AutoAdapt: Automated Segmentation Network Search for Unsupervised Domain Adaptation

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Abstract

Neural network-based semantic segmentation has achieved remarkable results when large amounts of annotated data are available, that is, in the supervised case. However, such data is expensive to collect and so methods have been developed to adapt models trained on related, often synthetic data for which labels are readily available. Current adaptation approaches do not consider the dependence of the generalization/transferability of these models on network architecture. In this paper, we perform neural architecture search (NAS) to provide architecture-level perspective and analysis for domain adaptation. We identify the optimization gap that exists when searching architectures for unsupervised domain adaptation which makes this NAS problem uniquely difficult. We propose bridging this gap by using maximum mean discrepancy and regional weighted entropy to estimate the accuracy metric. Experimental results on several widely adopted benchmarks show that our proposed AutoAdapt framework indeed discovers architectures that improve the performance of a number of existing adaptation techniques.

1. Introduction

Fully connected convolutional neural networks have shown to be effective for per-pixel classification (semantic segmentation) in images particularly in the supervised case \cite{2, 3, 11, 52}. However, performance degrades when the networks are applied to domains which they were not trained on, that is, when there is a domain shift. Labeling data in the new domain is expensive so researchers have explored adapting the networks in an unsupervised manner \cite{18, 17}, a technique known as unsupervised domain adaptation (UDA).

UDA seeks to narrow the domain gap between a source dataset, for which we have images and labels, and a target dataset, for which we have only images. While good progress has been made in UDA for image classification \cite{31, 32, 44}, UDA for semantic segmentation remains a challenge since knowledge of both the image features and the image structure is needed in order to adapt.

Work has been proposed to address UDA at the feature-level \cite{18}, at the image-level \cite{17, 55, 5} and at the output space-level \cite{42, 46, 35, 24}. However, we find some interesting observations at the architecture-level, in particular the lack of correlation between how well a model performs on a supervised problem and how well it performs for UDA. As shown in Fig. 1 DeepLabV3+ \cite{3} and DANet \cite{11} both outperform DeepLabV2 \cite{2} on supervised semantic segmentation but perform worse in the UDA case. Model improvements in the supervised case do not necessarily translate to improvements for UDA. Model search must be performed separately for UDA but doing this manually is a significant undertaking especially since the optimal model can be dataset dependent. We therefore turn to the burgeoning field of NAS.
of neural architecture search (NAS). We design a search space over semantic segmentation models for UDA that includes advanced modules and configurations. We then develop a search framework that finds effective models that can be used with existing UDA approaches.

However, as we will point out, performing automated search over candidate model architectures for UDA including different training and adaptation configurations is a difficult problem. Simply combining existing NAS search methods with UDA approaches is not effective. Tighter integration between these two concepts is needed particularly regarding how to evaluate candidate architectures when labeled data is not available for the target domain. We study the optimization gap that results when using NAS for UDA and bridge this gap by simulating the target domain evaluation metric. We incorporate these contributions into a complete search framework.

We make the following contributions in this work:

- We approach UDA from a novel perspective, namely architecture. We propose AutoAdapt, the first framework to our knowledge to perform automated network search for UDA.
- We show that a tight integration between network search and domain adaptation is necessary, that it is not enough to simply combine existing NAS and UDA.
- We propose a novel evaluation metric for model selection to guide the search controller so that it finds architectures close to those that would result if target domain labels were available.

2. Related work

UDA for semantic segmentation Various UDA techniques have been applied for semantic segmentation. Adversarial training [42, 46, 43, 5, 34, 47, 17, 25, 8], has been used where one network predicts the segmentation mask of an image, which can be from either the source or target domain, and another network tries to discriminate which domain the image and mask are from. A second category of methods use self-training to iteratively adapt models using target-set pseudo labels generated by the previous state of the model [55, 24, 25, 53]. Other frameworks to UDA have also been proposed [9, 41, 20, 23, 1, 50, 48, 22]. However, all the above methods approach UDA from the image, feature or output-space level. In contrast, our AutoAdapt framework investigates UDA at the architecture level.

