Fine-tuning or top-tuning?  
Transfer learning with pretrained features and fast kernel methods

Paolo Didier Alfano  
MaLGa - DIBRIS, University of Genova, Italy  
paolodidier.alfano@edu.unige.it

Vito Paolo Pastore  
MaLGa - DIBRIS, University of Genova, Italy  
vito.paolo.pastore@unige.it

Lorenzo Rosasco  
MaLGa - DIBRIS, University of Genova, Italy  
Istituto Italiano di Tecnologia, Genova, Italy  
lorenzo.rosasco@unige.it

Francesca Odone  
MaLGa - DIBRIS, University of Genova, Italy  
francesca.odone@unige.it

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Abstract
The impressive performances of deep learning architectures are associated to massive increase of models complexity. Millions of parameters need be tuned, with training and inference time scaling accordingly. But is massive fine-tuning necessary? In this paper, focusing on image classification, we consider a simple transfer learning approach exploiting pretrained convolutional features as input for a fast kernel method. We refer to this approach as top-tuning, since only the kernel classifier is trained. By performing more than 2500 training processes we show that this top-tuning approach provides comparable accuracy w.r.t. fine-tuning, with a training time that is between one and two orders of magnitude smaller. These results suggest that top-tuning provides a useful alternative to fine-tuning in small/medium datasets, especially when training efficiency is crucial.

1 Introduction
In the last decade deep learning has led to unprecedented successes in computer vision, at par with human performances in several tasks[12, 95, 60]. In particular, Convolutional Neural Networks (CNNs)[65, 22, 74] proved successful in a wide range of domains[50], from medical images[3, 98, 90, 49]
Figure 1: The two pipelines: orange arrows represent model weights update. (Left) The Fine-Tuning pipeline. All the model weights are updated. (Right) The Top-tuning pipeline. Only the fast kernel weights are updated.

to robotics [5, 2, 61, 44] and cyber-security [103, 51], to name a few examples. These advances have been associated to a frenetic increase in model complexity [89, 46, 102, 24, 94], demand for data [22, 56], and corresponding growth of computations [6]. Several solutions have been proposed to alleviate the need for labeled data, from few-shot learning [83, 96] to self supervision techniques [14, 100, 20], and also to reduce the inference time, e.g. via pruning techniques [75, 48, 54]. When resources are budgeted, training models from scratch can be prohibitive [47, 86]. Transfer learning [67, 104, 97] is an approach that can tackle both the issues of data scarcity [33] and long training times, by leveraging pre-trained models to solve new problems. In particular an approach very common in image classification [32, 79, 80] is the so called fine-tuning [101, 50], where the networks weights are initialized with pre-trained models and only (fine) tuned rather than being trained from scratch. We show such approach in Figure 1 (Left).

In this paper, we consider a simple approach that uses convolutional features [81] produced by a state-of-the-art model pre-trained on ImageNet [13], with no further tuning. These features are used as input to train a fast and scalable kernel classifier [77, 58] trained anew. We refer to such approach as top-tuning and we show it in Figure 1 (Right). This is a simple idea [34, 18, 23, 1], that we re-examine in the light of common practices for transfer learning using deep nets. In particular, we have in mind scenarios where computational resources are budgeted and fast training is relevant. This may be typical in applications like robotics, where multiple training needs to be done on the fly [52, 69].

Our study shows that top-tuning is a promising alternative to fine-tuning for small-medium sized datasets. Indeed top-tuning provides comparable accuracy w.r.t. fine-tuning (sometimes slightly worse, and sometimes slightly better), with training times between one and two orders of magnitude smaller. In our analysis we focus on three different aspects: (a) Target dataset: to ensure the generality of our empirical observations, we consider 32 target datasets (b) Pre-trained model: to evaluate the influence of a specific model, we consider six different pre-trained models (c) Pre-training dataset: to assess dependency on the source dataset, we consider four distinct datasets for pre-training.

Accuracy and training times results are confirmed across the different considered
scenarios.
In summary, the main contributions of this work are: (1) A systematic empirical study, comparing top-tuning and fine-tuning approaches on a large ensemble from small to medium size datasets, with different pre-trained models. (2) We show the effectiveness of a quality pre-training, which prioritizes the number of classes to the number of samples.

