Multi-Task Learning(MTL)即多任务学习,在一些领域也被称为多目标学习.MTL与常规单任务模型的区别在于,MTL仅使用一个模型就可以处理多个任务.例如手机语音助手唤醒,过去的方法需要两个模型,一个模型持续运行检测是否有语音,另外一个模型则模型一判断有语音后检测语音是否为关键词.而MTL的话一个模型就可以在监测语音的同时判断是否为关键词.我的理解就是,对于网络来说,通过训练模型最终学习到的知识就是以参数的形式表现,即参数空间中的一个点.而模型学习到的知识其实是又任务决定的,更具体的来说是有损失函数决定的,因为我们为任务设计损失函数,通过SGD等方法去探索参数空间,最终得到最优解.换而言之,相同结构的网络,对于不同的任务(分类和分割),假设我们现在可以获得损失函数的close form solution,那么得到的最优解对应的参数空间中的点是不同的.不同的任务的最优解.而对于,对于不同的任务,参数空间是相同(类似的)的,

Cross-stitch Networks for Multi-task Learning

CVPR2016

文笔不是很好,读起来比较累,没有语义连贯的流动,经常上下文不接,内容和idea也比较简单,不知道怎么中的CVPR

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卷积神经网络中的MTL在识别领域有了显著的进步,而这一进步在很大程度上都需要归因于卷积网络可以从多个不同的监督任务中学习到共享的表示.然而,现有的MTL方法都依赖于枚举适用于给定任务的网络结构(Task Specific)因此不具有泛化性.本文提出了通过MTL学习共享表示的原则.更具体的说,本文提出了新的共享单元:Cross-Stitch单元.这个单元能够结合多个网络的activation map并且可以进行端到端的训练.使用Cross-Stitch单元的模型能够学习到共享的参数和任务特定的参数的最佳的结合.实验结果表明,我们的方法极大地超越了Baseline的方法

Abstract

Multi-task learning in Convolutional Networks has displayed remarkable success in the field of recognition. This success can be largely attributed to learning shared representations from multiple supervisory tasks. However, existing multi-task approaches rely on enumerating multiple network architectures specific to the tasks at hand, that do not generalize. In this paper, we propose a principled approach to learn shared representations in ConvNets using multi-task learning. Specifically, we propose a new sharing unit: "cross-stitch" unit. These units combine the activations from multiple networks and can be trained end-to-end. A network with cross-stitch units can learn an optimal combination of shared and task-specific representations. Our proposed method generalizes across multiple tasks and shows dramatically improved performance over baseline methods for categories with few training examples.

1. Introduction

在过去的几年中,卷积网络在诸如分类,检测和分割这类识别任务上获得了极大地提升.而取得如此成功的一个原因就是卷积网络内在的参数共享机制,因此使得模型能够从不同的类别中学习到表示.自然而然,我们就会想问,这一从不同的类别中学习到共享的知识的特点能不能对比到不同任务的学习.这个猜想在26,19和21中已经通过分类和分割多任务学习实验被证实了.

Over the last few years, ConvNets have given huge performance boosts in recognition tasks ranging from classification and detection to segmentation and even surface normal estimation. One of the reasons for this success is attributed to the inbuilt sharing mechanism, which allows ConvNets to learn representations shared across different categories. This insight naturally extends to sharing between tasks (see Figure 1) and leads to further performance improvements, *e.g.*, the gains in segmentation [26] and detection [19, 21]. A key takeaway from these works is that multiple tasks, and thus multiple types of supervision, helps achieve better performance with the same input. But unfortunately, the network architectures used by them for multi-task learning notably differ. There are no insights or principles for how one should choose ConvNet architectures for multi-task learning.

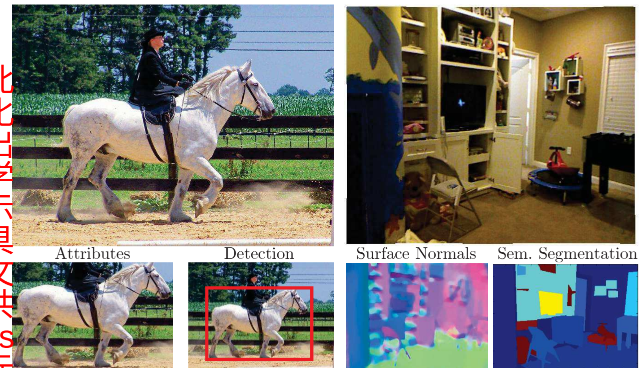
可是,由于他们的网络模型是显然不同的,因此他们之间的贡献就是告诉了我们多任务学习(多个监督/损失函数)的确可以在相同输入的情况下得到更好的性能,而无法提供更多的类似如何为MTL设计网络这样的认知

1.1. Multi-task sharing: an empirical study

How should one pick the right architecture for multi-task learning? Does it depend on the final tasks? Should we

*Both authors contributed equally

Multi-Class能不能视为Multi-Task?每一个Task就是一个二分类Task--CL



输入都是相同的,但是通过MTL可以提升性能

Figure 1: Given an input image, one can leverage multiple related properties to improve performance by using a multi-task learning framework. In this paper, we propose *cross-stitch* units, a principled way to use such a multi-task framework for ConvNets.

在进行MTL学习的过程中,我们会有很多的问题,例如:该如何选择MTL的结构?网络结构的设计和最终的人物之间有关系么?模型是否应该共享全部的参数?还是应该把模型的参数分为共享参数和任务参数两部分?以及是否存在一个总的原则能够回答上面的问题

have a completely shared representation between tasks? Or should we have a combination of shared and task-specific representations? Is there a principled way of answering these questions?

