**AutoMTL: A Programming Framework for Automated Multi-Task Learning**

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**Abstract**

Multi-task learning (MTL) jointly learns a set of tasks. It is a promising approach to reduce the training and inference time and storage costs while improving prediction accuracy and generalization performance for many computer vision tasks. However, a major barrier preventing the widespread adoption of MTL is the lack of systematic support for developing compact multi-task models given a set of tasks. In this paper, we aim to remove the barrier by developing the first programming framework AutoMTL that automates MTL model development. AutoMTL takes as inputs an arbitrary backbone convolutional neural network and a set of tasks to learn, then automatically produce a multi-task model that achieves high accuracy and has small memory footprint simultaneously. As a programming framework, AutoMTL could facilitate the development of MTL-enabled computer vision applications and even further improve task performance. Code of AutoMTL is available at https://github.com/zhanglijun95/AutoMTL.git.

**1 Introduction**

AI-powered applications increasingly adopt Convolutional Neural Networks (CNNs) for solving many vision-related tasks (e.g., semantic segmentation, object detection), leading to more than one CNN models running on resource-constrained devices. Supporting many models simultaneously on a device is challenging due to the linearly increased computation, energy, and storage costs. An effective approach to address the problem is multi-task learning (MTL) where a set of tasks are learned jointly to allow some parameter sharing among tasks. MTL has shown significantly reduced inference costs and improved generalization performance in several computer vision applications (Kokkinos, 2017; Ruder, 2017) such as self-driving cars and social robots.

A fundamental challenge that hinders the wide adoption of MTL is the difficulties in model development. Many prior works (Huang et al., 2015; Jou & Chang, 2016; Dvornik et al., 2017; Kokkinos, 2017; Ranjan et al., 2017) rely on manually-designed MTL model architectures which share several initial layers and then branch out at an ad hoc point for all tasks. They not only call for significant domain expertise when tweaking these architectures for every possible combination of learning tasks but also often result in unsatisfactory solutions due to the enormous architecture design space. The problem is exacerbated when the number of tasks increases and improper sharing strategies across unrelated tasks cause task interference and accuracy degradation (Kang et al., 2011; Standley et al., 2020).

To address the above problems of manually-designed architectures, several recent efforts (Sun et al., 2019; Ahn et al., 2019; Guo et al., 2020) focus on learning to share parameters across tasks. They embed policy-learning components into a backbone CNN to automatically determine which layers/filters in the network should be shared across which task or where to branch out for different tasks during the training process. While this line of work has obtained reasonable accuracy on commonly-used benchmark datasets, they suffer from two main drawbacks. Firstly, they fail to dynamically adjust model capacity based on given tasks, leading to sub-optimal solutions as the number of tasks grows. More importantly, the implementation of these works is deeply coupled with a specific backbone model and cannot be easily generalized to other CNNs without significant manual efforts. The lack of systematic support for efficient multi-task model development given any backbone CNN and a set of tasks remains a major barrier for adopting MTL in broader applications.

In this paper, we aim to remove this barrier by developing AutoMTL, the first programming framework that automates MTL model development. AutoMTL will take as inputs an arbitrary backbone CNN and a set of tasks to learn, and then produce a multi-task model that achieves high task accuracy and has small memory footprint (measured by the number of parameters) simultaneously. The main idea of AutoMTL
is to design a compiler to automatically transforms the user-provided backbone model to a supermodel that encodes the multi-task architecture search space. The compiler treats each operator in the backbone model as a basic unit for sharing, enabling the support of an arbitrary CNN backbone architecture without any manual efforts. AutoMTL then performs efficient architecture searches on the supermodel to identify the optimal sharing patterns among tasks. As a programming framework, AutoMTL would greatly facilitate the development of MTL-enabled applications. Besides, our experiments on several MTL benchmarks with different number of tasks show that AutoMTL could produce compact multi-task models with smaller memory footprint and higher task accuracy compared to state-of-the-art methods.

The main contributions of our work are as follows:

- We propose a Multi-Task Supermodel Compiler (MTS-Compiler), which transforms a user-provided backbone architecture to a multi-task supermodel that encodes the architecture search space. The compiler decouples architecture search with the backbone CNN model, removing the manual efforts in extending MTL to new backbone models and making the framework an easy-to-use solution for multi-task model development.
- The supermodel abstraction is based on a novel internal data structure called Virtual Computation Node (VCN), which allows the framework to flexibly explore parameter sharing patterns across tasks and adaptively adjust multi-task model capacity in a differentiable way.
- Built on top of the supermodel, we propose an efficient architecture search algorithm that jointly optimizes sharing policies and network weights using approximations and standard back-propagation. The algorithm applies a regularization term on the sharing policy to promote parameter sharing and learn compact multi-task models. We further provide a set of trainer functions that materialize a three-stage training pipeline to ease training efforts and reduce development difficulty.
- Experiments on three popular MTL benchmarks (CityScapes (Cordts et al., 2016), NYUv2 (Silberman et al., 2012), Tiny-Taskonomy (Zamir et al., 2018)) demonstrate that the multi-task model searched by the proposed algorithm outperforms state-of-the-art approaches in terms of model size and task accuracy.

## 2 Related Work

Multi-task learning tackles a set of tasks jointly by learning a multi-task model for all tasks. Compared to single-task learning, it can achieve higher prediction accuracy and improved efficiency for each task by leveraging commonalities across related tasks (Caruana, 1997; Baxter, 2000; Ruder, 2017). In the context of deep learning, MTL creates multi-task models based on popular deep neural network (DNN) architectures called backbone models. They fall into either hard parameter sharing or soft parameter sharing (Ruder, 2017). In hard parameter sharing, a set of the parameters in the backbone model are shared among tasks. In soft parameter sharing (Misra et al., 2016; Ruder et al., 2019; Gao et al., 2019), each task has its own set of parameters. Task information is shared by applying regularization on parameters during training (e.g., enforcing the weights of the model for each task to be similar).