2 Related works

In this section, we describe and compare recent papers relevant to our study. In [39] the authors evaluate the relationship between specific neural network architectures and transfer-learning, assessing whether models that achieve better performances on ImageNet show the same trend also on other vision tasks. They find that a model accuracy on the ImageNet pre-training task predicts fine-tuning performance on the target ones, with little or no benefit when fine-tuning on fine-grained dataset (i.e., stanford cars and FGVC aircraft). In [31] the authors perform an empirical investigation on ImageNet to identify the properties responsible for the outstanding performances when transfer knowledge from such dataset to various vision tasks. They pre-train AlexNet [43] on different subsets of ImageNet, varying the number of samples, classes, and the granularity. In [26] the authors focus on the impact of a Convolutional Neural Network’s (CNN) complexity on the training time, evaluating the accuracy with constrained time cost, considering the influence of different factors including depth, number of filters and filters size. In [38] the authors investigate on the paradigm of pre-training on large supervised datasets in a transfer-learning scenario for different vision tasks. They introduce a heuristic hyperparameters search procedure for transfer-learning, evaluating pre-training on different scales. In [55], different strategies to modify convolutional filters are proposed to speed-up the training and inference time for a CNN.

These works focus on transferability between different deep models or implementations, without specific references on training time comparison. In this paper, instead, we show that convolution features pre-trained on rich datasets such as ImageNet, provide general purpose pre-trained features which can be transferred to a new a task simply by training an external classifier, with a potential training time speed-up.

3 Methodology

The fine-tuning and top-tuning approaches are briefly described next, and illustrated in Figure 1. Given a state-of-the-art deep learning model pre-trained on a source dataset (e.g. ImageNet), and a target dataset of input-output pairs \( \{(x_i, y_i)\}_{i=1}^n \) on which we solve a classification problem, we can perform two different transfer approaches:

1. **Fine-tuning**: in a typical architecture for image classification, convolu-
tional layers are followed by fully connected layers:
\[ \Phi = \Phi_L \circ \Phi_{L-1} \circ \ldots \circ \Phi_{C+1} \circ \Phi_C \circ \ldots \circ \Phi_1 . \] (1)

In the basic idea of transfer learning by fine-tuning, fully connected layers are updated on the top of the pre-trained architecture. Then the model is fine tuned to fit the new task. Notice that this procedure may update both the parameters of the fully connected and of the pre-trained part in an end-to-end fashion minimizing an empirical error via back-propagation.

2. Top-tuning: in the top-tuning approach we consider the representation \( \Phi \) given by:
\[ \Phi = \Psi \circ \Phi_C \circ \ldots \circ \Phi_1 . \] (2)
where \( \Psi \) is a typically infinite dimensional feature map corresponding to a kernel \( k(z, z') \) on the pre-trained features. In our experiments, we consider the Gaussian kernel \( k(z, z') = e^{-\|z - z'\|^2 / \gamma^2} \), where \( \gamma \) is the kernel width. Unlike before, here the convolutional features \( \Phi_C, \ldots, \Phi_1 \) are assumed to be pre-trained but then fixed. The only free parameters \( W \) are computed by a ridge regression procedure minimizing:
\[ \sum_{i=1}^{n} \| W \Phi(x_i) - y_i \|^2 + \lambda \| W \|^2_F \] (3)
where \( \| \cdot \|_F \) if the Frobenious norm, \( \lambda \) is a regularization parameter.

To make ridge classifier massively faster we can rely on the representer theorem[78] and Nyström approximation[63]. All the details about this procedure can be found in[77, 58]. The resulting model can then be seen as an external classifier running on top of the pre-trained features.

3.1 Hyper-parameters tuning

In this section we provide details about how we tune hyper-parameters for our analysis. For both fine-tuning and top-tuning approaches we use a five-fold cross validation approach.

Fine-tuning:
- Training steps: inspired by previous studies on a similar context[39] we limited this quantity to 20,000 training steps, coupled with an early stopping criterion.
- Early stopping: we monitor the validation loss with patience parameter equal to 10.
- Batch size: taking into account previous studies about batch size[82, 25, 57]
we compute it as: \( b = \lfloor 2^{2 \log_{10}(n)} - 1 \rfloor \) where \( n \) is the number of points in the dataset.