To investigate these questions, we first perform extensive experimental analysis to understand the performance trade-offs amongst different combinations of shared and task-specific representations. Consider a simple experiment where we train a ConvNet on two related tasks (*e.g.*, semantic segmentation and surface normal estimation). Depending on the amount of sharing one wants to enforce, there is a spectrum of possible network architectures. Figure 2(a) shows different ways of creating such network architectures based on AlexNet [32]. On one end of the spectrum is a fully shared representation where all layers, from the first convolution (`conv2`) to the last fully-connected (`fc7`), are shared and only the last layers (two `fc8`s) are task specific. An example of such sharing is [21] where separate `fc8` layers are used for classification and bounding box regression. On the other end of the sharing spectrum, we can train two networks separately for each task and there is no cross-talk between them. In practice, different amount of sharing tends to work best for different tasks.

为了回答上面的问题,我们首先进行了一系列的实验,来研究共享参数的数量对性能的影响.具体来说我们在分割和法向量估计两个任务上使用相同的模型进行训练.根绝共享的参数的不同,就有了一系列的模型

这一系列的模型最左端是全共享数据(除了最后一个输出层)的而最右端则是完全独立的网络.而最终实验结果表明不同的任务最好的共享参数的数量是不同的

下面的实验以AlexNet为基础,尝试了几种可能的网络的结构

泛型网络,所有的参数都是共享的

任务特定网络,所有参数不共享

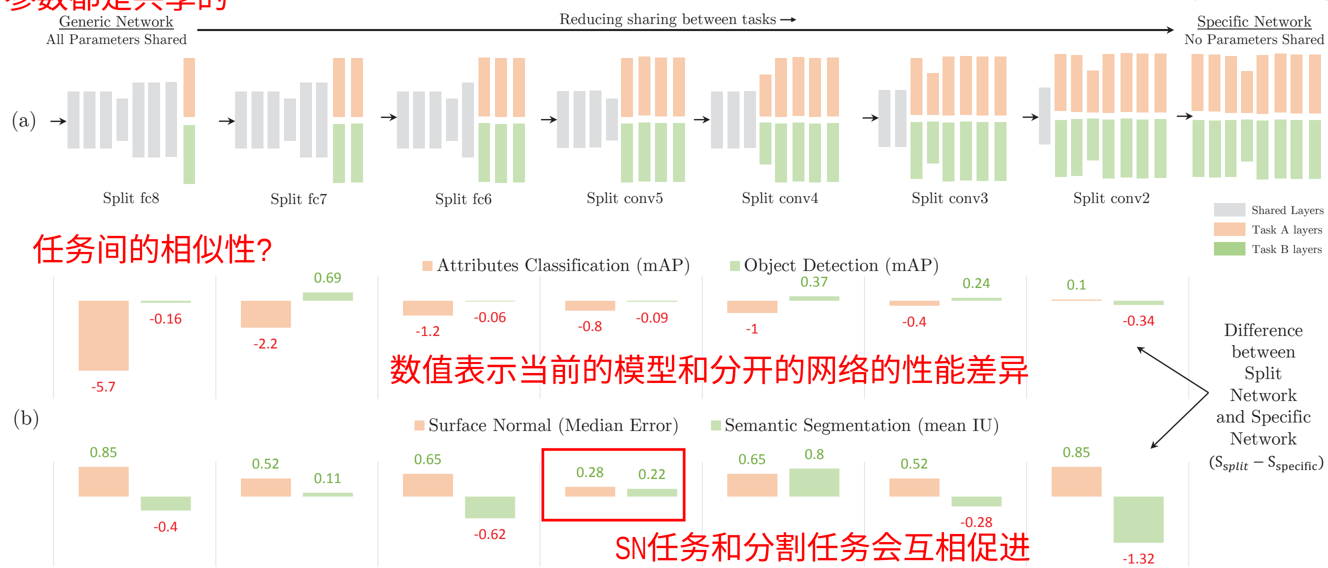


Figure 2: We train a variety of multi-task (two-task) architectures by splitting at different layers in a ConvNet [32] for two pairs of tasks. For each of these networks, we plot their performance on each task relative to the task-specific network. We notice that the best performing multi-task architecture depends on the individual tasks and does not transfer across different pairs of tasks.

当给定一对任务的时候,该如何选择对应的网络结构?为了能够从经验上来研究这个问题,我们选取了下面两对任务

So given a pair of tasks, how should one pick a network architecture? To empirically study this question, we pick two varied pairs of tasks:

第一组任务是语义分割任务和法向量预测任务.我们认为这两个任务是高度相关的,因为语义分割的边界和法向量的边界是相似的

- We first pair semantic segmentation (SemSeg) and surface normal prediction (SN). We believe the two tasks are closely related to each other since segmentation boundaries also correspond to surface normal boundaries. For this pair of tasks, we use NYU-v2 [47] dataset.

第二组任务是目标检测和属性预测任务.我们认为也是关联的.举例而言,一个被标记为车的物体会拥有有轮子这个属性

- For our second pair of tasks we use detection (Det) and Attribute prediction (Attr). Again we believe that two tasks are related: for example, a box labeled as "car" would also be a positive example of "has wheel" attribute. For this experiment, we use the attribute PASCAL dataset [12, 16].

实验中依次尝试了所有可能的分离的网络结构,具体实验网络结构和结果展示在图中.

We exhaustively enumerate all the possible *Split* architectures as shown in Figure 2(a) for these two pairs of tasks and show their respective performance in Figure 2(b). The best performance for both the SemSeg and SN tasks is using the "Split conv4" architecture (splitting at conv4), while for the Det task it is using the Split conv2, and for Attr with Split fc6. These results indicate two things – 1) Networks learned in a multi-task fashion have an edge over networks trained with one task; and 2) The best Split architecture for multi-task learning depends on the tasks at hand.