In this paper, we focus on the first type as it produces computational and memory-efficient multi-task models. One of the widely-used hard parameter sharing strategies is proposed by Caruana (Caruana, 1993; 1997), which shares the bottom layers of a model across tasks. Following this paradigm, researchers (Long et al., 2017; Nekrasov et al., 2019; Suteu & Guo, 2019; Chemnupati et al., 2019; Leang et al., 2020) manually design multi-task models that share several bottom layers and then branch out at an ad hoc point for some tasks. Due to the enormous architecture design space, it is unclear how to effectively decide what parameters to share given a backbone model with a set of tasks in interest.

Inspired by the recent progress on Neural Architecture Search (NAS) (Zoph & Le, 2016; Real et al., 2017; Elsken et al., 2019; Real et al., 2019), recent works attempt to learn the sharing patterns across tasks. Deep Elastic Network (DEN) (Ahn et al., 2019) use reinforcement learning (RL) to determine whether each filter in convolutional layers is shared across tasks or not. Similarly, AdaShare (Sun et al., 2019) learns task-specific policies that select which layers to execute for a given task.

However, these works cannot dynamically adapt MTL model capacity based on given tasks. They attempt to pack multiple tasks into a single backbone model where each task executes a subnetwork in the backbone model. The capacity of the multi-task model is limited by the backbone model and would suffer from performance degradation as the number of tasks and task difficulties increase (Kokkinos, 2017).

More importantly, existing studies focus on search algorithms but ignoring the ease of programming and extensibility. Their implementation is highly coupled with the backbone model. It is difficult to extend the algorithms to other backbone models and customized models for general users, hindering their adoption in practical applications. Although AutoKeras (Jin et al., 2019) is able to generate multi-task models automatically for given tasks, it limits all tasks to share the entire backbone architecture for feature extraction. The underlying architecture search process aims at choosing a suitable backbone model, instead of learning adaptive sharing patterns for multiple tasks.

To summarize, there is a strong need of a programming
framework for efficient MTL that allows an arbitrary CNN model as the backbone model, can dynamically adjust multi-task model capacity based on the number and difficulties of input tasks, and reduce manual efforts in multi-task model development. We expect AutoMTL proposed in this paper to fill this research gap.

3 OVERVIEW OF AUTO-MTL

The goal of AutoMTL is to allow users to provide an arbitrary backbone CNN model and a set of vision tasks, and then automatically generate a multi-task model with high accuracy and low memory footprint. A high-level overview of the proposed framework is illustrated in Figure 1. The two major components are MTS-Compiler and Architecture Search. Given a backbone model, the compiler parses the model architecture and generates a multi-task supermodel that encodes the entire search space. The second component architecture search aims to find the optimal multi-task model architecture from the supermodel. The difference between the input backbone model, the multi-task supermodel, and the final multi-task model is illustrated in Figure 2.

AutoMTL currently supports the specification of the backbone model in the format of prototxt as it is general enough to support various CNN architectures and also simple for our compiler to analyze. prototxt files are serialized using Google’s Protocol Buffers serialization library. They contain: (1) an ordered list of the neural network layers a model contains; (2) each layer’s parameters, including its name, type, input dimensions, and output dimensions; (3) specifications for connections between layers. As a well-structured model description, users can define the backbone model prototxt file manually on any document editing tool. Also in case users specify the backbone model through PyTorch APIs, we provide a pytorch_to_prototxt script to automate the converting process. We leave the support of more input formats to future work.

In the next two sections, we elaborate on the two major components of this framework.

4 MULTI-TASK SUPERMODEL COMPILER

The Multi-Task Supermodel Compiler (MTS-Compiler) transforms the input backbone model into a multi-task supermodel that encodes the entire architecture search space based on the structure of the input backbone model. The challenge is how to design the architecture search space and the multi-task supermodel so that they are applicable to an arbitrary input backbone architecture and the transformation can be fully automated.

To address the challenge, our basic idea is to treat each operator in the backbone model as the basic unit for sharing. The compiler duplicates each operator in the backbone model so that each task can determine whether it wants to share parameters with other tasks by selecting which operator to use. As illustrated in Figure 2(a), a backbone model essentially specifies a computation graph (or dataflow graph) where each node is an operator (e.g., convolution operator) and each edge represents a data dependency. Some operators are parameterized because they contain a set of model parameters. Given such a backbone model, AutoMTL aims at determining which operators to share across which tasks in order to achieve both high task accuracy and memory efficiency. We next explain the encoded architecture search space, multi-task supermodel, and the compiling procedure in detail.

Architecture Search Space. For each operator in the backbone model, we offer three options for each task to choose from: (1) the operator, (2) a task-specific copy of the operator, and (3) a skip connection. Skip connection is materialized as an identity function if the input and output dimension matches or a down-sample function otherwise so that a task can skip the operator for improved model efficiency. We allow each task to select one from the three options to indicate whether it wants to share the operator with other tasks. Assume a set of $N$ tasks $T = \{t_1, t_2, ..., t_n\}$ defined over a dataset. As depicted in Figure 2(b), the task $t_i$ can select the operator $op$, implying that it can share the parameters in this operator with other tasks. Otherwise, it can select the task-specific copy $sp^{t_i}$ of $op$ or the skip connection $sk^{t_i}$.

Multi-Task Supermodel. A suitable multi-task supermodel abstraction is necessary to encode both the network structure defined by the given backbone model and the entire search space designed above. Our idea is to represent the multi-task supermodel as a computation graph whose topology remains the same as that of the backbone model but nodes are replaced with Virtual Computation Nodes (VCNs), a novel data structure designed to embed the search space.

Specifically, for each operator in the given backbone model, the corresponding VCN in the multi-task supermodel contains: (1) a list of parent VCN nodes, recording where inputs come from; (2) the operator; (3) task-specific copies of the
operator, one for each task; (4) skip connections, one for each task; (5) policy variables, one for each task determining which operator to execute for each task. Specifically, (1) and (2) encode the computation graph of the backbone model. (2), (3), and (4) together encode the architecture search space. (5) determines the sharing patterns across tasks when conducting architecture search. Figure 2(b) illustrates a multi-task supermodel. Details about the policy variable will be presented in Section 5.