- Optimizer: we use default Stochastic Gradient Descent (SGD). As suggested by [21], we use two different learning rates: \( l = \{0.1, 0.01\} \)

  All the hyper-parameters for our neural network model are fixed but the learning rate. Hence we run one training instance per each considered learning rate value, taking the best performing one for the results. The training time reported in the results is the sum of the computational time requested for both the training instances.

**Top-tuning:**

- Kernel width: as shown in Equation 2, we use a kernel feature map \( \Psi \) corresponding to a Gaussian kernel. We use two different kernel width: \( \gamma = \{10^2, 10^3\} \).

- Regularization: we consider two values for the regularization term: \( \lambda = \{10^{-5}, 10^{-6}\} \)

  With two possible values for both kernel width and regularization, we run four different training instances, taking the best performing one for the results. The training time reported in the results is the sum of the computational time requested for the four training instances.

### 4 Empirical analysis

We now describe the details of the empirical analysis. We include 32 image classification datasets in our experiments, including popular benchmarks, as well as more challenging small dimensional datasets. More details are available in the supplementary material.

We first compare fine-tuning and top-tuning in terms of accuracy and training time. Then, we consider six different pre-trained neural networks, to weight the results dependency w.r.t. the architecture. Next, we evaluate the importance of pre-training. Finally we provide preliminary results by using transformers as features extractor. All the experiments have been carried out on a single Quadro RTX 6000 GPU, 24Gb VRAM.

#### Fine-tuning vs Top-tuning on different target datasets.

To compare fine-tuning and top-tuning approaches, we first fix the neural network model and the pre-training dataset, considering an ImageNet pre-trained DenseNet201.
architecture. This model represents a good compromise between predictive power and size in terms of number of parameters. We consider the 6 different configurations defined in subsection 3.1, averaging the results of a 5-folded procedure over the 32 datasets, resulting in $6 \cdot 5 \cdot 32 = 960$ distinct training processes.

In Figure 2(Left) we show the overall accuracy results. Each point represents a different dataset. Its position is given by the accuracy obtained by the best fine-tuning configuration on the x-axis, and by the best top-tuning configuration on the y-axis. The diagonal is marked for readability purposes. Intuitively, when a point is lying below the diagonal, the fine-tuning model is performing better w.r.t the top-tuning one, and vice versa.

Most of the datasets lie around the diagonal, showing similar accuracy between fine-tuning and top-tuning methods. Indeed, $\Delta Acc = Acc_{top-tuning} - Acc_{fine-tuning} \in [-2.5\%, +2.5\%]$ in 60% of our experiments. Only on few datasets, e.g. FGVC aircraft and Stanford Cars(SC), fine-tuning provides a benefit. This behaviour could be related to two factors. (i) Representation in ImageNet: as pointed out by [39], in ImageNet cars and planes are represented at a coarse-grained level. For instance, ImageNet contains only two planes classes; (ii) Dataset hardness in terms of number of classes, granularity and number of images per class.

In Figure 2(Right) we show the overall results in terms of training time. Each column refers to a different dataset, reporting the speed-up obtained when avoiding fine-tuning. The top-tuning models are always highly faster to train than the fine-tuning ones. The speed-up is in range $[10,150]$ with mean $84.64 \pm 38.97$ across the datasets. On larger datasets, e.g. CIFAR100, the training time
Table 1: Quantitative results about the analysis on different datasets. The second column reports the $\Delta \text{Acc} = \text{Acc}_{\text{top-tuning}} - \text{Acc}_{\text{fine-tuning}}$. The third one refers to the corresponding speed-up obtained when using the top-tuning procedure.

