
Supplementary Materials for FlexiBO: Cost-Aware Multi-Objective Optimization of Deep Neural Networks

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Abstract

In this paper, we propose FlexiBO, a flexible Bayesian multi-objective optimization algorithm to address this issue. We formulate a new acquisition metric based on the improvement of Pareto hyper-volume that includes the measurement cost of each objective. Our hyper-volume improvement calculation uses the acquisition metric to select the next sample and objective with maximum information gain per cost for evaluation, rather than all objectives. We apply FlexiBO to optimize 8 state-of-the-art DNN architectures for object detection, natural language processing, and speech recognition. Our results indicate that, for the same evaluation cost, the Pareto-front obtained using FlexiBO has a 46.79% higher contribution to the true Pareto-front and a 33.45% better diversity compared to other state-of-the-art methods.

1 Introduction

Default hyperparameters used for different architectures in FlexiBO experiments are shown in Table 1. Hardware and OS/Kernel level configuration options are chosen using the causal graphical models shown in Figure 1, Figure 2 and Figure 3 for Image recognition, natural language processing (NLP) and speech recognition, respectively. If a configuration option has a direct connection to a performance objective (energy consumption) then the options is said to causally influence performance.

Table 1: Network hyperparameters for different architectures of object detection, NLP and speech recognition DNN systems.

Hyperparameter	Object detection				NLP		Speech recognition	
	Xception	MobileNet	LeNet	resnet	SqueezeNet	BERT-base		
Num. channels, ζ	3	3	3	3	3	-	-	-
Num. classes, $ C $	100	1000	1000	10	10	-	-	-
Epochs, ϵ	200	100	200	200	200	-	-	-
Batch size, b	20	32	32	32	32	-	-	-
Learning rate, η	0.00001	0.0001	0.0001	0.0001	0.0001	0.00003	0.0001	0.0001
Decay, λ	$1e^{-6}$	$1e^{-6}$	$1e^{-6}$	$1e^{-6}$	$1e^{-6}$	$3e^{-6}$	$1e^{-6}$	$1e^{-6}$
Dropout, p	0.5	0.5	0.5	0.5	0.5	0.248	0.2367	0.2367
Loss function, L	categorical cross-entropy	categorical cross-entropy	categorical cross-entropy	categorical cross-entropy	categorical cross-entropy	categorical cross-entropy	categorical cross-entropy	categorical cross-entropy
Width multiplier, α	1	1	1	1	1	-	-	-
Data augmentation	Yes	Yes	Yes	Yes	Yes	-	-	-
Default standard deviation, σ	-	-	-	-	-	-	0.046875	0.046875
Doc stride	-	-	-	-	-	128	-	-

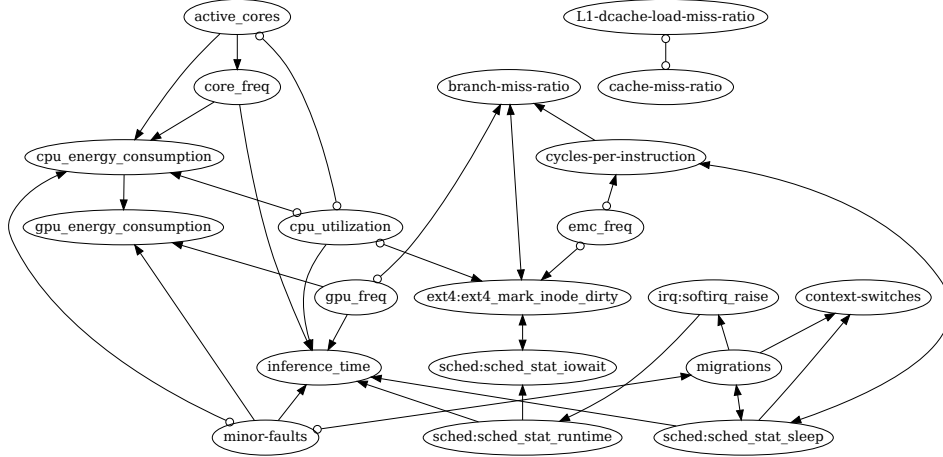


Figure 1: A partial causal model of the NLP DNN system. Performance nodes are inference_time, cpu_energy_consumption and gpu_energy_consumption.