Compiling Procedure. MTS-Compiler takes as inputs a user-specified backbone model in the format of prototxt and a task list, and then generates a multi-task supermodel represented as a graph of VCNs. Algorithm 1 elaborates the compiling procedure. The backbone is first parsed into a list of operators ops (line 4). Then the compiler will iterate over ops to initialize the corresponding VCNs (line 5-7). The final multi-task supermodel mtSuper is a list of VCNs.

In summary, MTS-Compiler automatically constructs a multi-task supermodel that encodes an architecture search space and enables flexible architecture search. Unlike the prior work (Sun et al., 2019) which limits each task to use a subnetwork within the backbone model, the proposed search space can extend the representation power of the backbone model if needed by preserving more task-specific operators. This alleviates the burden of pre-selecting the backbone model with the right model capacity to avoid over-fitting and under-fitting at the beginning. Besides, the supermodel abstraction decouples architecture search from backbone models; users can easily plug in an arbitrary backbone model and different architecture search algorithms including the one we propose next.

5 ARCHITECTURE SEARCH

Based on the multi-task supermodel, the architecture search component aims at efficiently exploring the search space to determine which operator to use for each task in each VCN. Formally, for the \(i\)-th task \(t_i\) and the \(l\)-th VCN, a policy variable \(P^t_i\) determines whether the task selects operator \(op_l\), or the task-specific copy \(sp^t_l\), or the skip connection \(sk^t_l\). \(P^t_i\) is zero if \(op_l\) is used for the task, one if \(sp^t_l\) is adopted, and two otherwise. Given a multi-task supermodel with \(L\) VCNs, architecture search is to find the optimal sharing policy \(P = \{P^t_i \mid l \leq L, i \leq N\}\) that yields the best overall performance over the set of \(N\) tasks \(T\). As the number of potential configurations for \(P\) is \(2^L \times N\), which grows exponentially with the number of layers and tasks, it is not practical to manually find such a \(P\) to get the optimal sharing pattern.

To address the challenge, we propose to optimize the sharing policy \(P\) and the multi-task model parameters jointly via standard back-propagation. Specifically, we adopt Gumbel-Softmax Sampling (Jang et al., 2016) to replace the discrete policy with its continuous and differentiable approximation during the architecture search. After the policy training finishes, we can get multi-task models by sampling from the learned policy distribution to decide which operator to execute in each VCN for each task. Figure 2(c) illustrate a multi-task model given a sharing policy. For instance in VCN\(_1\), \(t_1, ..., t_i\) choose to share the operator, \(t_{i+1}, ..., t_j\) preserve its own operator, and the rest \(t_{j+1}, ..., t_n\) skip the operator directly.

This section starts with the differentiable policy approximation that enables joint training of policy and the supermodel.
Algorithm 1 Compiling Procedure

1: Input: backbone: a backbone model in prototxt format; tasks: the IDs of tasks to learn.
2: Output: mtSuper: a multi-task supermodel
3: mtSuper = [ ]
4: ops = parse_prototxt(backbone)
5: for op in ops do
6:   mtSuper.append(VCN(op, tasks))
7: end for
8: Class VCN:
9: function init(op, tasks)
10:   self.op = op
11:   self.parents = [ ]
12:   for p in op.parentOps do
13:     self.parents.append(getVCN(p))
14:   end for
15:   for l in tasks do
16:     self.sp[l] = op.deepcopy()
17:     self.sk[l] = SkipConnection()
18:     self.P[l] = Gumbel-Softmax([0., 0., 0.])
19:   end for
20: end function

It then introduces a policy regularization mechanism we developed to promote parameter sharing for memory efficiency and elaborates the proposed three-stage training pipeline.

Differentiable Policy Approximation. The policy $P$ is discrete and thus non-differentiable. In order to optimize the policy with the model parameter jointly, we approximate $P$ with its differentiable counterparts via Gumbel-Softmax Sampling. For simplification, we explain the approximation of a single policy variable $P \in \{0, 1, 2\}$.

Assume the discrete variable $P$ is encoded as a one-hot vector. The most common way of sampling $P$ is to sample from its distribution vector $\pi = [\pi_0, \pi_1, \pi_2]$ where $\pi_0 + \pi_1 + \pi_2 = 1$. For instance, if we have $\pi = [0.1, 0.3, 0.6]$, it will be more likely to get the third choice (i.e. skip connection) from sampling and the one-hot vector would be [0, 0, 1]. However, it is hard to compute the gradient with respect to the parameters of a distribution.

In order to obtain a differentiable approximation, we firstly apply the Gumbel-Max trick, which provides a different formula for sampling $P$,

$$P = \text{onehot}(\text{argmax}_{i \in \{0,1,2\}} \{G_i + \log(\pi_i)\})$$

(1)

where $G_i \sim \text{Gumbel}(0, 1)$ are i.i.d samples drawn from the standard Gumbel distribution. This is a “reparameterization trick”, refactoring the sampling of $P$ into a deterministic function of the parameters and some independent noise with a fixed distribution.

The refactoring of the sampling process does not make it differentiable because of the argmax function. As a widely-used differentiable approximation to argmax, the softmax function is adopted to enable standard back-propagation. The soft policy $P'$ is now given by,

$$P'(i) = \frac{\exp((G_i + \log(\pi_i))/\tau)}{\sum_{i \in \{0,1,2\}} \exp((G_i + \log(\pi_i))/\tau)}$$

(2)

for every $i = 0, 1, 2$. $\tau$ is the temperature parameter that controls how closely the new samples approximate discrete, one-hot vectors. As $\tau \to 0$, the softmax computation smoothly approaches the argmax, which means that the soft policy $P'$ approaches the one-hot policy $P$.

In short, the above Gumbel-Softmax Sampling (Jang et al., 2016) is a simple and effective way to substitute the original non-differentiable sample from a discrete distribution with a differentiable sample from a corresponding Gumbel-Softmax distribution. During the policy training, we use the soft policy $P'$ given by Equation 2 to enable forward and backward passes through gradient descent (Wu et al., 2019). Also, the initial $\tau$ is set to 5 and gradually decreased to 0 as in (Guo et al., 2019; Wu et al., 2019). After learning the policy distribution $\pi$ for each task in VCNs, the discrete task-specific policy $P$ is sampled from the learned distribution and the multi-task architecture can be constructed accordingly.