| Dataset          | $\Delta \text{Acc}$ | SpUp  | Dataset          | $\Delta \text{Acc}$ | SpUp  |
|------------------|----------------------|-------|------------------|----------------------|-------|
| AFHQ             | +0.10%               | 94.70x| Football vs Rugby| +1.90%               | 124.8x|
| Beans            | +0.90%               | 116.3x| Gemstones        | −0.20%               | 147.6x|
| Best artworks    | +3.10%               | 65.90x| Horses vs Humans | +5.20%               | 131.3x|
| Boat types       | +0.50%               | 131.5x| iCub World subset| −1.00%               | 32.60x|
| Caltech-101      | +1.10%               | 94.00x| Indian Food      | −1.10%               | 122.6x|
| Cassava          | −4.50%               | 44.00x| Make up         | +1.70%               | 102.5x|
| Cats vs Dogs     | −0.20%               | 60.00x| Malaria        | −2.00%               | 46.80x|
| Chest xray       | +0.50%               | 62.40x| Meat Quality    | +0.00%               | 163.6x|
| CIFAR10          | −2.80%               | 28.90x| Oxford Flowers102| +4.50%               | 96.30x|
| CIFAR100         | −3.70%               | 12.10x| Oxford-IIT Pets | +4.50%               | 94.60x|
| Citrus leaves    | +7.30%               | 109.5x| Plankton        | +0.00%               | 75.50x|
| Colorect. histology | +0.50%        | 89.20x| Sars Covid      | −0.40%               | 107.0x|
| Deep weeds       | −9.10%               | 57.70x| Stanford Cars   | −15.7%               | 76.90x|
| DTD              | +2.90%               | 82.80x| Stanford Dogs   | +5.20%               | 22.50x|
| EuroSAT          | −2.40%               | 39.10x| Tensorflow flowers | −1.40%             | 62.40x|
| FGVC Aircraft    | −10.6%               | 60.90x| Weather         | +0.90%               | 152.4x|

was reduced from $\sim$ 2 hours to $\sim$ 10 minutes; computed as the training time sum of the two fine-tuning and four top-tuning configurations, respectively.

We can relate the faster training time to: (i) number of parameters: top-tuning model have a number of parameters on average two order of magnitude lower than the fine-tuning ones; (ii) impact of backpropagation: every layer needs to wait the subsequent layer computation.

Table 1 summarizes the quantitative results obtained with our experiments both in terms of accuracy and training time speed-up.

Lastly, although in this work we do not focus on inference time, we report for completeness that the two pipelines needed similar time for prediction.

Results with different pre-trained neural networks. We extend the results obtained with DenseNet201 on five state-of-the-art pre-trained models: (i) EfficientNetB0 \cite{tan2019efficientnet}; (ii) InceptionResNetV2 \cite{szegedy2017inception}; (iii) MobileNetV2 \cite{howard2017mobilenets}; (iv) ResNet152 \cite{he2016deep}; (v) Xception \cite{chollet2017xception}.

We test these models on four different datasets where: fine-tuning has only marginal benefits (Caltech-101, CIFAR100), top-tuning approach provides better results w.r.t. fine-tuning (DTD), and fine-tuning outperforms top-tuning approach (Stanford Cars).

The training procedure is analogous to the one performed for DenseNet201 with 5 additional models and the subset of 4 datasets, performing 600 additional training processes.
Figure 3: Overall results on different pre-trained models. (Left) Accuracies obtained over different target datasets with different pre-trained models. (Right) Speed-up obtained by the top-tuning model w.r.t the fine-tuning one for each dataset and for each pre-trained model.

Table 2: Analysis on different pre-trained models: variation in accuracy (ΔAcc) and speedup (SpUp), between fine-tuning and top-tuning.

|               | Caltech-101 | CIFAR100 | DTD   | Stanford Cars |
|---------------|-------------|----------|-------|---------------|
| ΔAcc          |             |          |       |               |
| DenseN201     | +1.10%      | 94.00    | -3.70%| -21.9%        |
| Eff.NB0       | -5.60%      | 109.3    | -12.1%| 76.80         |
| Inc.R.NV2     | -2.80%      | 85.10    | -11.1%| 126.3         |
| MobileNV2     | +14.3%      | 39.40    | +0.10%| 89.80         |
| ResN152       | +2.90%      | 82.60    | -5.10%| 150.2         |
| Xception      | -4.60%      | 67.10    | -15.4%| 81.00         |

Figure 3 shows the overall results. Each color refers to a different target dataset, each symbol corresponds to a different pre-trained neural network. The additional neural networks show a similar trend to the one obtained by DenseNet201. Table 2 summarizes the quantitative results obtained both in terms of accuracy and training time speed-up. Such results suggest that our findings are low-dependent from the pre-trained neural network adopted.

