

Learning the Regularization Strength for Deep Fine-Tuning via a Data-Emphasized **Variational Objective**

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Introduction

A number of popular transfer learning methods rely on grid search to select regularization hyperparameters that control over-fitting. This grid search requirement has several key disadvantages:

- the search is computationally expensive,
- requires carving out a validation set that reduces the size of available data for model training,
- 3) and requires practitioners to specify candidate values. In this paper, we propose an alternative to grid search: directly learning regularization hyperparameters on the full training set via model selection techniques based on the evidence lower bound ("ELBo") objective from variational methods.

Background

Deep learning view.

$$L(\theta, \lambda^{-1}) := \frac{1}{N} \left(\sum_{i=1}^{N} \ell(y_i, f_{\theta}(x_i)) + \frac{\lambda^{-1}}{2} ||\theta||_2^2 \right)$$

$$\theta_{t+1} \leftarrow \theta_t - \eta \nabla_{\theta_t} L(\theta_t, \lambda^{-1})$$

Grid search learning rate η and regularization strength λ^{-1} .

Methods

Bayesian view.

$$L_{\text{DE-ELBo}}(\theta, \sigma, \lambda) := -\kappa \mathbb{E}_{q(\theta)} \left[\log \sum_{i=1}^{N} p(y_i | \theta) \right] + \mathbb{KL}(q(\theta) || p(\theta | \lambda))$$

$$\lambda_t^* \leftarrow \frac{1}{D} \left[\sigma_t^2 \operatorname{Tr}(\Sigma_p^{-1}) + (\mu_p - \theta_t)^T \Sigma_p^{-1} (\mu_p - \theta_t) \right]$$
$$\theta_{t+1} \leftarrow \theta_t - \eta \nabla_{\theta_t} L_{\text{DE-ELBo}}(\theta_t, \sigma_t, \lambda_t^*)$$
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approx. w/ 1 sample approx. w/ 1 sample

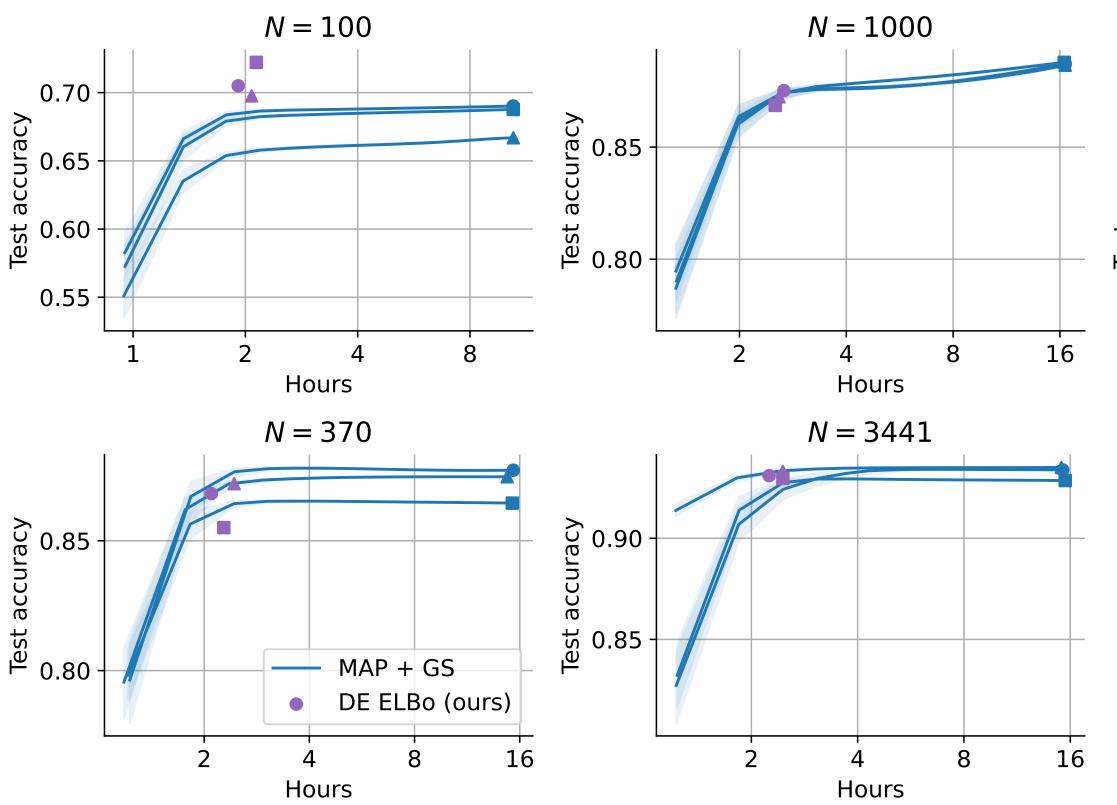
Grid search learning rate η .

Need for validation set and grid search. Selecting λ^{-1} to directly minimize $L(\theta, \lambda^{-1})$ on the training set alone is not a coherent way to guard against over-fitting.

Backbone prior mean/covariance. Several recent transfer learning approaches correspond to specific settings of the backbone mean and covariance μ_p , Σ_p .

Table 1: Mean and covariance of backbone weights w for several transfer learning approaches.