AutoML AutoML has been applied recently to search solutions to problems such as augmentation policy [27]. In the context of NAS, numerical techniques have been proposed to compress or find a tiny model architectures. Recently, [30] proposed a gradient-based method (DARTS) to make the architecture search differentiable. This makes it faster than other search methods based on reinforcement learning [5] or evolutionary algorithms [36, 29] and reduces the cost from hundreds or thousands of GPU days to just a few GPU. This has increased the scope of problems that NAS has been applied to. For example, DARTS has been applied to search model architectures for generative networks for image synthesis [15, 12], for semantic segmentation [28] and for object detection [13], etc. However, to our knowledge, we are the first to search model architectures for unsupervised domain adaptation.

3. AutoAdapt: Domain adaptation at the architecture level

We now describe our novel AutoAdapt framework for unsupervised domain adaptation in semantic segmentation. We provide background material and identify and analyze the challenges in searching network architectures for UDA in Sec. 3.1. We illustrate how we address these challenges by proposing a novel joint evaluation criterion for model selection in Sec. 3.2. Finally, we summarize our proposed AutoAdapt framework in Sec. 3.3. Algo. 1 provides an overview of AutoAdapt.

3.1. Preliminaries and motivation

NAS searches the space of valid architectures guided by an objective function. If the space of architectures is parameterized by $\alpha$ and the network weights are parameterized by $w$ then the joint architecture and weight search for a specific problem can be formulated as minimizing an objective function $J(\alpha, w)$ as follows:

$$
\min_{\alpha} J_{\text{search}}(\alpha, w^*(\alpha))
\quad \text{s.t.} \quad w^*(\alpha) = \arg\min_w L_{\text{train}}(\alpha, w).
$$

This implies a bilevel optimization problem. In order to optimize $\alpha$, we first need to optimize $w$. For most supervised tasks, $J_{\text{search}}$ and $L_{\text{train}}$ can be easily minimized by using a training set to update $w$ and a validation set to update $\alpha$. This is because, the proxy datasets (training and validation) are derived from the same dataset. However, the situation is different for UDA where accuracy can be only computed for the source dataset $(x^S \in X^S, y^S \in Y^S)$. Due to the lack of labels, the accuracy for target dataset $(x^T \in X^T)$ cannot be computed and so there is no way to update $\alpha$.

Focusing on the details of UDA approaches helps explain this problem. We take adversarial learning as an example since it is a common approach to UDA [42, 43, 46, 33]. Since the source dataset has class labels, it can be incorporated into a segmentation loss such as a 2D cross entropy loss. However, the target dataset does not have class labels and so can only be incorporated into an adversarial loss such
as a binary cross entropy loss in which the domains become the labels. While the class labels provide semantic information, the domain labels only help the model identify if the input is from source (1) or target (0) in order to align the distributions. We have the following situation

\[ \mathcal{L}_{\text{seg}}^S(x^S, y^S) = -y^S \log(p_{x^S}) \]  \tag{2} 

\[ \mathcal{L}_{\text{adv}}^T(x^T) = -\log(D(G(x^T))) \]  \tag{3} 

where \( S \) and \( T \) denote the source and target datasets, and the corresponding losses are denoted as \( \mathcal{L}_{\text{seg}}^S \) and \( \mathcal{L}_{\text{adv}}^T \) which are the segmentation loss (2D cross-entropy loss with class labels) and the adversarial loss (binary cross entropy loss with domain labels). \( G(x^T) \) is the segmentation network treated as a generator which can operate in the feature, pixel or output space. \( D \) is the discriminator network. Information from the segmentation model (feature, pixel, output space, etc.) is fed to \( D \) to try fool it. \( p_{x^S} \) denotes the probability output by the segmentation network. The segmentation network is then jointly optimized as follows:

\[ \min_w \mathcal{L}_{\text{seg}}^S(x^S, y^S) + \lambda\mathcal{L}_{\text{adv}}^T(x^T) \]  \tag{4} 

Once the segmentation network is updated, the discriminator network is optimized as follows:

\[ \min_D - (1 - z) \log(1 - D(p)) + z \log D(p) \]  \tag{5} 

where \( z = 0 \) if the sample is drawn from the target domain, and \( z = 1 \) if it is from the source domain. This two-player game forces the model to generate predictions from the target domain that are close to predictions from the source.