Policy Regularization. AutoMTL aims to find compact multi-task models that achieve high task accuracy with small memory footprint. Task-specific losses, however, provide guidance for improving task accuracy only without considering taking memory and computation efficiency. To address the problem, we propose a policy regularization term $L_{\text{reg}}$ to encourage sharing operators across tasks to reduce the memory overhead. Specifically, for the soft policy $P' = \{P'_l | l \leq L, i \leq N\}$, we minimize the sum of the SoftPlus (Dugas et al., 2001) of $P'_l(1) - P'_l(0)$ and $P'_l(2) - P'_l(0)$ for each task in each VCN. To further reduce the computation cost, the regularization term is weighted for different layers to promote the sharing of bottom layers. More formally, we define $L_{\text{reg}}$ as,

$$L_{\text{reg}} = \sum_{i \leq N} \sum_{l \leq L} \frac{L-l}{L} \left\{ \ln(1 + \exp(P'_l(1) - P'_l(0))) + \ln(1 + \exp(P'_l(2) - P'_l(0))) \right\}$$

(3)

where $P'_l(0), P'_l(1), P'_l(2)$ are the probability of selecting the shared operator, the task-specific copy, and the skip connection for the $i$-th task in the $l$-th VCN respectively. $\ln(1 + \exp^x)$ is the SoftPlus function. $i$ is considered as the depth of the current VCN and $L$ is the maximum depth.
Finally, the overall loss $\mathcal{L}$ is defined as,

$$\mathcal{L} = \sum_i \lambda_i \mathcal{L}_i + \lambda_{\text{reg}} \mathcal{L}_{\text{reg}} \quad (4)$$

where $\mathcal{L}_i$ represents the task-specific loss, $\lambda_i$ is a hyper-parameter controlling how much each task contributes to the overall loss, and $\lambda_{\text{reg}}$ is a hyper-parameter balancing task-specific losses and $\mathcal{L}_{\text{reg}}$.

The proposed architecture search algorithm could identify a sharing policy that leads to both high task accuracy and memory efficiency. Besides, co-optimizing the sharing policy and model parameters usually allows faster architecture search compared with traditional reinforcement learning (Ahn et al., 2019) or evolutionary algorithm-based approaches (Liang et al., 2018).

**Training Strategies.** To largely automate the architecture search and model training process, AutoMTL provides a set of trainer functions that materialize a three-stage training pipeline and eventually generate the best multi-task model. Figure 3 illustrates the proposed training pipeline.

The first stage pre-train aims at obtaining a good initialization for the multi-task supermodel by pre-training it on tasks jointly. The compiler will firstly translate the backbone model into a multi-task supermodel and initialize the operators in each Virtual Computation Node (VCN). During pre-training, for each task, the output of each VCN is the average of the three operator choices (i.e., the operator, the task-specific copy, and the skip connection) so that all the parameters could get warmed up at the same time.

The second stage policy-train jointly optimizes the sharing policy and the model parameters. Similar to (Xie et al., 2018; Wu et al., 2019), the model parameters and the policy distribution parameters are trained alternately to stabilize the training process. After the policy distribution parameters converge, AutoMTL samples a sharing policy from the policy distribution to generate a multi-task model.

The last stage post-train aims at training the identified multi-task model to further improve its performance. The network parameters are trained from scratch while the sharing policy is fixed.

Together the MTS-Compiler, the architecture search algorithm, and the above three-stage training pipeline make up the proposed programming framework AutoMTL, which lives in $\sim$ 2300 lines of code. We wrote AutoMTL based on the PyTorch (Paszke et al., 2019) stack.

## 6 Experiments

We conduct a set of experiments to examine the superiority of AutoMTL compared to several state-of-the-art approaches in terms of task accuracy and memory footprint.

Our experiments are designed to answer the following major questions: (1) How do the task accuracy and model size of the multi-task model generated by AutoMTL compared with baselines? (2) How effective are the architecture search and the policy regularization? (3) Does the learned sharing policy reveal any insights on the multi-task architecture? (4) Is AutoMTL effective across different network architectures?

We first describe the experiment settings (datasets, baselines, metrics, etc.) in Section 6.1 and then report our experiment results in Sections 6.2 ~ 6.5 to answer each of the questions.

### 6.1 Experiment Settings

**Datasets and Tasks.** Our experiments use three popular datasets in multi-task learning (MTL), CityScapes (Cordts et al., 2016), NYUv2 (Silberman et al., 2012), and TinyTaskonomy (Zamir et al., 2018). The details of each dataset are listed as below.

- The inputs of CityScapes are street-view images in high resolution and we use it for two tasks, semantic segmentation and depth estimation, as in (Liu et al., 2019). The dataset contains 19 classes for pixel-wise semantic segmentation, together with ground-truth inverse depth labels.
- The NYUv2 dataset consists of RGB-D indoor scene images and we evaluate on three tasks, 13-class semantic segmentation defined in (Couprie et al., 2013), depth estimation whose ground truth is recorded by depth cameras from Microsoft Kinect, and surface normal prediction with labels provided in (Eisen & Fergus, 2015).
- Considering the huge size of the full Taskonomy dataset (~12TB in size), we use the official tiny train/val/test splits, which consists of 381,840 indoor images from 35 buildings with annotations for 26 tasks. Following (Standley et al., 2020), we select 5 representative tasks for experiments. They are semantic segmentation, surface normal prediction, depth estimation, keypoint detection and edge detection.

**Loss Functions and Evaluation Metrics.** Different tasks have their own task-specific loss $\mathcal{L}_i$, as shown in Section 5. For semantic segmentation, we apply a pixel-wise cross-entropy loss for each predicted class label, while for surface normal prediction, we apply the inverse of cosine similarity between the normalized prediction and ground truth. For all other tasks, the L1 loss is adopted.