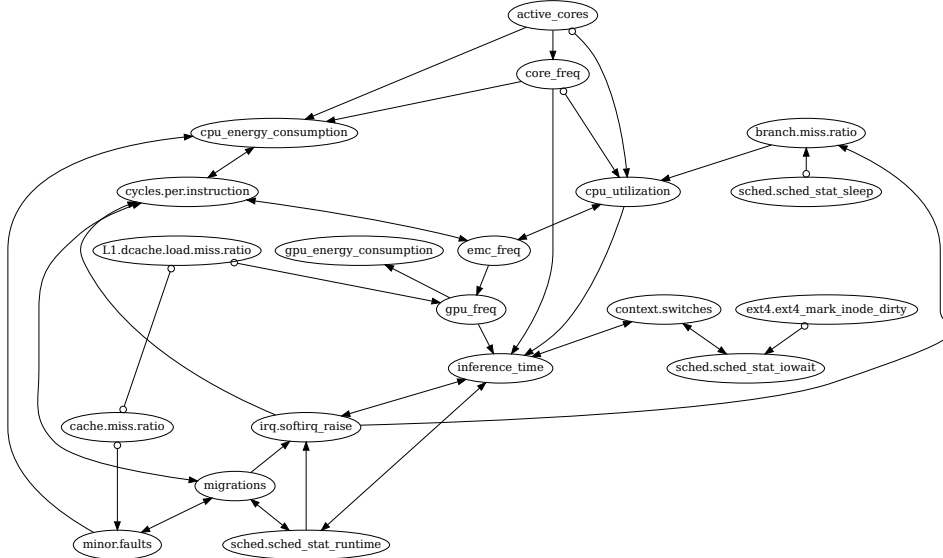


Figure 2: A partial causal model of the NLP DNN system. Performance nodes are inference_time, cpu_energy_consumption and gpu_energy_consumption.

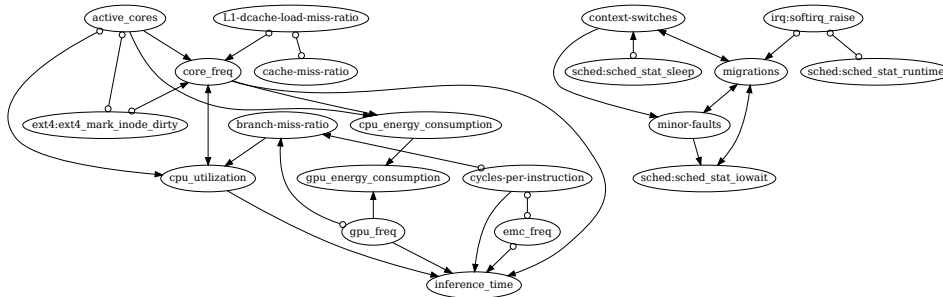


Figure 3: A partial causal model of the NLP DNN system. Performance nodes are inference_time, cpu_energy_consumption and gpu_energy_consumption.

