1. An alternative optimization approach
There exists an alternative construction (inspired by (Goodfellow et al., 2014)) that leads to the same updates (4)-(6). Rather than using the gradient reversal layer, the construction introduces two different loss functions for the domain classifier. Minimization of the first domain loss \( L_d^+ + \lambda L_d^- \) should lead to a better domain discrimination, while the second domain loss \( L_d^- \) is minimized when the domains are distinct. Stochastic updates for \( \theta_f \) and \( \theta_d \) are then defined as:

\[
\theta_f \leftarrow \theta_f - \mu \left( \frac{\partial L_f y}{\partial \theta_f} + \frac{\partial L_d^-}{\partial \theta_f} \right), \\
\theta_d \leftarrow \theta_d - \mu \frac{\partial L_d^-}{\partial \theta_d},
\]

Thus, different parameters participate in the optimization of different losses.

In this framework, the gradient reversal layer constitutes a special case, corresponding to the pair of domain losses \((L_d^+, -\lambda L_d^-)\). However, other pairs of loss functions can be used. One example would be the binomial cross-entropy (Goodfellow et al., 2014):

\[
L_d^+(q, d) = \sum_{i=1}^{N} d_i \log(q_i) + (1 - d_i) \log(1 - q_i),
\]

where \( d \) indicates domain indices and \( q \) is an output of the predictor. In that case “adversarial” loss is easily obtained by swapping domain labels, i.e. \( L_d^-(q, d) = L_d^+(q, 1 - d) \). This particular pair has a potential advantage of producing stronger gradients at early learning stages if the domains are quite dissimilar. In our experiments, however, we did not observe any significant improvement resulting from this choice of losses.

2. CNN architectures
Four different architectures were used in our experiments (first three are shown in Figure 1):

- A smaller one (a) if the source domain is MNIST. This architecture was inspired by the classical LeNet-5 (LeCun et al., 1998).
- (b) for the experiments involving SVHN dataset. This one is adopted from (Srivastava et al., 2014).
- (c) in the SYN SINGS \( \rightarrow \) GTSRB setting. We used the single-CNN baseline from (Ciresan et al., 2012) as our starting point.
- Finally, we use pre-trained AlexNet from the Caffe-package (Jia et al., 2014) for the OFFICE domains. Adaptation architecture is identical to (Tzeng et al., 2014): 2-layer domain classifier \((x \rightarrow 1024 \rightarrow 1024 \rightarrow 2)\) is attached to the 256-dimensional bottleneck of \( \mathcal{E}_C \).

The domain classifier branch in all cases is somewhat arbitrary (better adaptation performance might be attained if this part of the architecture is tuned).

3. Training procedure
We use stochastic gradient descent with 0.9 momentum and the learning rate annealing described by the following formula:

\[
\mu_p = \frac{\mu_0}{(1 + \alpha \cdot p)^\beta},
\]

where \( p \) is the training progress linearly changing from 0 to 1, \( \mu_0 = 0.01 \), \( \alpha = 10 \) and \( \beta = 0.75 \) (the schedule was optimized to promote convergence and low error on the source domain).

Following (Srivastava et al., 2014) we also use dropout and \( \ell_2 \)-norm restriction when we train the SVHN architecture.

References


Srivastava, Nitish, Hinton, Geoffrey, Krizhevsky, Alex, Sutskever, Ilya, and Salakhutdinov, Ruslan. Dropout:
Figure 1. CNN architectures used in the experiments. Boxes correspond to transformations applied to the data. Color-coding is the same as in Figure 1.