While the gain from multi-task learning is encouraging, getting the most out of it is still cumbersome in practice. This is largely due to the task dependent nature of picking architectures and the lack of a principled way of exploring them. Additionally, enumerating all possible architectures for each set of tasks is impractical. This paper proposes *cross-stitch units*, using which a single network can capture all these Split-architectures (and more). It automatically learns an optimal combination of shared and task-specific representations. We demonstrate that such a *cross-stitched* network can achieve better performance than the networks found by brute-force enumeration and search.

实验结果表明:1.相比对于每一个任务使用单独的网络,多任务学习的方式会有gap. 2.最佳的分离结构是依赖于当期的任务的

SN和Seg任务互相促进这一现象非常振奋人心,但是我们通过暴力搜索网络结构得到最佳的分离点,这样做是非常消耗资源的

而消耗大的原因在于网络选择是依赖于任务这一特性,以及我们缺乏有效探索网络结构的方式.

因此,本文提出了Cross-Stitch结构,该结构可以捕捉到所有列出的,未列出的分离结构

他可以自动的学习到最优的共享和分离结构的组合.我们的实验表明,corss-stitch网络相比于暴力搜索得到的网络,拥有更好的表现

2. Related Work

Generic Multi-task learning [5, 48] has a rich history in machine learning. The term *multi-task learning* (MTL) itself has been broadly used [2, 14, 28, 42, 54, 55] as an umbrella term to include representation learning and selection [4, 13, 31, 37], transfer learning [39, 41, 56] *etc.* and their widespread applications in other fields, such as genomics [38], natural language processing [7, 8, 35] and computer vision [3, 10, 30, 31, 40, 51, 53, 58]. In fact, many times multi-task learning is implicitly used without reference; a good example being fine-tuning or transfer learning [41], now a mainstay in computer vision, can be viewed as sequential multi-task learning [5]. Given the broad scope, in this section we focus only on multi-task learning in the context of ConvNets used in computer vision.

Multi-task learning is generally used with ConvNets in computer vision to model related tasks jointly, *e.g.* pose estimation and action recognition [22], surface normals and edge labels [52], face landmark detection and face detection [57, 59], auxiliary tasks in detection [21], related

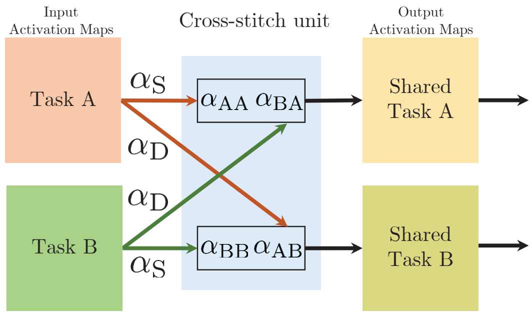


Figure 3: We model shared representations by learning a linear combination of input activation maps. At each layer of the network, we learn such a linear combination of the activation maps from both the tasks. The next layers' filters operate on this shared representation.

classes for image classification [50] *etc*. Usually these methods share some features (layers in ConvNets) amongst tasks and have some task-specific features. This sharing or split-architecture (as explained in Section 1.1) is decided after experimenting with splits at multiple layers and picking the best one. Of course, depending on the task at hand, a different Split architecture tends to work best, and thus given new tasks, new split architectures need to be explored. In this paper, we propose *cross-stitch units* as a principled approach to explore and embody such Split architectures, without having to train all of them.

In order to demonstrate the robustness and effectiveness of cross-stitch units in multi-task learning, we choose varied tasks on multiple datasets. In particular, we select four well established and diverse tasks on different types of image datasets: 1) We pair semantic segmentation [27, 45, 46] and surface normal estimation [11, 18, 52], both of which require predictions over all pixels, on the NYU-v2 indoor dataset [47]. These two tasks capture both semantic and geometric information about the scene. 2) We choose the task of object detection [17, 20, 21, 44] and attribute prediction [1, 15, 33] on web-images from the PASCAL dataset [12, 16]. These tasks make predictions about localized regions of an image.

本文我们针对多任务学习为卷积网络提出了Cross-Stitch结构.Cross-Stitch结构尝试为多任务学习寻找最佳的共享参数.Corss-Stitch模型使用线性结构来共享权重,并且从一组任务中学习到最优的结合

3. Cross-stitch Networks

In this paper, we present a novel approach to multi-task learning for ConvNets by proposing cross-stitch units. Cross-stitch units try to find the best shared representations for multi-task learning. They model these shared representations using linear combinations, and learn the optimal linear combinations for a given set of tasks. We integrate these cross-stitch units into a ConvNet and provide an end-to-end learning framework. We use detailed ablative studies to better understand these units and their training procedure. Further, we demonstrate the effectiveness of these units for two different pairs of tasks. To limit the scope of this paper, we only consider tasks which take the same single input, *e.g.*, an image as opposed to say an image and a depth-map [25].

我们进行了详细的消融实验来表明Cross-Stitch的有效性,以及对Cross-Stitch结构有深入的理解.我们接下来在两组任务上表明了我们的结构的有效性

为了限定文章的讨论范围,我们只考虑使用相同的输入,即对于法向量估计和语义分割,都是输入一张图像,而非一章图像和对应的深度图像

当给定一张输入图像和多个标签的时候,我们可以想图二一样设计出来Split结构,即将网络分任务特定的结构和共享的结构.在比较低的部分开始分离,那么模型就会有更多的针对任务的参数和更少的共享的参数

3.1. Split Architectures

Given a single input image with multiple labels, one can design "Split architectures" as shown in Figure 2. These architectures have both a shared representation and a task specific representation. 'Splitting' a network at a lower layer allows for more task-specific and fewer shared layers. One extreme of Split architectures is splitting at the lowest convolution layer which results in two separate networks altogether, and thus only task-specific representations. The other extreme is using "sibling" prediction layers (as in [21]), which allows for a more shared representation. Thus, Split architectures allow for a varying amount of shared and task-specific representations.

split结构的一个极限就是从头开始分裂,这样的话就得到了两个不相干的模型

3.2. Unifying Split Architectures

Given that Split architectures hold promise for multi-task learning, an obvious question is – At which layer of the network should one split? This decision is highly dependent on the input data and tasks at hand. Rather than enumerating the possibilities of Split architectures for every new input task, we propose a simple architecture that can learn how much shared and task specific representation to use.