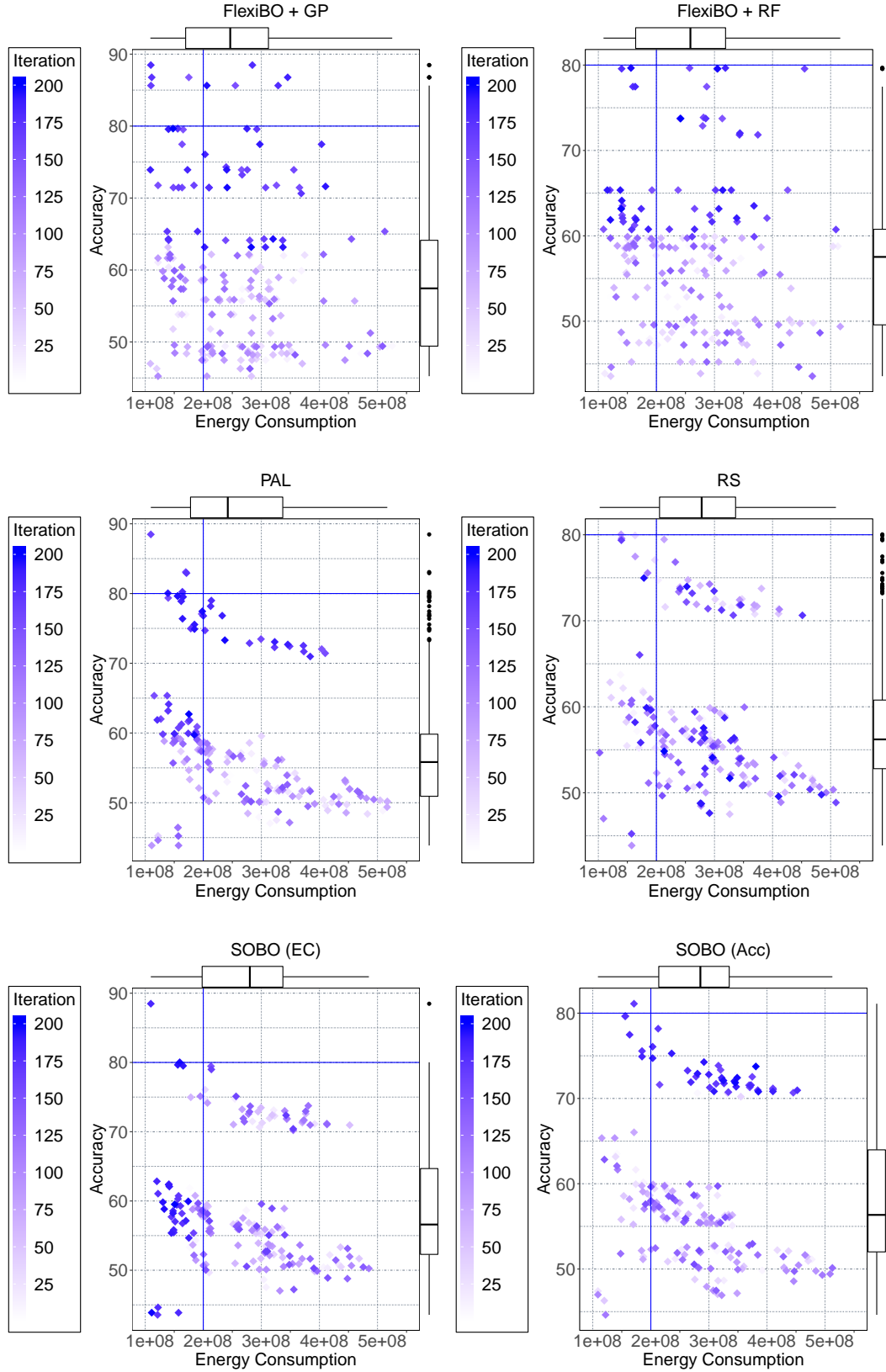


Figure 4: Exploration results in BERT-IMDB. It is desirable to have more evaluations to the top left half of the figure for optimization. FlexiBO outperforms other methods, finding more accurate and more efficient DNN architectures.