The importance of the pre-training dataset. We now explore the results dependency on the pre-training dataset. To this purpose we consider three alternative pre-training datasets:

- **CIFAR100**: we consider CIFAR100 as a simplified version of ImageNet. With this dataset, we test the impact of reduced number of images, classes and image size.
Figure 4: Overall results on different pretrains. For each target dataset, each color represents one of the four different pre-trains datasets. (Left) Accuracies obtained by top-tuning approach (Right) Accuracies obtained by fine-tuning approach.

- **ImageNet100**: we extract an ImageNet subset with the same number of images and classes of CIFAR100. To make this dataset as more similar as possible to CIFAR100 in terms of label semantic: 75% of labels selected from ImageNet is the same in CIFAR100, 15% of them are similar and 10% are different. With this dataset, we test the impact of image quality on the obtained results.

- **ImageNet 50k**: we extract an ImageNet subset that contains all the classes in ImageNet with the same number of data points contained in CIFAR100, that is 50k. The obtained dataset has 1000 classes with only 50 points per class. With this dataset, we test how the total number of classes affects the obtained results.

First, we train a DenseNet201 model from scratch on each of the three pre-training datasets. Then, we apply the two investigated pipelines on five target datasets: one of the most difficult and one of the easiest datasets for both approaches (DTD and CIFAR10, respectively), one where top-tuning approach outperforms fine-tuning (Citrus Leaves) and the opposite case (Deep Weeds). Lastly, we consider the fine grained Oxford Flowers 102. With five target datasets, three different pre-training, we perform 450 additional training instances.

**Figure 4 (Left)** refers to top-tuning accuracy for each pre-train. ImageNet pre-training brings to the best results on the target datasets. ImageNet 50k is the best alternative, suggesting that the number of classes for the pre-training dataset has a great impact on the top-tuning approach. The only exception corresponds to CIFAR10, where CIFAR100 corresponds to the best pre-train. This behavior depends on CIFAR10 being de facto a CIFAR100 subset.

**Figure 4 (Right)** refers to fine-tuning accuracy for each pre-train. ImageNet pre-training corresponds to the best accuracy. The difference between the other
Table 3: Accuracy drops for pre-training alternative to ImageNet. Each column represents a different target dataset, each row a different pre-train source. The reported value corresponds to the accuracy drop w.r.t. the original ImageNet pre-training. The lower the value, the better.

| Pre-training Configurations | CIFAR10 | Citrus Leaves | Deep Weeds | DTD | Oxf Flow |
|-----------------------------|---------|---------------|------------|-----|---------|
| CIFAR100 Top-Tn.            | 7.30%   | 4.7%          | 15.2%      | 26.3% | 24.0%   |
| ImageNet100                 | 16.8%   | 6.7%          | 11.1%      | 22.0% | 24.3%   |
| ImageNet 50k                | 12.7%   | 1.0%          | 5.70%      | 17.5% | 13.9%   |
| Fine-Tn. Top-Tn.            | 4.9%    | 0.0%          | 10.9%      | 18.3% | 12.6%   |
| CIFAR100                    | 6.3%    | -0.6%         | 6.7%       | 13.0% | 13.0%   |
| ImageNet100                 | 5.3%    | 1.7%          | 5.5%       | 13.1% | 16.7%   |

Preliminary results with transformers. In the last few years a new generation of models, called transformers, has been introduced. Such models are usually composed by hundreds of million of parameters, obtaining state-of-the-art performances. Commonly, they are pre-trained on an extended version of ImageNet called ImageNet21k [76]. In the following experiments we replace the first convolutional part of the pipeline with a Vision Transformer (ViT-L/16) as presented in [15]. With 32 target datasets for the top-tuning approach and 2 target datasets for the fine-tuning one, we perform 650 additional training processes.

For the top-tuning pipeline, we were able to replicate our analysis on all the 32 target datasets. We report the results in Table 4 where $\Delta Acc = Acc_{\text{transform}} - Acc_{\text{Conv}}$ is the accuracy gain of transformer w.r.t. the usual DenseNet201. On average $\Delta Acc = 4.58\% \pm 5.36\%$ showing good improvements by using the pre-trained transformer as features extractor.