We can see from the above equations that \( \mathcal{L}_{\text{adv}}^T(x^T) \) is only an adversarial training loss and so is meaningless for evaluating the model performance on the target domain. The situation is thus different from NAS for supervised problem where \( J_{\text{search}} \) is equal to \( \mathcal{L}_{\text{val}} \) which is the same loss as \( \mathcal{L}_{\text{train}} \) (training set) but just with a different dataset (validation set). In the supervised NAS problem, \( \mathcal{L}_{\text{val}} \) reflects how well the model is performing. However, when NAS is used for UDA, Eq. 4 and Eq. 5 form the \( \mathcal{L}_{\text{train}} \) to update \( w \). Since the adversarial loss provides no feedback on how the model performs on the target dataset, \( \alpha \), and thus the model architecture, cannot be updated in a meaningful way. We identify this as an optimization gap when applying NAS to UDA.
3.2. Bridging the gap without labels

Then main challenge of the search problem is bridging this optimization gap that results when labels are not available for the target domain. The form of the objective used to guide the search is an open problem. Further, it is clear that the performance of a candidate model on the target dataset can only be approximated. We seek a joint metric to approximate this performance. Specifically, maximum mean discrepancy (MMD) is used for computing the distance between source and target domains and entropy is used for determining the model confidence based on output structure.

Maximum Mean Discrepancy (MMD) has been widely used as a regularizer for domain adaptation beyond feature and output spaces. As a confidence measurement, entropy indicates where a model is struggling. We therefore investigate using entropy to evaluate how candidate architectures perform on the target dataset. Specifically, given a softmax score map $p$ for a target image $x^T$, denoted as $p^{(h,w,c)}_{x^T}$ where $h, w, c \in H, W, C$ indicate the indices along height, width and class dimensions of the last softmax layer of the model, we compute the entropy as

$$\text{Ent}_{x^T}^{(h,w)} = \frac{-1}{\log(C)} \sum_{c=1}^{C} p^{(h,w,c)}_{x^T} \log p^{(h,w,c)}_{x^T}. \quad (7)$$

Here, $C$ indicates the number of semantic classes. $\text{Ent}_{x^T}^{(h,w)}$ is a 2D matrix, and in order to produce a consistent metric, we average the entropy over all pixel locations as follows:

$$\text{Ent}_{x^T} = \frac{1}{HW} \sum_{h=1}^{H} \sum_{w=1}^{W} \text{Ent}_{x^T}^{(h,w)} \quad (8)$$

However, average entropy does not achieve our goal of evaluating the structure of the output. We therefore propose an improved Regional weighted Entropy (ReEnt) to measure adaptation performance with respect to output structure. We first partition the input image into regions $R$ based on the appearance similarity computed using the low-level features. We then compute the entropy value for each region as follows:

$$\text{ReEnt}_{x^T}^{(r,c)} = \beta \frac{1}{\log(r)} \sum_{h',w'}^{r} p_{x^T}^{(h',w',c)} \log p_{x^T}^{(h',w',c)} \quad (9)$$

where $h', w'$ represent the location of the region $r$. Since the areas of the regions vary, $\beta$ is used to weight their importance as measured by their proportion of the total area:

$$\beta = \frac{\text{Area}_r}{\sum_{r' \in R} \text{Area}_{r'}} \quad (10)$$

This is different from standard entropy which is used to characterize the probability distribution along class dimensions. Our goal instead is to determine if a model produces smooth predictions within regions that have similar appearance. If the probability is evenly distributed (smooth prediction) within a region, then the entropy will be large entropy. So that all the metrics are consistent (smaller is better), we take the opposite value. Finally we derive the regional weighted entropy for the whole image as:

$$\text{ReEnt}_{x^T} = \frac{1}{C} \sum_{c=1}^{C} \sum_{r \in R} \text{ReEnt}_{x^T}^{(r,c)} \quad (11)$$
Joint Metric for Model Selection Our metric for evaluating the performance of UDA which is also used for model selection consists of two parts, one to evaluate domain alignment and another to evaluate output structure. In order to also limit the computational cost of the searched segmentation models, we add a computation complexity (MACs) constraint as a regularization term in the objective function. Our search goal thus becomes minimizing the objective function as follows:

\[
\min_{\alpha} \text{MMD}(\mathcal{X}^S, \mathcal{X}^T) + \text{ReEnt}(w^*(\alpha), \alpha, \mathcal{X}^T) + \lambda \text{MACs}(\alpha)
\]

\[
\text{s.t. } w^*(\alpha) = \arg\min_w L_{DA}(\alpha, w, \mathcal{X}^S, \mathcal{X}^T).
\]