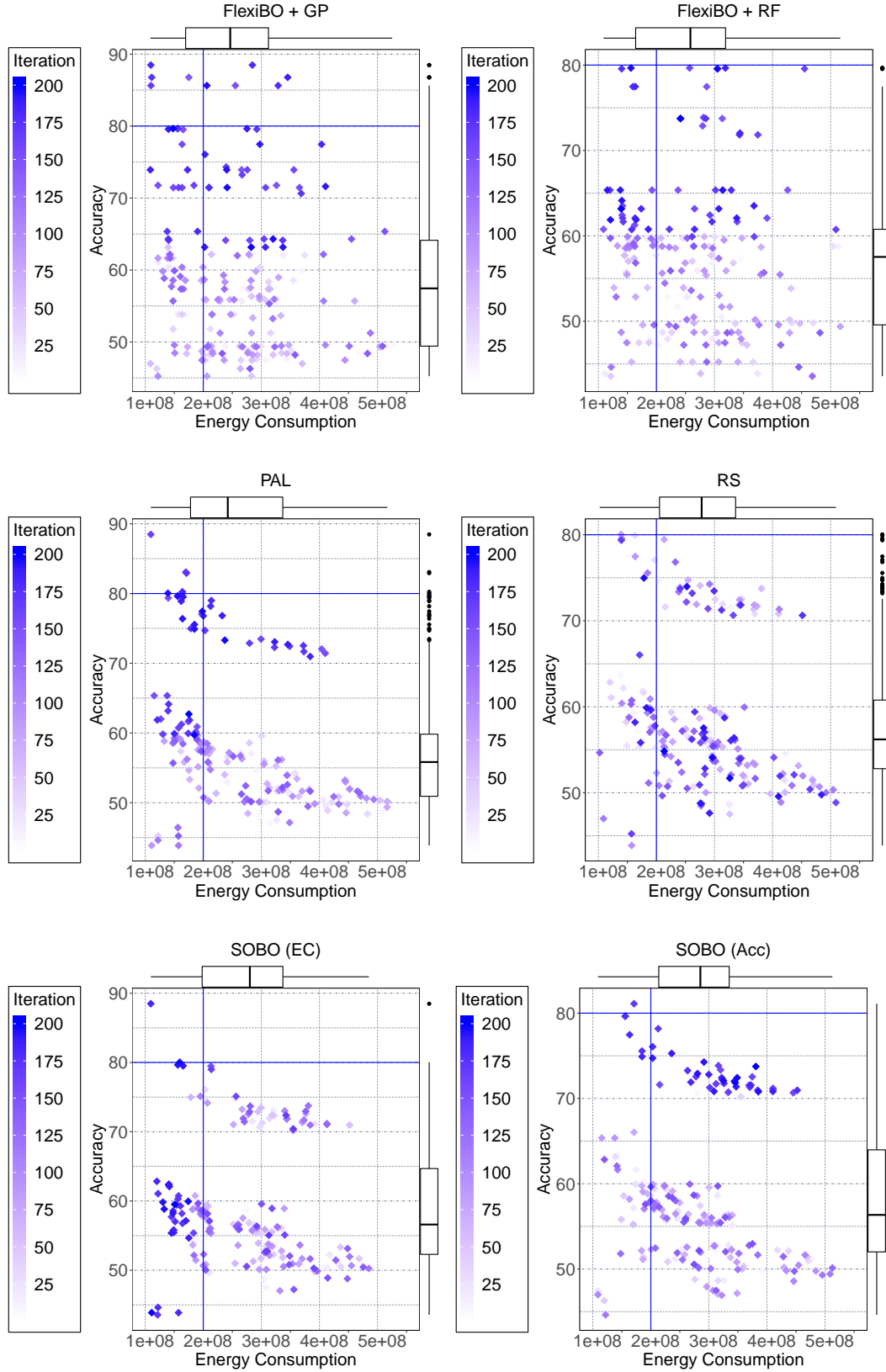


Figure 5: Exploration results in Resnet. It is desirable to have more evaluations to the top left half of the figure for optimization. FlexiBO outperforms other methods, finding more accurate and more efficient DNN architectures.