For the fine-tuning approach, due to long training times, we could not replicate the analysis on all the datasets. We carried out the whole analysis on two small datasets (Citrus Leaves and Oxford Flowers) where we reached an absolute accuracy of 97.5% and 99.1%, respectively. If we compare these values with the ones obtained by the top-tuning pipeline (98.3% and 99.5%, respectively) the results confirm the marginal accuracy benefits of fine-tuning a transformer model. On the training time, we obtain an even more remarkable speedup (226.19× and 185.05×, respectively).
| Dataset   | ΔAcc  | Dataset   | ΔAcc  | Dataset   | ΔAcc  | Dataset   | ΔAcc  |
|-----------|-------|-----------|-------|-----------|-------|-----------|-------|
| AFHQ      | −0.03%| CIF10     | 5.92% | Foot Ru   | 8.98% | Oxf Flo   | 12.0%|
| Beans     | 3.91% | CIF100    | 14.56%| Gemst     | 6.08% | Oxf Pet   | 5.75%|
| Best art  | 10.1% | Citr lea  | 2.67% | Hor Hu    | 0.00% | Plankt    | 0.00%|
| Boat      | 7.89% | Col hist  | 0.72% | iCub      | 0.12% | Sa Cov    | −0.96%|
| Cal101    | 1.78% | Deep w    | 11.1% | Ind Fd    | 13.0% | St Cars   | 4.72%|
| Cassav    | 8.07% | DTD       | 9.98% | MkNoM     | 7.02% | St Dog    | 13.7%|
| Cat Do    | 1.14% | EuSAT     | 0.87% | Malaria   | 1.84% | Ten Fl    | 6.98%|
| Ch xra    | −0.65%| FG Air    | −9.40%| Meat qu   | −0.63%| Weath     | −0.53%|

Table 4: Analysis on the transformer model for the top-tuning pipeline. $\Delta Acc = Acc_{transform} - Acc_{conv}$ is the accuracy gain of transformer model w.r.t. convolutional model.

5 Conclusions

A popular solution to deal with scarcity of training data is fine-tuning a pre-trained model. However, fine-tuning may require significant computational resources, in terms of data need, training time, GPU-CPU involvement and memory usage. This is due to backpropagation and the potentially huge amount of parameters involved.

An alternative consists in adopting a pre-trained model as-it-is as features extractor, coupling it with a classifier. In this work, we discuss benefits and costs of this alternative, when a fast kernel classifier is adopted, reporting a wide experimental analysis involving 32 target datasets, 99 different settings, through 2660 distinct training processes.

Most of our experiments, confirm that fine-tuning has only marginal benefits, w.r.t. top-tuning approach. In 60% of our experiments, in fact, $\Delta Acc$ between fine-tuning and top-tuning is in range $[-2.5\%, +2.5\%]$. Furthermore, using a pre-trained model just as a feature extractor corresponds to a huge reduction in terms of training time, even from hours to few minutes in different scenarios.

Finally, our results show that the marginal benefit of fine-tuning is low dependent from the neural network architecture used as pre-trained model. On the other hand, the choice of an appropriate pre-training dataset has a significant impact on the accuracy, especially in the case of top-tuning.

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Supplementary Materials

## A Datasets details

We include 32 datasets in our experiments, from a wide range of contexts and scenarios (see Table 5).

Our collection includes popular datasets in the computer vision community, like CIFAR10/100 and Caltech101, as well as more challenging datasets where