(12)

It is noted that, the proposed evaluation metric cannot be served as the training objective. Since the proposed ReEnt is not differentiable resulting in not available for backpropagation while training.

3.3. Framework

We now summarize the proposed AutoAdapt framework for unsupervised domain adaptation. As is done in most NAS techniques, we create a proxy task to perform NAS. Once the optimal architecture is determined, the model is retrained using the entire dataset.

As shown in Algo. 1, AutoAdapt has two stages. Stage I: Search and build model Given a specified search space and a pretrained backbone (seed-net), a child model (super-net) will be created by the search controller (which could be based on reinforcement learning, evolutionary algorithms, gradient descent, etc.). Stage II: Domain adaptation Given the child model, our goal is to update the model weights by adapting from the source to the target, that is to compute \( w^*(\alpha) \). Note that any domain adaptation method can be used to accomplish this. We then evaluate the adapted model using the proposed joint metric \( \text{MMD}(\mathcal{X}^S, \mathcal{X}^T) + \text{ReEnt}(w^*(\alpha), \alpha, \mathcal{X}^T) \), and, through the optimization in Eq. 12 provide feedback to the controller to generate the next novel architecture. Through such interactions, the final optimal solution will be derived from the minimum evaluation score. To improve efficiency, the search is based on a proxy task, that is to find \( \alpha \) using a small number of training iterations and with a simple UDA method (AdvEnt[46]). Finally, the discovered architecture \( \alpha^* \) is retrained with the full datasets and with a sufficient number of iterations. Note that we can consider different UDA methods during retraining. In the experiments below, we investigate AdvEnt [46], IntraDA [53] and CCM [24].

4. Search strategy

Now that we have described a general framework for search optimization, we can investigate it with a specific search strategy. Note that any search algorithm can be used as the search controller. We find search based on evolutionary algorithms is easily incorporated into our framework.
Figure 3: Correlation between entropy and mIoU. Entropy is highly (inversely) correlated with mIoU as indicated by Spearman’s rank correlation (p) for all metrics used in AutoAdapt. All experiments are performed on GTA5→Cityscapes. (Zoom in for details.)

| Source Only | road | side | build. | wall | fence | pole | light | sign | veg | terr. | sky | pers. | rider | car | truck | bus | train | make | bike | mIoU |
|-------------|------|------|--------|------|-------|------|-------|------|-----|-------|-----|-------|-------|-----|-------|-----|-------|------|------|------|
|             |      |      |        |      |       |      |       |      |     |       |     |       |       |     |       |     |       |      |     |      |
| CRST [55]   | 60.6 | 17.4 | 73.9   | 17.6 | 20.6  | 21.9 | 31.7  | 15.3 | 79.8| 18.1   | 71.1| 55.2  | 22.8  | 68.1| 32.3  | 23.8| 3.4   | 34.1| 21.2 | 35.7 |
| PLCA [21]   |      |      |        |      |       |      |       |      |     |       |     |       |       |     |       |     |       |      |     |      |
|             | 34.1 |      |        |      |       |      |       |      |     |       |     |       |       |     |       |     |       |      |     |      |
| BDL [25]    |      |      |        |      |       |      |       |      |     |       |     |       |       |     |       |     |       |      |     |      |
|             | 35.7 |      |        |      |       |      |       |      |     |       |     |       |       |     |       |     |       |      |     |      |
| CAG [51]    |      |      |        |      |       |      |       |      |     |       |     |       |       |     |       |     |       |      |     |      |
| AdvEnt [46]|      |      |        |      |       |      |       |      |     |       |     |       |       |     |       |     |       |      |     |      |
| Ours (Auto-AdvEnt) |      |      |        |      |       |      |       |      |     |       |     |       |       |     |       |     |       |      |     |      |
| IntraDA [35]|      |      |        |      |       |      |       |      |     |       |     |       |       |     |       |     |       |      |     |      |
| Ours (Auto-IntraDA) | 90.8 | 38.6 | 82.4   | 35.3 | 24.8  | 32.2 | 36.8  | 24.5 | 85.5| 34.6   | 83.3| 57.7  | 24.6  | 84.1| 27.8  | 30.1| 42.3  | 47.1 |
| CCM [24]    |      |      |        |      |       |      |       |      |     |       |     |       |       |     |       |     |       |      |     |      |
| Ours (Auto-CCM) |      |      |        |      |       |      |       |      |     |       |     |       |       |     |       |     |       |      |     |      |