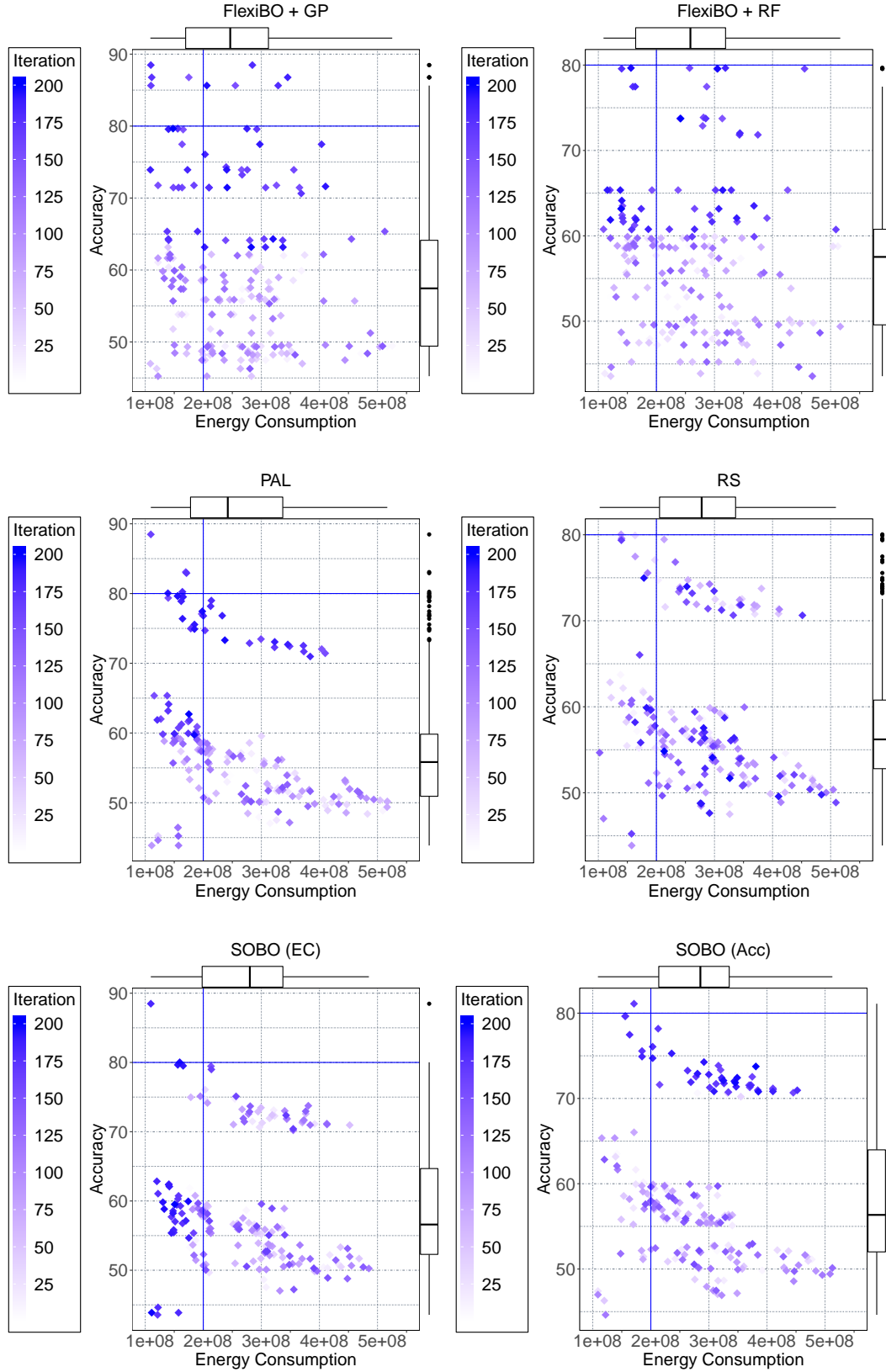


Figure 6: Exploration results in Mobilenet. It is desirable to have more evaluations to the top left half of the figure for optimization. FlexiBO outperforms other methods, finding more accurate and more efficient DNN architectures.