As for the evaluation metrics, semantic segmentation is evaluated via mean Intersection over Union and Pixel Accuracy (mIoU and Pixel Acc, the higher the better) in both CityScapes and NYUv2. For surface normal prediction, we use mean and median angle distances between the prediction and the ground truth (the lower the better), and the
percentage of pixels whose prediction is within the angles of 11.25°, 22.5° and 30° to the ground truth as (Eigen & Fergus, 2015) (the higher the better). For depth estimation, the absolute and relative errors between the prediction and the ground truth are computed (the lower the better). In addition, the percentage of pixels whose prediction is within the thresholds of 1.25, 1.25², 1.25³ to the ground truth, i.e. \( \delta = \max \{ \frac{\text{pred}}{\text{gt}}, \frac{\text{gt}}{\text{pred}} \} < \text{thr} \), is used following (Eigen et al., 2014) (the higher the better). Besides, in Tiny-Taskonomy, the task-specific loss of each task is taken as the performance measurement directly.

Because evaluation metrics from different tasks have different scales, we also use a single relative performance metric (Maninis et al., 2019) with respect to the single-task baseline to compare different approaches. The relative performance \( \Delta t_i \) of a method \( A \) on task \( t_i \) is computed as follows,

\[
\Delta t_i = \frac{1}{|M|} \sum_{j=0}^{s_j} (-1)^{s_j} \frac{(M_{A,j} - M_{STL,j})}{M_{STL,j}} \times 100\%
\]

(5)

where \( s_j \) is 1 if the metric \( M_j \) is the lower the better and 0 otherwise. \( M_{A,j} \) and \( M_{STL,j} \) are the values of the metric \( M_j \) for the method \( A \) and the single-task baseline respectively. Besides, the overall performance is the average of the above relative values over all tasks, namely \( \Delta t = \frac{1}{N} \sum_{i=1}^{N} \Delta t_i \) where \( N \) is the number of tasks. Model size is evaluated using the number of model parameters.

**Baselines for Comparison.** We compare with following baselines.

- Each task has its own model and is trained independently. We call it the Single-Task baseline.
- All tasks share the backbone model but have separate prediction heads. This is a commonly used hard parameter sharing practice (Caruana, 1997) and called the Multi-Task baseline.
- Three soft-parameter sharing based methods are also competitive when handling MTL. They are Cross-Stitch (Misra et al., 2016), Sluice (Ruder et al., 2019) and NDDR-CNN (Gao et al., 2019), which adopt feature fusion layers between task-specific backbones.
- Attention-based method (e.g. MTAN (Liu et al., 2019)) and NAS-based methods (e.g. DEN (Ahn et al., 2019) and AdaShare (Sun et al., 2019)) are state-of-the-art MTL approaches with outstanding performance on typical datasets, and deserve thorough comparison.

We use the same backbone model in all baselines and in our proposed programming framework for fair comparisons. We use DeepLab-ResNet-34 as the backbone model and the Atrous Spatial Pyramid Pooling (ASPP) architecture as the task-specific head (Chen et al., 2017). Both of them are popular architectures for pixel-wise prediction tasks. Results on two other backbone architectures MobileNetV2 (Sandler et al., 2018) and M NasNet (Tan et al., 2019) are reported in the appendix.

**Hyper-parameter Settings.** Table 1 summarizes the hyper-parameters used in training. For CityScapes and NYUv2, AutoMTL spends 10,000 iterations on pre-training the supermodel (pre-train), then 20,000 iterations for training policy and supermodel jointly (policy-train), and finally 30,000 iterations for training the identified multi-task model (post-train). As for Tiny-Taskonomy, the three stages need 20,000, 50,000, 30,000 iterations respectively to converge.

### 6.2 Quantitative Results

Table 2–5 report the task performance on each dataset respectively. For CityScapes, both the absolute values of all metrics and the relative performance are reported (see Table 2 and 3). Due to the limited space, only the relative performance is reported for NYUv2 and Tiny-Taskonomy (see Table 4 and 5). Details of the full comparison on all metrics can be found in the appendix.

According to Table 2, AutoMTL outperforms all the baselines on 4 metrics (bold) and is the second-best on 2 metrics (underlined) in terms of task performance. With 17.7% increase in the number of model parameters, the task performance of AutoMTL is far better than the vanilla Multi-Task baseline. Compared to the soft-parameter sharing methods, Cross-Stitch, Sluice, and NDDR-CNN, which are unable to reduce the memory overhead, AutoMTL could achieve higher task performance with fewer parameters. When comparing with DEN and AdaShare, the most competitive approaches in MTL, AutoMTL is better in terms of the task performance but with more parameters (11.7%/17.7%). This is because, unlike DEN and AdaShare which pack tasks into...
AutoMTL: A Programming Framework for Automated Multi-Task Learning

Table 1. Hyper-parameters for training CityScapes, NYUv2, and Tiny-Taskonomy.

| DATASET       | WEIGHT LR | POLICY LR | WEIGHT LR DECAY | λseg  | λsn    | λdepth | λkp   | λedge | λreg  |
|---------------|-----------|-----------|-----------------|-------|--------|--------|-------|-------|-------|
| CityScapes    | 0.001     | 0.01     | 0.5/4.000 ITERS | 1     | 20     | 5      | -     | -     | 0.0005|
| NYUv2         | 0.001     | 0.01     | 0.5/4.000 ITERS | 5     | 20     | 5      | -     | -     | 0.001 |
| Tiny-Taskonomy| 0.0001    | 0.01     | 0.3/10.000 ITERS| 1     | 3      | 2      | 7     | 7     | 0.0005|

Table 2. Quantitative results on CityScapes. (Abs. Prf.)