Table 2: Experimental results of GTA5→Cityscapes. We show results of Auto-AdvEnt, Auto-IntraDA, Auto-CCM.

and has an acceptable search speed. In this section, we first describe the specific search space we design for UDA. We then present our evolutionary algorithm for searching.

4.1. Search space

The NAS search space defines a set of basic network operations as well as ways to combine these operations to construct valid network architectures. Here, we design our search space that is unique for domain adaptation. We describe our search space in three aspects: training configurations, segmentation model and adaptation configurations. The operations used in each aspect are listed below. More details can be found in the supplementary materials.

- Training configuration: We consider a set of crop sizes (Op1) by multiplying the original image dimensions by reduction ratios of \( \frac{1}{8}, \frac{1}{4}, \frac{1}{2}, \frac{3}{4} \) and \( \frac{3}{4} \). Once the crop size is determined, random cropping is used to generate the input image.

- Segmentation model: We consider both the network backbone and the segmentation head. For the backbone, we design the search space as the number of layers (Op2), the kernel size (Op3), and the dilation rates (Op4). We sample kernel sizes from \( \{3 \times 3, 5 \times 5\} \) and dilation rates from \( \{1, 2, 4\} \). We also consider incorporating an SE-Layer [19] (Op6) into the backbone. For the segmentation head (Op5), we choose from \{ASPP [2], spatial attention [11] and low-level features

- Adaptation configuration: Multi-level adaptation is commonly used in UDA approaches [42, 46] by constructing an auxiliary loss using features from the early layers of the network. We also adopt this and consider features from different layers in our search space.

4.2. Evolutionary algorithm

Initialization We first randomly sample 100 models from the search space. Given a pretrained backbone, this sampling is accomplished by randomly changing one part of the backbone, selecting a different training configuration, or selecting a different adaptation method. We train and evaluate these models and pick the top 20 based on our joint criterion to initialize the population.

Evolution After initialization, the evolutionary algorithm is used to improve the population over \( M \) cycles. Tournament selection [14] is used to update and generate new populations. At each cycle, 25% of the models are randomly sampled as the tournament. The model with the lowest entropy is selected as a parent. A new model, called a child, is constructed from this parent by modifying one part of the model randomly. This process is called a mutation. The child model is then trained, evaluated and added back to the
population. More details of our evolutionary algorithm can be found in the supplementary material.

5. Experiments

5.1. Datasets

GTA5: The synthetic dataset GTA5 [37] contains 24,966 synthetic images with a resolution of 1,914×1,052 and corresponding ground-truth annotations. These synthetic images are collected from a video game based on the urban scenery of Los Angeles city. The ground-truth annotations are generated automatically and contain 33 categories. For training, we consider the 19 categories in common with the Cityscapes dataset. During evaluation, we consider the 16 categories in common with the Cityscapes dataset. During training, 16- and 13-class subsets are used to evaluate the performance. Cityscapes: A real world dataset, Cityscapes [7] contains 3,975 images with fine segmentation annotations. We use 2,975 images for training and 500 images from the evaluation set to evaluate the performance of our models.