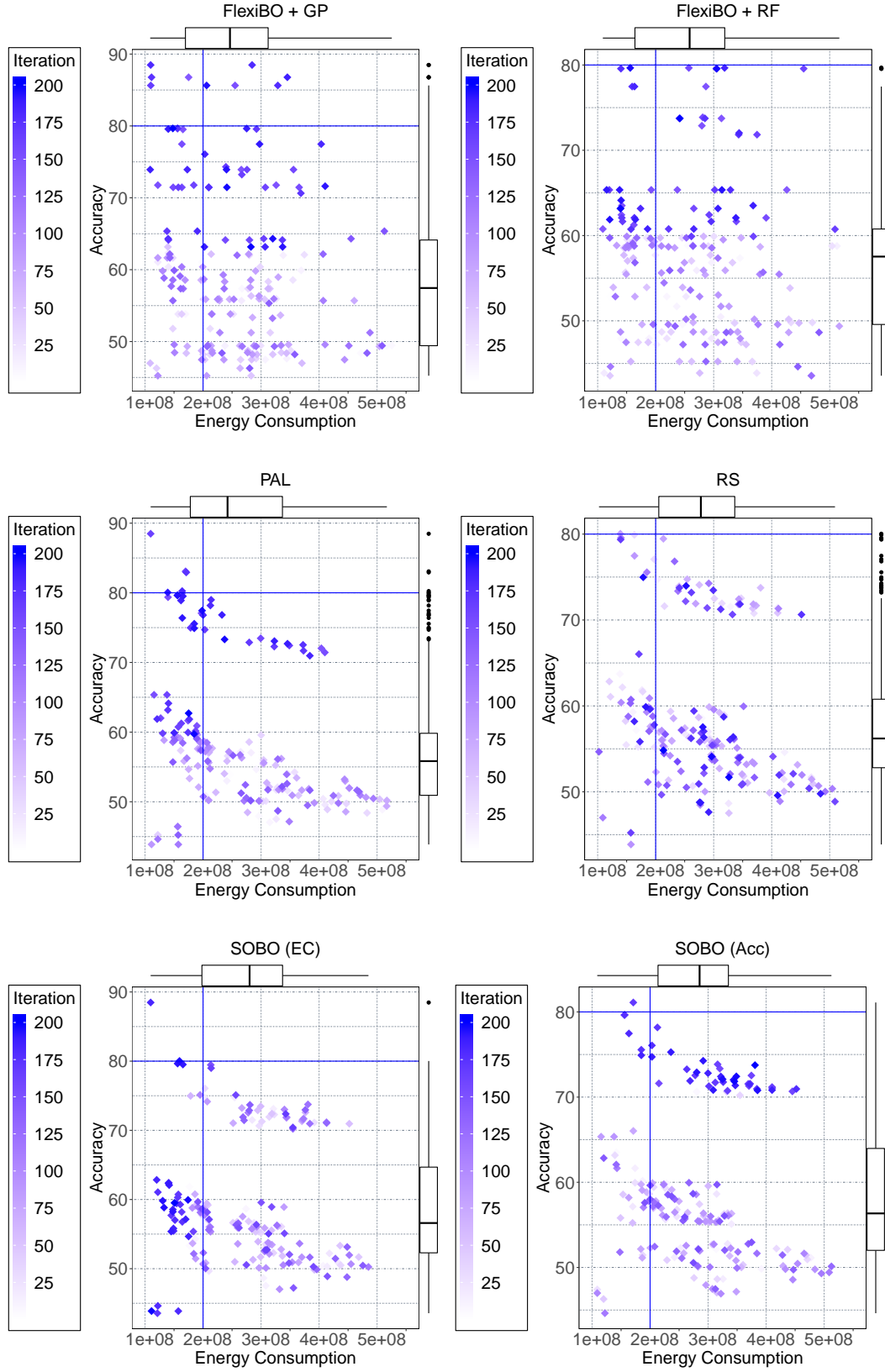


Figure 7: Exploration results in Lenet. It is desirable to have more evaluations to the top left half of the figure for optimization. FlexiBO outperforms other methods, finding more accurate and more efficient DNN architectures.