然而,关键的问题就是从那一层开始分裂得到的效果最好

所以针对这个问题,本文提出了一个统一的结构

3.3. Cross-stitch units

Consider a case of multi task learning with two tasks A and B on the same input image. For the sake of explanation, consider two networks that have been trained separately for these tasks. We propose a new unit, *cross-stitch unit*, that combines these two networks into a multi-task network in a way such that the tasks supervise how much sharing is needed, as illustrated in Figure 3. At each layer of the network, we model sharing of representations by learning a linear combination of the activation maps [4, 31] using a *cross-stitch unit*. Given two activation maps x_A, x_B from layer l for both the tasks, we learn linear combinations $\tilde{x}_A, \tilde{x}_B$ (Eq 1) of both the input activations and feed these combinations as input to the next layers' filters. This linear combination is parameterized using α. Specifically, at location (i, j) in the activation map,

考虑到任务A和任务B,两个任务的输入数据是相同的.为了便于解释,想象两个网络是独立的训练的.我们提出的Cross-Stitch单元,通过结合这两个模型得到

cross-stitch结构通过结合两个网络来得到一个Multi-task网络,而该单元使得模型能够决定每一层到底要共享多少的参数.在每一层通过线型组合来建模共享表示.具有来说当给定两个任务相同层输出的激活输出后,对于(i,j)这个位置的值,用一个矩阵线型变换来获得.我们称这个操作为十字绣操作.而网络在训练的时候可以通过决定alpha_AB或者alpha_BA的值为0来确定共享的程度

$$\begin{bmatrix}\tilde{x}_A^{ij}\\ \tilde{x}_B^{ij}\end{bmatrix} = \begin{bmatrix}\alpha_{AA} & \alpha_{AB}\\ \alpha_{BA} & \alpha_{BB}\end{bmatrix}\begin{bmatrix}x_A^{ij}\\ x_B^{ij}\end{bmatrix} \qquad (1)$$

We refer to this the *cross-stitch* operation, and the unit that models it for each layer l as the *cross-stitch unit*. The network can decide to make certain layers task specific by setting α_{AB} or α_{BA} to zero, or choose a more shared representation by assigning a higher value to them.

实现起来比较简单,写为x^ij_A=a_AA X^ij_A + a_AB X^ij_b
用四个(1,1)的卷积核,不要bias, step设为(1,1),padding=0

Backpropagating through cross-stitch units. Since cross-stitch units are modeled as linear combination, their partial derivatives for loss L with tasks A, B are computed as

为什么要给我看这个,这个不需要我来做

$$\begin{bmatrix}\frac{\partial L}{\partial x_{\mathrm{A}}^{ij}}\\ \frac{\partial L}{\partial x_{\mathrm{B}}^{ij}}\end{bmatrix} = \begin{bmatrix}\alpha_{\mathrm{AA}} & \alpha_{\mathrm{BA}}\\ \alpha_{\mathrm{AB}} & \alpha_{\mathrm{BB}}\end{bmatrix}\begin{bmatrix}\frac{\partial L}{\partial \tilde{x}_{\mathrm{A}}^{ij}}\\ \frac{\partial L}{\partial \tilde{x}_{\mathrm{B}}^{ij}}\end{bmatrix} \tag{2}$$

$$\frac{\partial L}{\partial \alpha_{\mathrm{AB}}} = \frac{\partial L}{\partial \tilde{x}_{\mathrm{B}}^{ij}} x_{\mathrm{A}}^{ij}, \quad \frac{\partial L}{\partial \alpha_{\mathrm{AA}}} = \frac{\partial L}{\partial \tilde{x}_{\mathrm{A}}^{ij}} x_{\mathrm{A}}^{ij} \tag{3}$$

我们将\alpha_AB和\alpha_BA记为alpha_D,称为不同任务值.我们记\alpha_AA和\alpha_BB为alpha_S,称为相同任务值

We denote $\alpha_{\mathrm{AB}}, \alpha_{\mathrm{BA}}$ by α_{D} and call them the *different*-task values because they weigh the activations of another task. Likewise, $\alpha_{\mathrm{AA}}, \alpha_{\mathrm{BB}}$ are denoted by α_{S}, the *same*-task values, since they weigh the activations of the same task. By varying α_{D} and α_{S} values, the unit can freely move between shared and task-specific representations, and choose a middle ground if needed.

通过更改alpha_D和alpha S的值,模型可以自由的在任务特定的表示和共享的表示中自由的切换

4. Design decisions for cross-stitching

感觉这句话才是关键上面的子网络A会直接从任务A中得到监督信息,而通过Cross-Stitch结构从任务B中隐式的得到监督

十字绣网络通过结合激活输出的方式来帮助模型正则化两个任务

We use the cross-stitch unit for multi-task learning in ConvNets. For the sake of simplicity, we assume multi-task learning with two tasks. Figure 4 shows this architecture for two tasks A and B. The sub-network in Figure 4(top) gets direct supervision from task A and indirect supervision (through cross-stitch units) from task B. We call the sub-network that gets direct supervision from task A as network A, and correspondingly the other as B. Cross-stitch units help regularize both tasks by learning and enforcing shared representations by combining activation (feature) maps. As we show in our experiments, in the case where one task has less labels than the other, such regularization helps the "data-starved" tasks.

这个是重点,一个有很少的label的时候,另外一个任务可以帮助他

Next, we enumerate the design decisions when using cross-stitch units with networks, and in later sections perform ablative studies on each of them.