Method	p(w)	Init.
L2-zero L2-SP PTYL	$\mathcal{N}(0, \lambda I)$ $\mathcal{N}(\mu, \lambda I)$ $\mathcal{N}(\mu, \lambda \Sigma)$	μ μ μ



 -10^{3} Test accuracy: 87.5 -10^{4} Test NLL: 0.39 ELBo (ours) Test accuracy: 34.9 -10^{5} Test NLL: 2.30 -10^{6} -10^{7} DE -10^{8} -10^{9} 10^{-7} 10^{-1} 10^{-4} 10^{-4} 10^2 10^{-1} λ, τ

Figure 1: Model selection comparison between the ELBo (left) and our data-emphasized ELBo (DE ELBo) for two ResNet-50s trained on CIFAR-10 N = 1000. For both models, we fix the estimated posterior q and vary λ , τ . Takeaway: Without enough training data or with too many model parameters, the ELBo has a preference for simpler models.

Table 2: Computational time comparison between methods for transfer learning with informative priors using grid search and using our data-emphasized ELBo (DE ELBo) for CIFAR-10 at N=50000. Runtime measured on one NVIDIA A100 40GB PCIe GPU.

 Model	Method	Avg. SGD runtime	lr search space	λ, au search space	Total GS time
L2-SP	MAP + GS	39 mins. 11 secs.	4	6	16 hrs. 15 mins.
	DE ELBo	39 mins. 0 secs.	4	n/a	2 hrs. 36 mins.
PTYL	MAP + GS	37 mins. 15 secs.	4	60	149 hrs. 36 mins.
	DE ELBo	40 mins. 0 secs.	4	n/a	2 hrs. 39 mins.

Table 3: Accuracy on CIFAR-10 test set for different probabilistic models and methods. We report mean (min-max) over 3 separatelysampled training sets.

Model	Method	N = 100 (10/cl.)	1000 (100/cl.)	10000 (1k/cl.)	50000 (5k/cl.)
L2-zero	MAP + GS	67.7 (66.0-68.6)	87.8 (87.5-88.4)	95.0 (94.4-95.5)	97.2 (97.1-97.2)
	DE ELBo	60.9 (58.9-63.1)	87.2 (87.0-87.4)	91.2 (90.7-92.0)	93.2 (93.0-93.3)
L2-SP	MAP + GS	68.1 (66.7-68.9)	87.3 (87.2-87.3)	95.3 (95.1-95.7)	97.1 (97.0-97.1)
	DE ELBo	70.6 (68.7-72.7)	87.2 (86.8-87.4)	95.0 (94.8-95.2)	96.8 (96.7-96.9)
PTYL	MAP + GS	67.5 (65.7-68.4)	87.9 (86.9-89.2)	95.2 (95.0-95.4)	97.3 (97.3-97.3)
	DE ELBo	70.6 (68.7-72.6)	87.2 (86.9-87.6)	95.1 (94.9-95.4)	96.9 (96.8-96.9)

Outlook. Our proposed approach saves practitioners time by learning an optimal regularization strength without need for expensive grid search. We hope our data-emphasized ELBo for efficient hyperparameter tuning may eventually prove useful across a wide array of classifier tasks beyond transfer learning, such as semisupervised learning, few-shot learning, continual learning, and beyond.

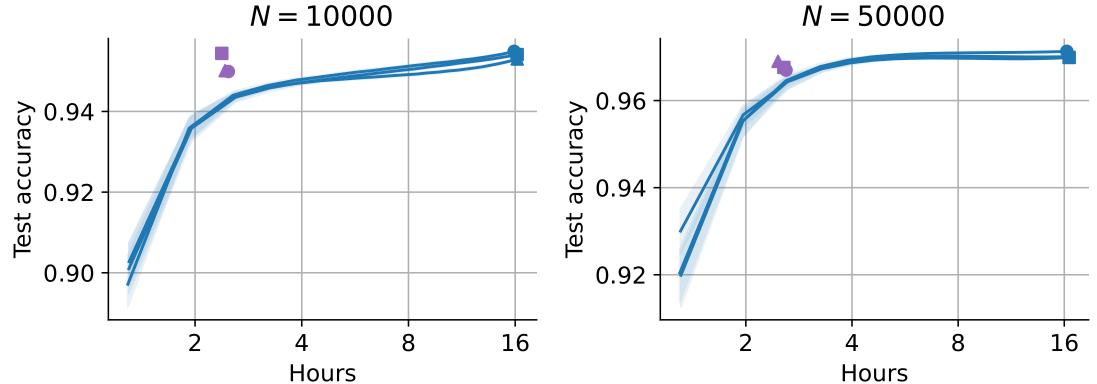


Figure 2: Test-set accuracy on CIFAR-10 (top row) and Oxford-IIIT Pet (bottom row) over training time for L2-SP with MAP + grid search (GS) and our data-emphasized ELBo (DE ELBo). We run each method on 3 separate training sets of size N (3 different marker styles). Takeaway: Our DE ELBo achieves as good or better performance at small dataset sizes and similar performance at large dataset sizes with far less compute time. To make the blue curves, we did the full grid search once (markers). Then, at each given shorter compute time, we subsampled a fraction of all hyperparameter configurations with that runtime and chose the best via validation NLL. Averaging this over 500 subsamples at each runtime created each blue line.