5.2. Implementation details

We use the PyTorch deep learning framework to AutoAdapt. For AutoAdapt Stage-I, we first randomly generate 100 models with ResNet-101 which are then trained for 20,000 iterations. We pick the top 20 models as our population and start evolving them through mutation. Once a child model is created, parameter remapping [10] is used to transfer the weights from the pretrained ResNet-101. The model is now ready for to be trained for domain adaptation (Stage-II). We split the target dataset into two folds, 85% for domain adaptation and 25% for performance evaluation. We stop the searching early if the best model in the effective population remains the same for over 25 cycles. Once the architecture search is finished, we retrain the model with the full dataset and sufficient training iterations. Three UDA methods AdvEnt [46], IntraDA [35] and CCM [24] are used for retraining and thus we term our final results Auto-AdvEnt, Auto-IntraDA and Auto-CCM. More details can be found in the supplementary materials.

6. Experimental results

6.1. Effectiveness of AutoAdapt

In this section, we perform comparisons to answer the question “Is automated model search really necessary and effective for UDA?”. That is, how does automated model search for UDA compare with selecting hand-crafted architectures and then applying UDA. We simulate manual design by humans by selecting various advanced backbones and segmentation networks and follow this with different UDA methods. Details of the results and methods are shown in Tab. 1. Adaptation is conducted from GTA5--Cityscapes. We report mIoU on the Cityscape validation set.

1) Comparisons to hand-crafted methods: We replace the commonly used semantic segmentation network DeeplabV2 [2] with the state-of-the-art networks DeeplabV3+ [3] and DANet [11] in a UDA framework. For fair comparison, the backbone remains the same for all three segmentation models. Rows 1-3 show the results of using advanced segmentation networks with various UDA methods. We can see DANet and DeeplabV3 outperform DeeplabV2 in the non-domain adaptation case (oracle=training using the target dataset) by large margins of over 10%. But, when there is domain adaptation, they perform worse than DeeplabV2, often with over 2% lower mIoU. We also investigate how state-of-the-art backbone affects UDA. We replace the backbone of DeeplabV2 which is a ResNet-101 network with SENet [19] and call this DeepLabV2-S. We realize there are other advanced backbones like Xception [6] that could be considered. But, for fair comparison, we only consider SE-Net [19] as it is included in our search space. Row 4 shows the results for DeepLabV2-S. We observe that an advanced backbone does not improve performance as it achieves only 42.3%, 43.9% and 45.7% mIoU when used with AdvEnt, IntraDA and CCM which is lower than the DeeplabV2-ResNet101 results. We conclude therefore that manually designing segmentation networks (backbone or head) for non-domain adaptation scenarios does not necessarily lead to improved UDA results. This raises the question “what kinds of modules/architecture lead to improvement for UDA?”. We answer this question by providing architecture-level analysis and conclusions in Sec. 6.3.

2) Comparisons to searched methods: We select the NAS discovered backbone DARTS [10] with an ASPP (DeeplabV2-D) in DeeplabV2 and the NAS discovered segmentation network AutoDeepLab [28] to separately replace the segmentation networks for different UDA methods. Rows 5 and 6 show these architectures perform poorly for UDA. We conclude that replacing the network with architectures discovered using existing NAS techniques is not effective for UDA. This is because these architectures are discovered in supervised manner which does not take into account the transferability/generalization of the models.

3) Comparisons to NAS methods: We modify the search loss function with a UDA loss in DARTS [10], PC-DARTS [49] and AutoDeepLab [28] to see if existing NAS methods can find effective architectures for UDA. Rows 8-11 show the performance of the modified NAS methods with a UDA loss. Replacing the search loss function does not provide a reasonable search space for UDA due to the
4) Comparison to state-of-the-art We compare our method to state-of-the-art domain adaptation methods on two unsupervised domain adaptation tasks: GTA5→Cityscapes and SYNTHIA→Cityscapes. The results are presented in Tabs. 2 and 3. Our AutoAdapt method outperforms all the baselines. For GTA5→Cityscapes, we achieve an mIoU of 50.2%, comparable to the previous state-of-the-art method CAG (50.1%). The other AutoAdapt methods (Auto-AdvEnt and Auto-IntraDA) outperform their baselines by 1.5% and 1.4% respectively. For SYNTHIA→Cityscapes, we report mIoU on 13 classes (excluding “Wall”, “Fence”, and “Pole”) and 16 classes. Similar observations are made. All AutoAdapt methods outperform their baselines. And our Auto-CCM achieves 53.3% and 45.6% mIoU on 13 classes and 16 classes respectively, both of which outperform previous state-of-the-art.