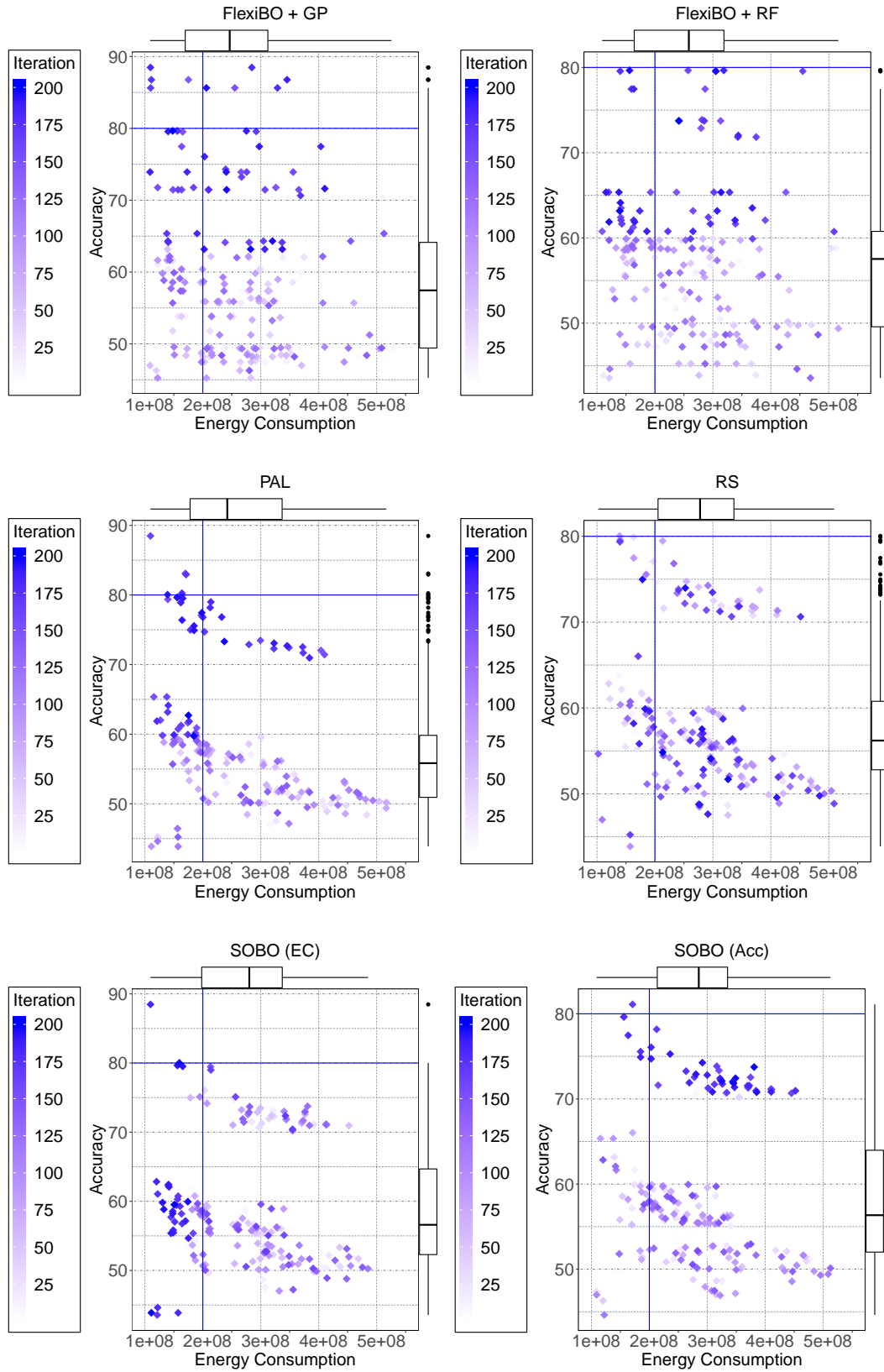


Figure 8: Exploration results in Squeezenet. It is desirable to have more evaluations to the top left half of the figure for optimization. FlexiBO outperforms other methods, finding more accurate and more efficient DNN architectures.