| MODEL          | # PARAMS (%)↓ | SEMANTIC SEG. | DEPTH ESTIMATION |
|----------------|---------------|---------------|-----------------|
|                | MOU↑| PIXEL ACC.↑ | ERROR↓ | δ, WITHIN ↑| ABS. Rel. | 1.25 | 1.25² | 1.25³ |
| SINGLE-TASK    | -  | 36.5 | 73.8 | 0.026 | 0.38 | 57.5 | 76.9 | 87.0 |
| MULTI-TASK     | -50.0 | 42.7 | 68.1 | 0.026 | 0.39 | 58.8 | 80.5 | 89.9 |
| CROSS-STITCH   | +0.0 | 40.3 | 74.3 | 0.017 | 0.34 | 70.0 | 86.3 | 93.1 |
| SLUICE         | +0.0 | 39.8 | 74.2 | 0.018 | 0.35 | 68.9 | 85.8 | 92.8 |
| NDDR-CNN       | +3.5 | 41.5 | 74.2 | 0.018 | 0.35 | 69.9 | 86.3 | 93.0 |
| MTAN           | -20.5 | 40.8 | 74.3 | 0.017 | 0.36 | 71.0 | 86.3 | 92.8 |
| DEN            | -44.0 | 38.0 | 74.2 | 0.018 | 0.41 | 68.2 | 84.5 | 91.6 |
| ADASHARE       | -50.0 | 40.6 | 74.7 | 0.018 | 0.37 | 71.4 | 86.8 | 93.1 |
| AUTO MTL       | -32.3 | 42.8 | 74.8 | 0.018 | 0.33 | 70.0 | 86.6 | 93.4 |

Table 3. Quantitative results on CityScapes. (Rel. Prf.).

| MODEL         | Δt1↑ | Δt2↑ | Δt↑  |
|---------------|------|------|------|
| MULTI-TASK    | +4.6 | +1.5 | +3.1 |
| CROSS-STITCH  | +5.5 | +17.2| +11.4|
| SLUICE        | +4.8 | +15.3| +10.1|
| NDDR-CNN      | +7.1 | +15.9| +11.5|
| MTAN          | +6.2 | +16.4| +11.3|
| DEN           | +2.3 | +11.3| +6.8 |
| ADASHARE      | +6.2 | +15.5| +10.9|
| AUTO MTL      | +9.3 | +17.1| +13.2|

Table 4. Quantitative results on NYUv2. (Rel. Prf.).

| MODEL         | Δt1↑ | Δt2↑ | Δt3↑ | Δt↑  |
|---------------|------|------|------|------|
| MULTI-TASK    | -66.7| -11.4| +2.0 | +4.3 | -1.7 |
| CROSS-STITCH  | +0.0 | -2.6 | +8.7 | +3.9 | +3.3 |
| SLUICE        | +0.0 | -6.2 | +7.1 | +3.3 | +1.4 |
| NDDR-CNN      | +5.0 | -12.9| +7.0 | -4.4 | -3.5 |
| MTAN          | +3.7 | -1.8 | +11.5| +2.9 | +4.2 |
| DEN           | -62.7| -7.7 | +5.6 | -38.9| -13.7|
| ADASHARE      | -66.7| -4.3 | +9.3 | +6.2 | +3.8 |
| AUTO MTL      | -45.1| +0.2 | +8.0 | +7.8 | +5.3 |

The superiority of AutoMTL can be observed more clearly via the relative performance in Tables 3~5. AutoMTL outperforms most of the baselines in both task performance and model size. When compared with DEN and AdaShare, AutoMTL could achieve a substantial increase in task performance with only a few more parameters.

Although DEN and AdaShare need fewer model parameters, the representation power of their multi-task models is limited by the backbone model, making it essential for users to select a suitable backbone model with sufficient capacity for multiple tasks. This problem goes worse when the number of tasks increases. As shown in Table 5, DEN and AdaShare have limited task performance improvement or even suffer from task performance degradation (see columns Δt2 and Δt3) on the Taskonomy dataset with five tasks. In contrast, AutoMTL alleviates the burden of pre-selecting the backbone model with the right model capacity. It could generate the optimal multi-task model with a larger capacity if necessary, leading to higher task performance, 13.6% higher than DEN and 3.1% higher than AdaShare.

Furthermore, for semantic segmentation in NYUv2 (see columns Δt1 in Table 4) and surface normal prediction in Taskonomy (see columns Δt2 in Table 4), the performance of all the multi-task baselines are worse than the Single-Task baseline. It indicates that this particular task is negatively interfered by the other tasks when sharing parameters across

the given backbone model, our search space allows each task to select more task-specific operators to increase the capability of the backbone model if necessary. It turns out that a small amount of increase in model parameters could translate to a significant gain in task performance.

The superiority of AutoMTL can be observed more clearly via the relative performance in Tables 3~5. AutoMTL outperforms most of the baselines in both task performance and model size. When compared with DEN and AdaShare, AutoMTL could achieve a substantial increase in task performance with only a few more parameters.
them. In contrast, AutoMTL is still able to improve the performance of the two tasks because the two tasks tend to select more task-specific operators in our search space in order to reduce the interference from the other tasks. Such sharing pattern can be observed from the learned policy distributions for NYUv2 and Taxonomy in Appendix.

### 6.3 Ablation Studies

We present ablation studies to show the effectiveness of the architecture search process (the policy-train stage) and the proposed policy regularization term (Eq. 3). In Figure 4, we use a boxplot to show the distributions of different evaluation metrics for three groups of multi-task models. The orange group (Random) of models are generated from policies that are randomly initialized without policy-train, while the green (AutoMTL w/o $L_{reg}$) and the blue (AutoMTL w/ $L_{reg}$) groups are sampled from policies after the policy-train stage. The policy of the blue group is trained with the regularization but that of the green group is not. We generate six different models in each group to compare their performance with less bias.

We make two main observations from Figure 4. First, both AutoMTL w/o $L_{reg}$ and AutoMTL w/ $L_{reg}$ achieve better task performance than Random in terms of the mean and the standard deviation of all the evaluation metrics. It indicates that the architecture search process and especially the policy-train stage is necessary and effective in predicting a good sharing pattern among tasks. Second, the mean of all metrics for AutoMTL w/ $L_{reg}$ is also better than AutoMTL w/o $L_{reg}$. This phenomenon demonstrates that the proposed policy regularization term plays an important role in improving task performance. It echoes the well-recognized benefits of parameter sharing among tasks in reducing overfitting and improving prediction accuracy. Similar ablation studies on NYUv2 are shown in the Appendix.

### 6.4 Policy Visualization

We further visualize the learned sharing policies to reveal insights on the discovered multi-task architecture. Figure 5 shows the visualization of the learned policy distribution and the feature sharing pattern on CityScapes. Visualizations for the other datasets are in the Appendix.