Cross-stitch units initialization and learning rates: The α values of a cross-stitch unit model linear combinations of feature maps. Their initialization in the range $[0, 1]$ is important for stable learning, as it ensures that values in the output activation map (after cross-stitch unit) are of the same order of magnitude as the input values before linear combination. We study the impact of different initializations and learning rates for cross-stitch units in Section 5.

Network initialization: Cross-stitch units combine together two networks as shown in Figure 4. However, an obvious question is – how should one initialize the networks A and B? We can initialize networks A and B by networks that were trained on these tasks separately, or have the same initialization and train them jointly.

该如何初始化网络A和B的参数?可以分别训练,然后使用Cross-Stitch,也可以是从头开始联合训练

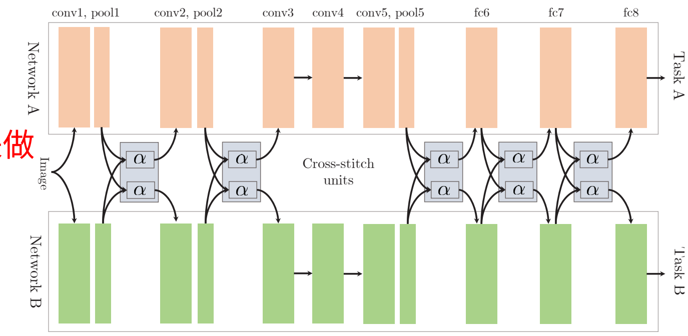


Figure 4: Using cross-stitch units to stitch two AlexNet [32] networks. In this case, we apply cross-stitch units only after pooling layers and fully connected layers. Cross-stitch units can model shared representations as a linear combination of input activation maps. This network tries to learn representations that can help with both tasks A and B. We call the sub-network that gets direct supervision from task A as network A (top) and the other as network B (bottom).

5. Ablative analysis

We now describe the experimental setup in detail, which is common throughout the ablation studies.

Datasets and Tasks: For ablative analysis we consider the tasks of semantic segmentation (SemSeg) and Surface Normal Prediction (SN) on the NYU-v2 [47] dataset. We use the standard train/test splits from [18]. For semantic segmentation, we follow the setup from [24] and evaluate on the 40 classes using the standard metrics from their work

Setup for Surface Normal Prediction: Following [52], we cast the problem of surface normal prediction as classification into one of 20 categories. For evaluation, we convert the model predictions to 3D surface normals and apply the Manhattan-World post-processing following the method in [52]. We evaluate all our methods using the metrics from [18]. These metrics measure the error in the ground truth normals and the predicted normals in terms of their angular distance (measured in degrees). Specifically, they measure the mean and median error in angular distance, in which case lower error is better (denoted by 'Mean' and 'Median' error). They also report percentage of pixels which have their angular distance under a threshold (denoted by 'Within t°' at a threshold of $11.25^\circ, 22.5^\circ, 30^\circ$), in which case a higher number indicates better performance.

Networks: For semantic segmentation (SemSeg) and surface normal (SN) prediction, we use the Fully-Convolutional Network (FCN 32-s) architecture from [36] based on CaffeNet [29] (essentially AlexNet [32]). For both the tasks of SemSeg and SN, we use RGB images at full resolution, and use mirroring and color data augmentation. We then finetune the network (referred to as *one-task network*) from ImageNet [9] for each task using hyperparame-

Table 1: Initializing cross-stitch units with different α values, each corresponding to a convex combination. Higher values for α_S indicate that we bias the cross-stitch unit to prefer task specific representations. The cross-stitched network is robust across different initializations of the units.

	Surface Normal					Segmentation		
	Angle Distance (Lower Better)		Within $t°$ (Higher Better)			(Higher Better)		
(α_S, α_D)	Mean	Med.	11.25	22.5	30	pixacc	mIU	fwIU
$(0.1, 0.9)$	34.6	18.8	38.5	53.7	59.4	47.9	18.2	33.3
$(0.5, 0.5)$	34.4	18.8	38.5	53.7	59.5	47.2	18.6	33.8
$(0.7, 0.3)$	**34.0**	**18.3**	38.9	54.3	60.1	48.0	18.6	33.6
$(0.9, 0.1)$	**34.0**	**18.3**	**39.0**	**54.4**	**60.2**	**48.2**	**18.9**	**34.0**

Table 2: Scaling the learning rate of cross-stitch units wrt. the base network. Since the cross-stitch units are initialized in a different range from the layer parameters, we scale their learning rate for better training.

	Surface Normal					Segmentation		
	Angle Distance (Lower Better)		Within $t°$ (Higher Better)			(Higher Better)		
Scale	Mean	Med.	11.25	22.5	30	pixacc	mIU	fwIU
1	34.6	18.9	38.4	53.7	59.4	47.7	18.6	33.5
10	34.5	18.8	38.5	53.8	59.5	47.8	18.7	33.5
10^2	**34.0**	18.3	39.0	54.4	60.2	**48.0**	18.9	33.8
10^3	34.1	**18.2**	**39.2**	**54.4**	**60.2**	47.2	**19.3**	**34.0**

ters reported in [36]. We fine-tune the network for semantic segmentation for 25k iterations using SGD (mini-batch size 20) and for surface normal prediction for 15k iterations (mini-batch size 20) as they gave the best performance, and further training (up to 40k iterations) showed no improvement. These *one-task networks* serve as our baselines and initializations for cross-stitching, when applicable.

Cross-stitching: We combine two AlexNet architectures using the cross-stitch units as shown in Figure 4. We experimented with applying cross-stitch units after every convolution activation map and after every pooling activation map, and found the latter performed better. Thus, the cross-stitch units for AlexNet are applied on the activation maps for `pool1`, `pool2`, `pool5`, `fc6` and `fc7`. We maintain one cross-stitch unit per 'channel' of the activation map, *e.g.*, for `pool1` we have 96 cross-stitch units.

