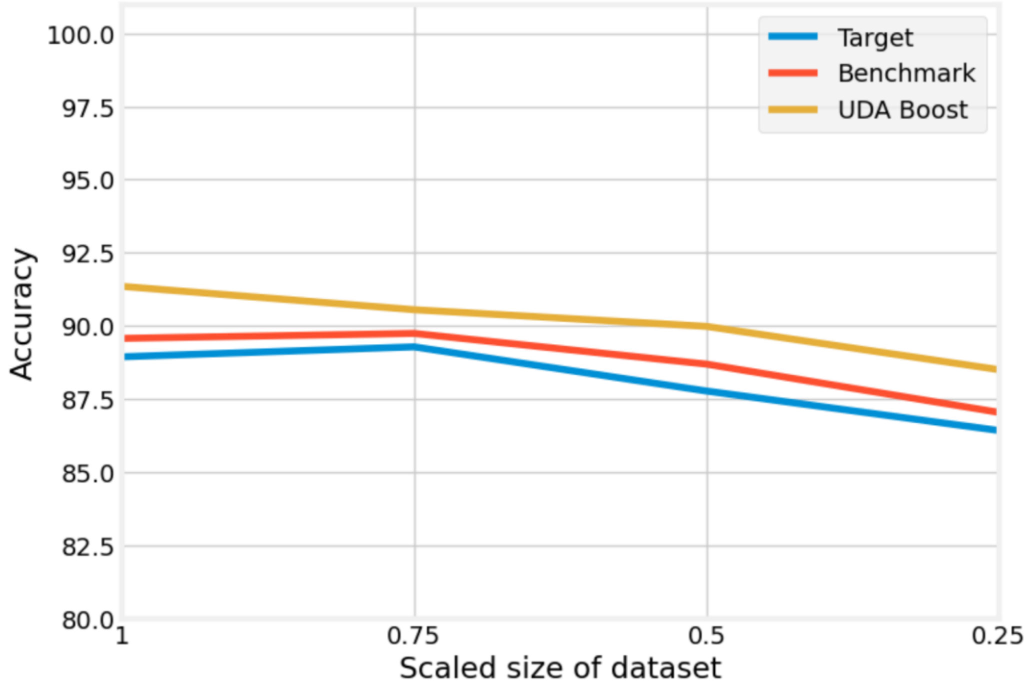
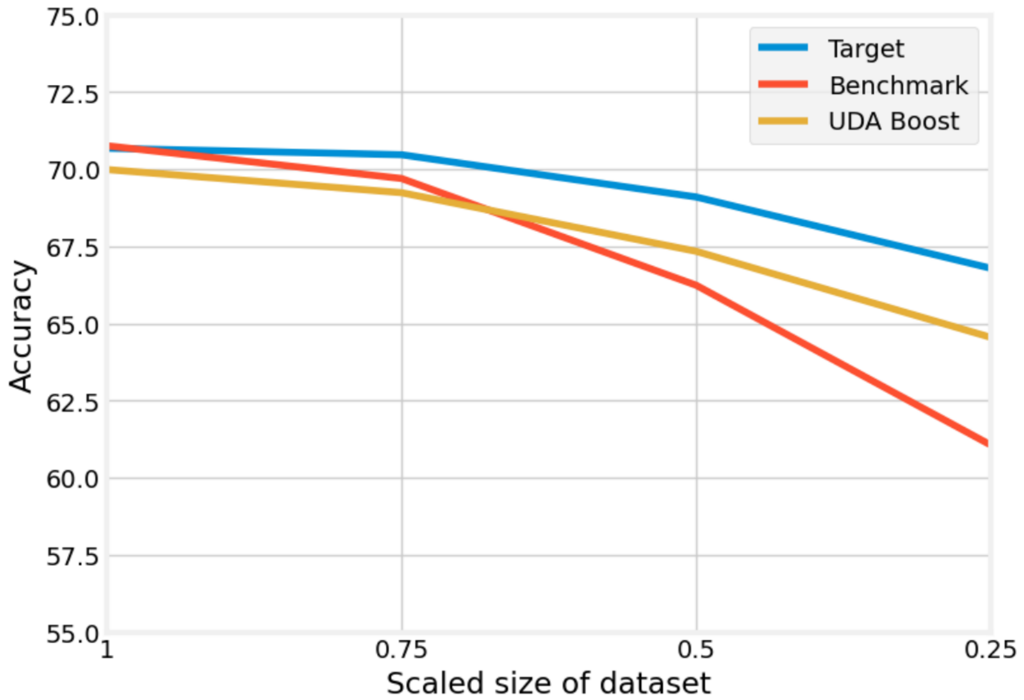


Results – Small Dataset (Office-31)