| Dataset name       | #images (Train/Test) | Size mean | #classes |
|--------------------|----------------------|-----------|----------|
| AFHQ (AF)          | 13.167/1.463         | 512 × 512 | 3        |
| Beans (BE)         | 1.167/128            | 500 x 500 | 3        |
| Best artworks (BA) | 7.896/878            | 980 x 921 | 50       |
| Boat types (BT)    | 1.315/147            | 905 x 1234 | 9       |
| Caltech-101 (C101) | 3.060/6.084          | 251 x 282 | 102      |
| Cassava (CSV)      | 7.545/1.885          | 573 x 611 | 5        |
| Cats vs Dogs (CVSD)| 20.935/2.327         | 365 x 410 | 2        |
| Chest xray (CXRAY) | 4.708/524            | 968 x 1321 | 2     |
| CIFAR10 (CIF10)    | 50.000/10.000        | 32 x 32  | 10       |
| CIFAR100 (CIF100)  | 50.000/10.000        | 32 x 32  | 100      |
| Citrus leaves (CLV)| 534/60               | 256 x 256 | 4        |
| Colorectal hist (COL) | 4.500/500       | 150 x 150 | 8        |
| Deep weeds (DW)    | 15.758/1.751         | 256 x 256 | 9        |
| DTD (DTD)          | 3.760/1.880          | 453 x 500 | 47       |
| EuroSAT (ES)       | 24.300/2.700         | 64 x 64  | 10       |
| FGVC Aircraft (AIR)| 6.667/3.333         | 353 x 1056 | 100     |
| Footb vs Rugby (FVSR)| 2.203/245       | 618 x 788 | 2        |
| Gemstones (GEM)    | 2.571/286            | 330 x 335 | 87       |
| Hors or Hum (HVSH) | 1.027/256            | 300 x 300 | 2        |
| iCubWorld (ICUB)   | 86.400/9.600         | 256 x 256 | 10       |
| Indian Food (IF)   | 3.600/400            | 550 x 610 | 80       |
| Make No Make(MVSN) | 1.355/151            | 211 x 246 | 2        |
| Malaria (MAL)      | 24.802/2.756         | 133 x 132 | 2        |
| Meat quality (MQA) | 1.706/190            | 720 x 1280 | 2     |
| Oxford Flowers (OF)| 2.040/6.149          | 538 x 624 | 102      |
| Oxford-IIIT Pets (OP)| 3.680/3.669       | 383 x 431 | 37       |
| Plankton (PL)      | 4.500/500            | 106 x 120 | 10       |
| Sars Covid (SCOV)  | 2.232/249            | 260 x 350 | 2        |
| Stanford Cars (SC) | 8.144/8.041          | 308 x 573 | 196      |
| Stanford Dogs (SD) | 12.000/8.580         | 386 x 443 | 120      |
| Tensorflow Flowers(TFF)| 3.303/367      | 272 x 365 | 5         |
| Weather (MW)       | 1.012/113            | 335 x 506 | 4        |

Table 5: The datasets adopted in our analysis.
the amount of data is limited with respect to the number of classes and complexity of the task (e.g., Stanford Cars and FGVC aircraft). Finally, we include datasets with a significant limited amount of images, to consider practical cases where transfer learning procedures may be fundamental (e.g., Beans and Citrus leaves). From Table 5 we can notice that both number of images and classes can vary deeply from one task to another. This can influence the task hardness. On average each dataset has $11746.46 \pm 18237.7$ images and $35.21 \pm 48.32$ classes. The average number of images per classes is $1780.24 \pm 3077.48$. It is worth noticing the very high standard deviation. The dataset with with most images per class is the Malaria dataset with 12401 images per class. The dataset with few images per class is Oxford Flowers with 20 images per class. As we were mentioning in section 4 (main paper) the most problematic datasets for the top-tuning approach (FGVC Aircraft and Stanford Cars) are fine grained with a high intra-class similarity and a low number of images per class: 66.67 and 41.55, respectively.

B Complete empirical analysis results

In this section we report not only the $\Delta Acc$ as we do in the paper. We report instead all the results to provide a complete overview about our experiments.

**Fine-tuning vs Top-tuning on different target datasets.** In Table 6 we report for each dataset, the absolute accuracy obtained both by top-tuning and fine-tuning approaches. From these accuracies we computed the values obtained in Table 1 (main paper).

**Results with different pre-trained neural networks.** In a similar way, in Table 7 we report for each pre-trained model and target dataset, the absolute accuracy obtained both by top-tuning and fine-tuning approaches. From these accuracies we computed the values obtained in Table 2 (main paper).

**The importance of the pre-training dataset.** In a similar way, in Table 8 we report for each pre-train source dataset and target dataset, the absolute accuracy obtained both by top-tuning and fine-tuning approaches. From these accuracies we computed the values obtained in Table 3 (main paper).
Table 6: Accuracies obtained over the 32 datasets by the top-tuning and fine-tuning pipelines. These results are visually represented in Figure 2, left (main paper).