5.1. Initializing parameters of cross-stitch units

Cross-stitch units capture the intuition that shared representations can be modeled by linear combinations [31]. To ensure that values after the cross-stitch operation are of the same order of magnitude as the input values, an obvious initialization of the unit is that the α values form a convex linear combination, *i.e.*, the different-task α_D and the same-task α_S to sum to one. Note that this convexity is not enforced on the α values in either Equation 1 or 2, but serves as a reasonable initialization. For this experiment, we initialize the networks A and B with *one-task* networks that were fine-tuned on the respective tasks. Table 1 shows the results of evaluating cross-stitch networks for different initializations of α values.

5.2. Learning rates for cross-stitch units

We initialize the α values of the cross-stitch units in the range $[0.1, 0.9]$, which is about one to two orders of magnitude larger than the typical range of layer parameters in AlexNet [32]. While training, we found that the gradient updates at various layers had magnitudes which were reasonable for updating the layer parameters, but too small for the cross-stitch units. Thus, we use higher learning rates for the cross-stitch units than the base network. In practice, this leads to faster convergence and better performance. To study the impact of different learning rates, we again use a cross-stitched network initialized with two *one-task networks*. We scale the learning rates (wrt. the network's learning rate) of cross-stitch units in powers of 10 (by setting the `lr_mult` layer parameter in Caffe [29]). Table 2 shows the results of using different learning rates for the cross-stitch units after training for 10k iterations. Setting a higher scale for the learning rate improves performance, with the best range for the scale being $10^2 - 10^3$. We observed that setting the scale to an even higher value made the loss diverge.

5.3. Initialization of networks A and B

When cross-stitching two networks, how should one initialize the networks A and B? Should one start with task specific *one-task networks* (fine-tuned for one task only) and add cross-stitch units? Or should one start with networks that have not been fine-tuned for the tasks? We explore the effect of both choices by initializing using two *one-task networks* and two networks trained on ImageNet [9, 43]. We train the *one-task* initialized cross-stitched network for 10k iterations and the ImageNet initialized cross-stitched network for 30k iterations (to account for the 20k fine-tuning iterations of the *one-task* networks), and report the results in Table 3. Task-specific initialization performs better than ImageNet initialization for both the tasks, which suggests that cross-stitching should be used after training task-specific networks.

5.4. Visualization of learned combinations

We visualize the weights α_S and α_D of the cross-stitch units for different initializations in Figure 4. For this experiment, we initialize sub-networks A and B using *one-task* networks and trained the cross-stitched network till convergence. Each plot shows (in sorted order) the α values for all the cross-stitch units in a layer (one per channel).

Table 3: We initialize the networks A, B (from Figure 4) from ImageNet, as well as task-specific networks. We observe that task-based initialization performs better than task-agnostic ImageNet initialization.

	Surface Normal					Segmentation		
	Angle Distance (Lower Better)		Within t° (Higher Better)			(Higher Better)		
Init.	Mean	Med.	11.25	22.5	30	pixacc	mIU	fwIU
ImageNet	34.6	18.8	38.6	53.7	59.4	**48.0**	17.7	33.4
One-task	**34.1**	**18.2**	**39.0**	**54.4**	**60.2**	47.2	**19.3**	**34.0**

We show plots for three layers: `pool1`, `pool5` and `fc7`. The initialization of cross-stitch units biases the network to start its training preferring a certain type of shared representation, *e.g.*, $(\alpha_{\text{S}}, \alpha_{\text{D}}) = (0.9, 0.1)$ biases the network to learn more task-specific features, while $(0.5, 0.5)$ biases it to share representations. Figure 4 (second row) shows that both the tasks, across all initializations, prefer a more task-specific representation for `pool5`, as shown by higher values of α_{S}. This is inline with the observation from Section 1.1 that Split `conv4` performs best for these two tasks. We also notice that the surface normal task prefers shared representations as can be seen by Figure 4(b), where α_{S} and α_{D} values are in similar range.

6. Experiments

We now present experiments with cross-stitch networks for two pairs of tasks: semantic segmentation and surface normal prediction on NYU-v2 [47], and object detection and attribute prediction on PASCAL VOC 2008 [12, 16]. We use the experimental setup from Section 5 for semantic segmentation and surface normal prediction, and describe the setup for detection and attribute prediction below.

Dataset, Metrics and Network: We consider the PASCAL VOC 20 classes for object detection, and the 64 attribute categories data from [16]. We use the PASCAL VOC 2008 [12, 16] dataset for our experiments and report results using the standard Average Precision (AP) metric. We start with the recent Fast-RCNN [21] method for object detection using the AlexNet [32] architecture.

Training: For object detection, Fast-RCNN is trained using 21-way 1-vs-all classification with 20 foreground and 1 background class. However, there is a severe data imbalance in the foreground and background data points (boxes). To circumvent this, Fast-RCNN carefully constructs mini-batches with $1 : 3$ foreground-to-background ratio, *i.e.*, at most 25% of foreground samples in a mini-batch. Attribute prediction, on the other hand, is a multi-label classification problem with 64 attributes, which only train using foreground bounding boxes. To implement both tasks in the Fast R-CNN framework, we use the same mini-batch sampling strategy; and in every mini-batch only the foreground samples contribute to the attribute loss (and background samples are ignored).

Scaling losses: Both SemSeg and SN used same classification loss for training, and hence we were set their loss weights to be equal $(= 1)$. However, since object detection is formulated as 1-vs-all classification and attribute classification as multi-label classification, we balance the losses by scaling the attribute loss by $1/64$.

Cross-stitching: We combine two AlexNet architectures using the cross-stitch units after every pooling layer as shown in Figure 4. In the case of object detection and attribute prediction, we use one cross-stitch unit per layer activation map. We found that maintaining a unit per channel, like in the case of semantic segmentation, led to unstable learning for these tasks.

6.1. Baselines

We compare against four strong baselines for the two pairs of tasks and report the results in Table 5 and 6.