For each layer in each task, Figure 5(a) illustrates its policy distribution $\pi$ introduced in Section 4. A brighter block indicates a higher probability of that operator being selected. The figure indicates that tasks tend to share bottom layers. Besides, Figure 5(b) provides a feature sharing pattern sampled from the learned policy distribution. The red arrows connect the operators used by semantic segmentation and the blue ones correspond to depth estimation. Operators that are not selected are semi-transparent. Overall, semantic segmentation is more likely to share operators with other tasks than depth estimation. Depth estimation has more than 25% of operators are skip connections, implying that this task prefers a more compact model than the backbone. These skip connections and operator sharing among the two tasks decrease the number of parameters in the multi-task model and thus lower memory footprint.

### 6.5 Results on Other Backbone Models

AutoMTL supports any input CNN model. We demonstrate the generality of AutoMTL by conducting experiments on CityScapes with two other typical backbone model MobileNetV2 (Sandler et al., 2018) and MnasNet (Tan et al., 2019). Without changing hyperparameters on this dataset, AutoMTL achieves 7.4% and 9.5% higher relative task performance with 33.5% and 35.9% fewer model parameters than the single-task baseline and 6.5% and 11.1% higher relative task performance than the Multi-Task baseline for MobileNetV2 and MnasNet respectively. Detailed results are reported in the Appendix.
7 CONCLUSION

In this work, we propose the first programming framework AutoMTL that generates compact multi-task models given an arbitrary input backbone CNN model and a set of tasks. AutoMTL features a multi-task supemodel compiler that automatically transforms any given backbone CNN into a multi-task supemodel to facilitate architecture search, and an efficient architecture search algorithm that jointly optimizes sharing policies and model parameters using approximations and standard back-propagation. The compiler decouples architecture search with the input backbone model, removing the manual efforts in generalizing the architecture search to other CNNs. The architecture search algorithm effectively identifies good sharing policies that lead to both high task accuracy and memory efficiency. Experiments on three popular multi-task learning benchmarks demonstrate the superiority of AutoMTL over state-of-the-art approaches in terms of task accuracy and memory footprint.

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APPENDIX

A. FULL COMPARISON OF ALL METRICS ON NYUv2 AND TASKONOMY

The full comparison of all metrics on NYUv2 and Taskonomy are summarized in Table 6 and 7. On NYUv2, AutoMTL could achieve outstanding performance on 7 out of 12 metrics, while on Taskonomy, AutoMTL outperforms all the baselines on all the 5 metrics.

B. ABERRATION STUDIES ON NYUv2

The ablation studies are also conducted on NYUv2. The same phenomenon as Section 6.3 in the main paper, can be observed in Figure 6. In short, both the architecture search process and the proposed policy regularization term are indispensable to obtain a feature-sharing pattern with high task performance.

C. POLICY VISUALIZATIONS ON NYUv2 AND TASKONOMY

Figure 7 visualizes the learned policy distribution on NYUv2. It can be seen that for top layers near the output, the semantic segmentation and the depth estimation tend to have their own computation operators instead of sharing with other tasks. This trend leads that the two tasks may suffer less from the negative interference between tasks, which becomes a possible explanation of why the model searched by AutoMTL can have better task performance on them than existing methods as analyzed in Section 6.2 in the main paper.

Figure 8 visualizes the learned policy distribution on Taskonomy. By comparing the brightness of the three branches in each layer (brighter means higher probability to be chosen), it can be found that the brightness differences between the three branches are more salient in layer No. 0~10 and No. 30~35, which indicates that tasks would be more likely to have branch preferences in top and bottom layers. While for intermediate layers (layer No. 18~28), the chance of each branch to be selected is basically equal. This phenomenon is consistent with traditional multi-task model design principles, which pay more attention to top and bottom layers to decide whether they should be shared or not.

D. TASK CORRELATION

We use cosine similarity between task-specific policies to quantify task correlations. Figure 9 illustrates the task correlations in Taskonomy (the darker the higher correlation) and we can make the following observations. (a) Semantic segmentation has a relatively weak correlation with depth estimation compared to other tasks. (b) Surface normal prediction has good correlations with all the other tasks. (c) Depth estimation has low correlations with keypoint and edge detection. (d) Keypoint detection has a strong correlation with edge detection.

E. EXTENSION TO OTHER ARCHITECTURES

As introduced in Section 4 in the main paper, the users are able to feed any convolution-based model into the proposed MTS-Compiler. We try to demonstrate this function by also conducting experiments on CityScapes with two other typical backbone models MobileNetV2 (Sandler et al., 2018) and MnasNet (Tan et al., 2019). Table 8 and 9 report the task performance when constructing multi-task models on them. AutoMTL always could search out a better multi-task architecture when compared to the vanilla multi-task model.
Table 6. Quantitative results on NYUv2. (Abs. Prf.)