Table 7: Accuracies obtained by embedding in our pipeline different pre-trained models (rows) applied on different target datasets (columns)

C Analysis with different external classifiers

To test the generality of our approach we decided to replace the fast kernel classifier on top of the pre-trained network with two external classifiers: a shallow net and a ridge regression classifier. We show the overall architecture of these two models in Figure 5. The training procedure is similar to the one presented in Subsection 3.1 (main paper).

For the shallow net we consider just two configurations with default Stochastic Gradient Descent (SGD) and two different learning rates: l = {0.1, 0.01}. The training time reported in the results is the sum of the computational time required for the two training instances. Notice that this model is identical in
| Pre-Train | CIFAR10 | Citrus Leaves | Deep Weeds | DTD | Oxf Flow |
|----------|---------|---------------|------------|-----|---------|
| ImageNet | 93.0%   | 95.7%         | 83.1%      | 70.8%| 87.5%   |
| CIFAR100 | 85.7%   | 91.0%         | 67.9%      | 44.5%| 63.6%   |
| ImageNet100 | 76.2% | 89.0%         | 72.0%      | 48.8%| 63.2%   |
| ImageNet50k | 80.2% | 94.7%         | 77.4%      | 53.3%| 73.6%   |
| ImageNet | 95.8%   | 88.3%         | 92.2%      | 67.9%| 83.0%   |
| CIFAR100 | 90.9%   | 88.3%         | 81.3%      | 49.6%| 70.4%   |
| ImageNet100 | 89.4% | 89.0%         | 85.4%      | 54.9%| 70.1%   |
| ImageNet50k | 90.5% | 86.7%         | 86.7%      | 54.8%| 66.3%   |

Table 8: Accuracies for pre-training alternative to ImageNet. Each column represents a different target dataset, each row a different pre-train source.

Figure 5: (Left) The top-tuning pipeline with a shallow net as external classifier. (Right) The top-tuning pipeline with a ridge regression classifier as external classifier.

its architecture to the fine-tuning one. The main difference lies in which part of the model is tuned. The shallow nets update only the parameters of the last three fully connected layers while the fine-tuning one update all the weights of the model.

For the Ridge regressor we use the default scikit-learn implementation with three different configurations corresponding to three different values of the regularization term $\alpha = \{10^1, 10^{-1}, 10^{-3}\}$. The training time reported in the results is the sum of the computational time required for the three training instances.

Overall we consider 5 different configurations averaging the results of a 5-folded procedure over the 32 datasets, resulting in $5 \times 5 \times 32 = 800$ distinct training processes.

In Figure 6 we compare, in terms of accuracy, the fine-tuning model with both the shallow net(left) and the ridge regressor(right) as external classifier. The obtained results are similar to the ones showed in Figure 2 (main paper). Most of the datasets lie around the diagonal for both shallow net and ridge as external classifier, showing similar accuracy between fine-tuning and top-tuning methods. In Figure 7 we compare, in terms of training time, the fine-tuning model with both the shallow net(left) and the ridge regressor(right) as external classifier. With the fast kernel classifier as external classifier the average speed-up is $84.64\pm38.97$. Instead, by using a shallow net as external classifier we obtain
Figure 6: Overall accuracy results on different target datasets with shallow net and ridge as external classifiers w.r.t the fine-tuning model. (Left) Accuracies obtained over different target datasets by using a shallow net as external classifier. (Right) Accuracies obtained over different target datasets by using ridge regressor as external classifier.

an average speedup of $40.74 \pm 12.43$. The speed-up is instead $16.37 \pm 9.57$ if we use the ridge regressor as external classifier. Nevertheless these results shows that across different external classifiers trained with pre-trained features we are able to speed-up the training process by at least one order of magnitude w.r.t. the fine-tuning pipeline.

Figure 7: Overall speed-up results on different target datasets with shallow net and ridge as external classifiers w.r.t the fine-tuning model. (Left) Speed-up obtained over different target datasets by using a shallow net as external classifier. (Right) Speed-up obtained over different target datasets by using ridge regressor as external classifier.