Single-task Baselines: These serve as baselines without benefits of multi-task learning. First we evaluate a single network trained on only one task (denoted by 'One-task') as described in Section 5. Since our approach cross-stitches two networks and therefore uses $2\times$ parameters, we also consider an ensemble of two one-task networks (denoted by 'Ensemble'). However, note that the ensemble has $2\times$ network parameters for only one task, while the cross-stitch network has roughly $2\times$ parameters for two tasks. So for a pair of tasks, the ensemble baseline uses $\sim 2\times$ the cross-stitch parameters.

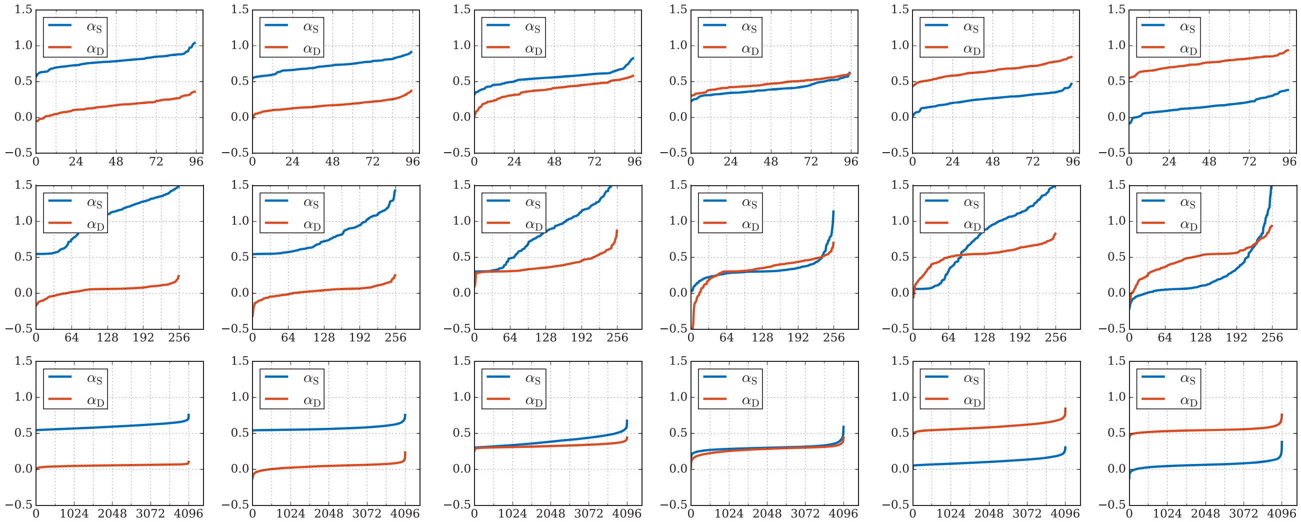
Multi-task Baselines: The cross-stitch units enable the network to pick an optimal combination of shared and task-specific representation. We demonstrate that these units remove the need for finding such a combination by exhaustive brute-force search (from Section 1.1). So as a baseline, we train all possible "Split architectures" for each pair of tasks and report numbers for the best Split for each pair of tasks.

There has been extensive work in Multi-task learning outside of the computer vision and deep learning community. However, most of such work, with publicly available code, formulates multi-task learning in an optimization framework that requires all data points in memory [6, 14, 23, 34, 49, 60, 61]. Such requirement is not practical for the vision tasks we consider.

So as our final baseline, we compare to a variant of [1, 62] by adapting their method to our setting and report this as 'MTL-shared'. The original method treats each category as a separate 'task', *a separate network* is required for each category and *all these networks are trained jointly*. Directly applied to our setting, this would require training 100s of ConvNets jointly, which is impractical. Thus, instead of treating each category as an independent task, we

Table 4: We show the sorted α values (increasing left to right) for three layers. A higher value of α_{S} indicates a strong preference towards task specific features, and a higher α_{D} implies preference for shared representations. More detailed analysis in Section 5.4. Note that both α_{S} and α_{D} are sorted independently, so the channel-index across them do not correspond.

Layer	(a) $\alpha_{\mathrm{S}} = 0.9, \alpha_{\mathrm{D}} = 0.1$		(b) $\alpha_{\mathrm{S}} = 0.5, \alpha_{\mathrm{D}} = 0.5$		(c) $\alpha_{\mathrm{S}} = 0.1, \alpha_{\mathrm{D}} = 0.9$	
	Segmentation	Surface Normal	Segmentation	Surface Normal	Segmentation	Surface Normal
pool1						
pool5						
fc7						



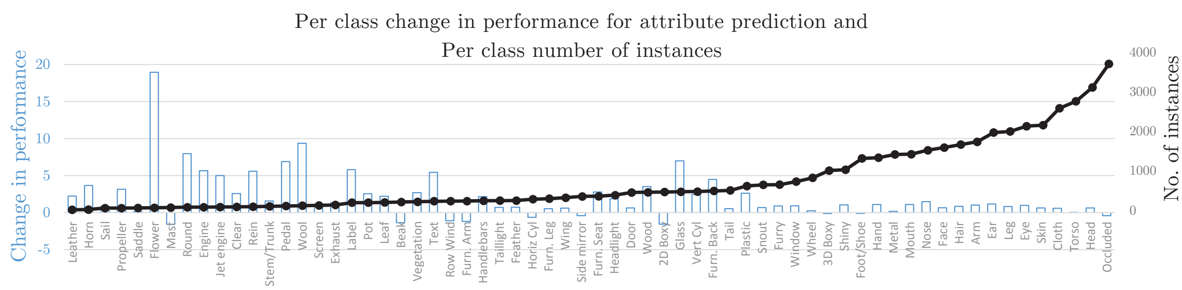


Figure 5: Change in performance for attribute categories over the baseline is indicated by blue bars. We sort the categories in increasing order (from left to right) by the number of instance labels in the train set, and indicate the number of instance labels by the solid black line. The performance gain for attributes with lesser data (towards the left) is considerably higher compared to the baseline. We also notice that the gain for categories with lots of data is smaller.

adapt their method to our two-task setting. We train these two networks jointly, using end-to-end learning, as opposed to their dual optimization to reduce hyperparameter search.