6.2. Ablation studies

We expect that an effective surrogate evaluation metric should be correlated with the standard metric if it could be computed (if labels were available for the target domain). Fig. 3 shows the (negative) correlation graphically as well as through Spearman’s rank correlation coefficient \( \rho \) between variations of our novel evaluation metric (MMD, Entropy (Ent), and Regional Weighted Entropy (ReEnt) and the combination of them) and mIoU for GTA5→Cityscapes adapted using AdvEnt. We stress that we only use the Cityscape labels to compute mIoU for this correlation analysis—we do not use the labels in our AutoAdapt framework. Fig. 3 shows that MMD which only measures the distribution distance between source and target domains performs the worst. Combining MMD and the output structure metric Ent or ReEnt improves the correlation significantly. The proposed ReEnt by itself shows higher correlation than standard entropy. The proposed joint metric which consists of MMD and ReEnt achieves the best correlation with \( \rho \approx 0.87 \). More details of the evaluation metric can be found in the supplementary materials.

6.3. Architecture-level analysis on UDA

We perform architecture-level UDA analysis in this section. Interesting observations can be made which, in some
Table 4: Comparative studies on replacing architectures with baseline DeeplabV2. Two operations are performed to create the new architecture, replace and add resulting in 2 and 1 edit distance respectively.

| Model         | Backbone | Head                      | MMD | ReEnt | $Params$  | #MACs  | mIoU(%) |
|---------------|----------|---------------------------|-----|-------|-----------|--------|---------|
| DeeplabV2     | Res101 [3,4,23,3] | ASPP + Attention           | 0.78 | -0.53 | 44.6M     | 380.5B | 43.8    |
| arch#1        | /        | ASPP + Attention           | 0.98 | -0.44 | 57.7M     | 490.1B | 39.8    |
| arch#2        | /        | + low-level                | 0.94 | -0.54 | 63.6M     | 601.4B | 41.2    |
| arch#3        | + SE-Layer at Res4 | -ASPP + ASPP{6,18,24,36} | 0.65 | -0.49 | 44.7M     | 380.5B | 44.7    |
| arch#4        | /        |                           | 0.78 | -0.58 | 44.6M     | 380.5B | 44.5    |
| arch#5        | -Res2 + Res2[3] |                          | 0.77 | -0.51 | 42.6M     | 376.5B | 43.7    |

Fig. 5 shows the final model that results from our search. It has slightly more parameters but the computational complexity does not change. This model benefits mainly from adding the SE-Layer and changing the dilatation rates for the ASPP based on the above observations. We conclude that the increase in parameter size is worthwhile for the improved adaptation performance. However, during search, we have the other models with less parameters and computational complexity which yield a bit worse adaptation performance compared to the final model but still outperform the baseline DeeplabV2.

7. Discussion and conclusion

UDA has not experienced the kinds of improvement that supervised semantic segmentation has recently. We therefore take a different approach to UDA, one based on architecture. We adapt NAS techniques to provide in-depth analysis on architecture for UDA. We overcome the optimization gap in NAS for UDA by developing a novel performance estimation metric. Our experimental results show that the architecture discovered using our AutoAdapt framework outperforms all the baseline UDA methods.

We now discuss some limitations. First, the search space is relatively small compared to the supervised cases for image classification, semantic segmentation, etc. It would make sense to develop a benchmark search space for UDA in the future. Second, we only identify the challenge of the optimization gap during search. Other challenges related to the search strategy remain unsolved. For example, efficient gradient-based methods cannot be used to search architectures for UDA in semantic segmentation. Since we are the first to investigate NAS for UDA, in the future, we will try to tackle this challenge to improve the search efficiency. Third, we only partially answer the open question “what is the role of architecture in UDA?” Based on our observations, architectures that have various levels of transferability/generalization benefit tasks like UDA. We still feel this is a promising direction to explain the role the neural network plays in UDA and how this role might be different than in other tasks.
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