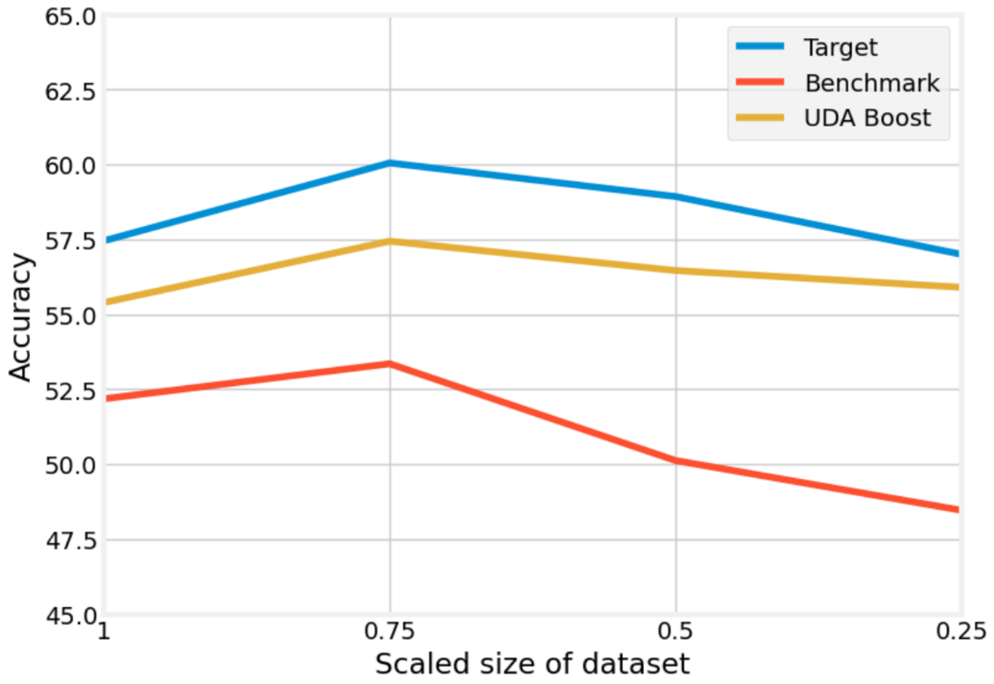
Dataset Size vs Accuracy – Office-31

Results – Medium Dataset (Office-Home)



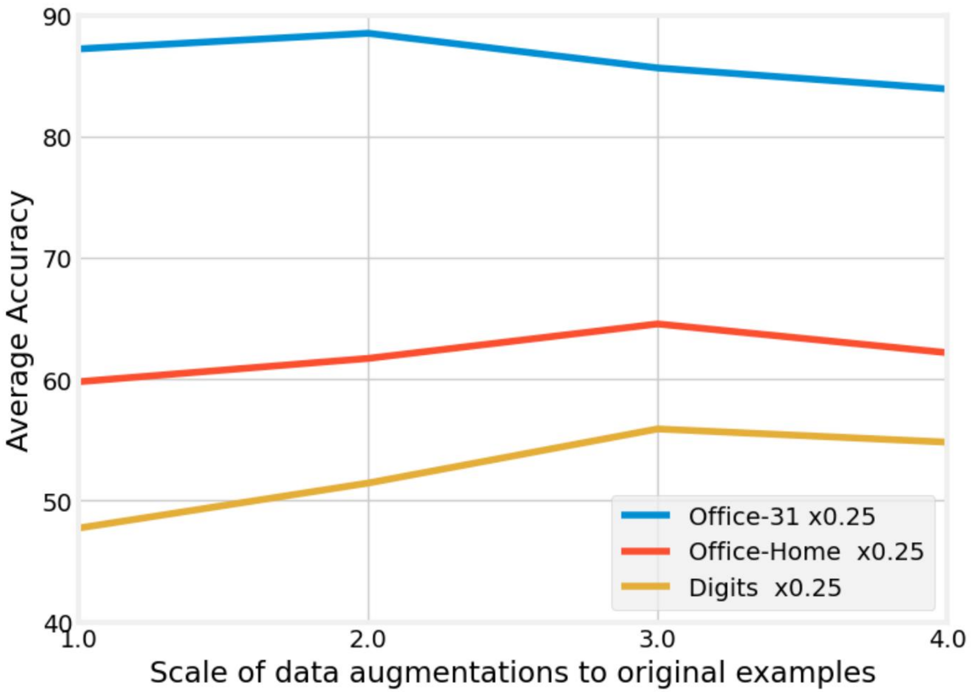
Dataset Size vs Accuracy – Office-Home

Results – Large Dataset (Digits)



Dataset Size vs Accuracy – Digits

Results – Data Augmentations



Ratio of augmented data to original data vs Accuracy

Conclusion

- The results demonstrated a slower rate of decrease in performance as the size of the target domain was reduced. This is a positive indication for the reliability of this method for real-life use cases.

- Main Limitation of the method was that it performed worse on larger datasets compared to the Benchmark and Target methods.

- Future work could adapt this method to different architectures such as Transformers, which have shown huge potential, but are limited by the need for more training data compared to CNNs.

References

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