6.2. Semantic Segmentation and Surface Normal Prediction

Table 5 shows the results for semantic segmentation and surface normal prediction on the NYUv2 dataset [47]. We compare against two one-task networks, an ensemble of two networks, and the best Split architecture (found using brute force enumeration). The sub-networks A, B (Figure 4) in our cross-stitched network are initialized from the one-task networks. We use cross-stitch units after every pooling layer and fully connected layer (one per channel). Our proposed cross-stitched network improves results over the baseline one-task networks and the ensemble. Note that even though the ensemble has $2\times$ parameters compared to cross-stitched network, the latter performs better. Finally, our performance is better than the best Split architecture network found using brute force search. This shows that the cross-stitch units can effectively search for optimal amount of sharing in multi-task networks.

6.3. Data-starved categories for segmentation

Multiple tasks are particularly helpful in regularizing the learning of shared representations[5, 14, 50]. This regularization manifests itself empirically in the improvement of "data-starved" (few examples) categories and tasks.

For semantic segmentation, there is a high mismatch in the number of labels per category (see the black line in Fig-

Table 5: Surface normal prediction and semantic segmentation results on the NYU-v2 [47] dataset. Our method outperforms the baselines for both the tasks.

	Surface Normal					Segmentation		
	Angle Distance (Lower Better)		Within $t°$ (Higher Better)			(Higher Better)		
Method	Mean	Med.	11.25	22.5	30	pixacc	mIU	fwIU
One-task	34.8	19.0	38.3	53.5	59.2	-	-	-
	-	-	-	-	-	46.6	18.4	33.1
Ensemble	34.4	18.5	38.7	54.2	59.7	-	-	-
	-	-	-	-	-	**48.2**	18.9	33.8
Split `conv4`	34.7	19.1	38.2	53.4	59.2	47.8	19.2	33.8
MTL-shared	34.7	18.9	37.7	53.5	58.8	45.9	16.6	30.1
Cross-stitch **[ours]**	**34.1**	**18.2**	**39.0**	**54.4**	**60.2**	47.2	**19.3**	**34.0**

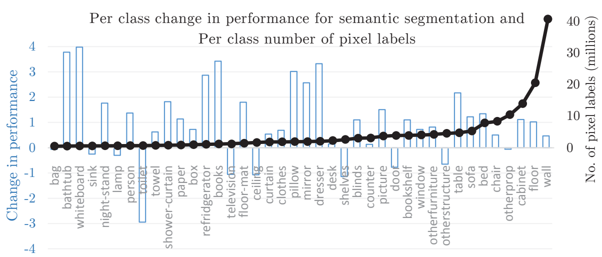


Figure 6: Change in performance (meanIU metric) for semantic segmentation categories over the baseline is indicated by blue bars. We sort the categories (in increasing order from left to right) by the number of pixel labels in the train set, and indicate the number of pixel labels by a solid black line. The performance gain for categories with lesser data (towards the left) is more when compared to the baseline one-task network.

ure 6). Some classes like *wall*, *floor* have many more instances than other classes like *bag*, *whiteboard etc*. Figure 6 also shows the per-class gain in performance using our method over the baseline one-task network. We see that cross-stitch units considerably improve the performance of "data-starved" categories (*e.g.*, *bag*, *whiteboard*).

6.4. Object detection and attribute prediction

We train a cross-stitch network for the tasks of object detection and attribute prediction. We compare against baseline one-task networks and the best split architectures per task (found after enumeration and search, Section 1.1). Table 6 shows the results for object detection and attribute prediction on PASCAL VOC 2008 [12, 16]. Our method shows improvements over the baseline for attribute prediction. It is worth noting that because we use a background class for detection, and not attributes (described in 'Scaling losses' in Section 6), detection has many more data points than attribute classification (only 25% of a mini-batch has attribute labels). Thus, we see an improvement for the data-starved task of attribute prediction. It is also interesting to note that the detection task prefers a shared representation (best performance by Split `fc7`), whereas the attribute task prefers a task-specific network (best performance by Split `conv2`).

Table 6: Object detection and attribute prediction results on the attribute PASCAL [16] 2008 dataset

Method	Detection (mAP)	Attributes (mAP)
One-task	44.9	-
	-	60.9
Ensemble	**46.1**	-
	-	61.1
Split `conv2`	44.6	61.0
Split `fc7`	44.8	59.7
MTL-shared	42.7	54.1
Cross-stitch **[ours]**	45.2	**63.0**

6.5. Data-starved categories for attribute prediction

Following a similar analysis to Section 6.3, we plot the relative performance of our cross-stitch approach over the baseline one-task attribute prediction network in Figure 5. The performance gain for attributes with smaller number of training examples is considerably large compared to the baseline (**4.6**% and **4.3**% mAP for the top 10 and 20 attributes with the least data respectively). This shows that our proposed cross-stitch method provides significant gains for data-starved tasks by learning shared representations.

7. Conclusion

We present *cross-stitch* units which are a generalized way of learning shared representations for multi-task learning in ConvNets. Cross-stitch units model shared representations as linear combinations, and can be learned end-to-end in a ConvNet. These units generalize across different types of tasks and eliminate the need to search through several multi-task network architectures on a per task basis. We show detailed ablative experiments to see effects of hyperparameters, initialization *etc*. when using these units. We also show considerable gains over the baseline methods for data-starved categories. Studying other properties of cross-stitch units, such as where in the network should they be used and how should their weights be constrained, is an interesting future direction.

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