| MODEL       | # PARAMS (%) ↓ | SEMANTIC SEG. | SURFACE NORMAL PREDITION | DEPTH EST. | KEYPOINT DET. | EDGE DET. |
|-------------|----------------|---------------|---------------------------|------------|---------------|-----------|
| SINGLE-TASK | -66.7          | 26.5          | 58.2                      | 17.7       | 16.3          | 29.4      |
| MULTI-TASK  | -80.0          | 0.575         | 0.807                     | 0.022      | 0.197         | 0.212     |
| CROSS-STITCH| -85.6          | 0.596         | 0.796                     | 0.023      | 0.197         | 0.207     |
| NDDR-CNN    | +5.0           | 21.6          | 53.9                      | 17.1       | 14.5          | 37.4      |
| MTAN        | +3.7           | 26.0          | 57.2                      | 17.2       | 14.0          | 41.4      |
| DENCH       | -62.7          | 23.9          | 54.9                      | 17.1       | 14.8          | 36.0      |
| ADASHARE    | -66.7          | 24.4          | 57.8                      | 17.7       | 13.8          | 42.3      |
| AUTO MTL w/| -45.1          | 26.6          | 58.2                      | 17.3       | 14.4          | 39.1      |
| AUTO MTL w/o|               | 26.5          | 58.2                      | 17.7       | 16.3          | 29.4      |
| Random      |                | 0.575         | 0.807                     | 0.022      | 0.197         | 0.212     |
| Mean        |                | 0.596         | 0.796                     | 0.023      | 0.197         | 0.207     |
| Median      |                | 0.596         | 0.795                     | 0.024      | 0.196         | 0.206     |
| Auto MTL w/o|               | 21.6          | 53.9                      | 17.1       | 14.8          | 36.0      |
| Auto MTL w/|               | 26.0          | 57.2                      | 17.2       | 14.0          | 41.4      |
| Auto MTL w/o|               | 23.9          | 54.9                      | 17.1       | 14.8          | 36.0      |
| Auto MTL w/|               | 24.4          | 57.8                      | 17.7       | 13.8          | 42.3      |
| Auto MTL w/o|               | 26.6          | 58.2                      | 17.3       | 14.4          | 39.1      |
| Auto MTL w/|               | 26.5          | 58.2                      | 17.7       | 16.3          | 29.4      |
| Auto MTL w/o|               | 0.575         | 0.807                     | 0.022      | 0.197         | 0.212     |
| Auto MTL w/|               | 0.596         | 0.796                     | 0.023      | 0.197         | 0.207     |
| Auto MTL w/o|               | 0.596         | 0.795                     | 0.024      | 0.196         | 0.206     |
| Auto MTL w/o|               | 21.6          | 53.9                      | 17.1       | 14.8          | 36.0      |
| Auto MTL w/|               | 26.0          | 57.2                      | 17.2       | 14.0          | 41.4      |
| Auto MTL w/o|               | 23.9          | 54.9                      | 17.1       | 14.8          | 36.0      |
| Auto MTL w/o|               | 24.4          | 57.8                      | 17.7       | 13.8          | 42.3      |
| Auto MTL w/|               | 26.6          | 58.2                      | 17.3       | 14.4          | 39.1      |
| Auto MTL w/o|               | 26.5          | 58.2                      | 17.7       | 16.3          | 29.4      |
| Auto MTL w/|               | 0.575         | 0.807                     | 0.022      | 0.197         | 0.212     |
| Auto MTL w/|               | 0.596         | 0.796                     | 0.023      | 0.197         | 0.207     |
| Auto MTL w/|               | 0.596         | 0.795                     | 0.024      | 0.196         | 0.206     |

Table 7. Quantitative results on Taskonomy. (Abs. Prf.)

| MODELS | # PARAMS (%) ↓ | SEMANTIC SEG. ↓ | SURFACE NORMAL ↑ | DEPTH EST. ↓ | KEYPOINT DET. ↓ | EDGE DET. ↓ |
|--------|----------------|-----------------|------------------|--------------|-----------------|-------------|
| SINGLE-TASK | -80.0         | 0.575           | 0.807            | 0.022        | 0.197           | 0.212       |
| MULTI-TASK | -80.0         | 0.575           | 0.807            | 0.022        | 0.197           | 0.203       |
| CROSS-STITCH  | -85.6         | 0.596           | 0.796            | 0.023        | 0.197           | 0.207       |
| NDDR-CNN     | +5.0          | 21.6            | 53.9             | 0.023        | 0.196           | 0.203       |
| MTAN         | +3.7          | 26.0            | 57.2             | 0.023        | 0.197           | 0.206       |
| DENCH        | -62.7         | 23.9            | 54.9             | 0.023        | 0.199           | 0.217       |
| ADASHARE     | -66.7         | 24.4            | 57.8             | 0.023        | 0.199           | 0.203       |

Figure 6. Ablation study on NYUv2. Distributions of different metrics for three groups of multi-task models are exhibited, including models generated from Random policies or those sampled from the trained policy with or without the policy regularization (AutoMTL w/o $L_{reg}$ and AutoMTL w/ $L_{reg}$).
Figure 7. Learned policy distributions for the three tasks in NYUv2.

Figure 8. Learned policy distributions for the five tasks in Taskonomy.

Figure 9. Task correlations in Taskonomy.
Table 8. Quantitative results with MobileNetV2 on CityScapes.

| MODEL         | # PARAMS (%) ↓ | SEMANTIC SEG. | DEPTH ESTIMATION | Δt ↑ |
|---------------|----------------|---------------|------------------|------|
|               |                | MIOU ↑ | PIXEL Acc. ↑ | Δt1 ↑ | ERROR ↓ | δ, WITHIN ↑ | Δt2 ↑ |
|               |                |        |               |       | Abs. Rel. | 1.25 | 1.25² | 1.25³ |
| SINGLE-TASK   | -              | 25.9   | 63.5          | -     | 0.043  | 0.53 | 32.1  | 71.1  | 86.5  | -      | -      |
| MULTI-TASK    | -50.0          | 26.3   | 63.4          | +0.7  | 0.042  | 0.48 | 33.6  | 66.5  | 82.9  | +1.2   | +0.9   |
| AUTO-MTL      | -33.5          | 25.8   | 63.7          | +0.0  | 0.035  | 0.47 | 44.4  | 74.8  | 87.3  | +14.9  | +7.4   |

Table 9. Quantitative results with MNasNet on CityScapes.

| MODEL         | # PARAMS (%) ↓ | SEMANTIC SEG. | DEPTH ESTIMATION | Δt ↑ |
|---------------|----------------|---------------|------------------|------|
|               |                | MIOU ↑ | PIXEL Acc. ↑ | Δt1 ↑ | ERROR ↓ | δ, WITHIN ↑ | Δt2 ↑ |
|               |                |        |               |       | Abs. Rel. | 1.25 | 1.25² | 1.25³ |
| SINGLE-TASK   | -              | 25.5   | 63.6          | -     | 0.040  | 0.49 | 36.7  | 73.3  | 87.3  | -      | -      |
| MULTI-TASK    | -50.0          | 25.1   | 63.5          | -0.9  | 0.040  | 0.48 | 35.9  | 67.8  | 84.2  | -2.2   | -1.6   |
| AUTO-MTL      | -35.9          | 25.5   | 63.7          | +0.1  | 0.028  | 0.43 | 53.7  | 77.1  | 87.8  | +18.9  | +9.5   |