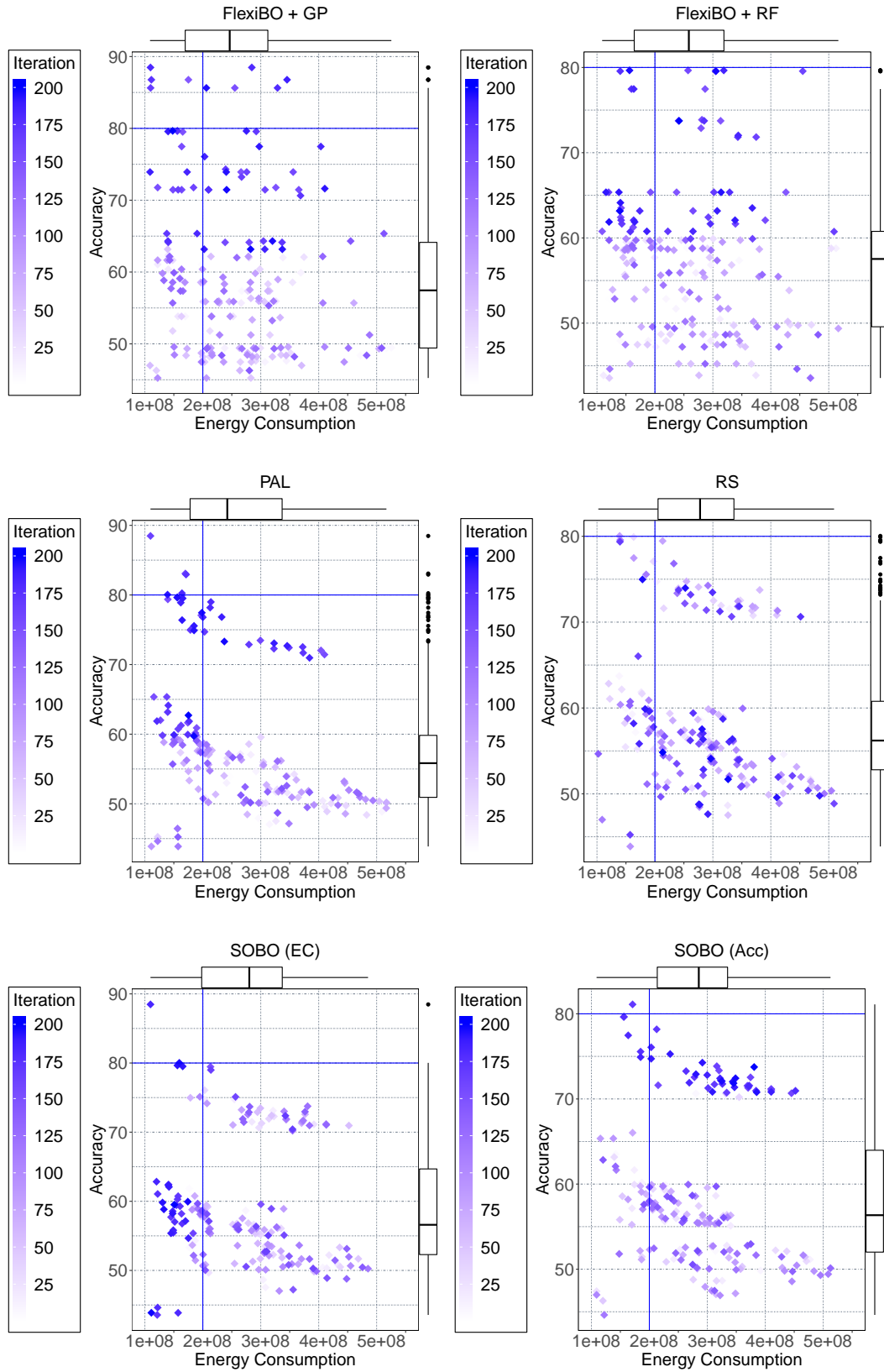


Figure 9: Exploration results in Deepspeech. It is desirable to have more evaluations to the top left half of the figure for optimization. FlexiBO outperforms other methods, finding more accurate and more efficient DNN architectures.

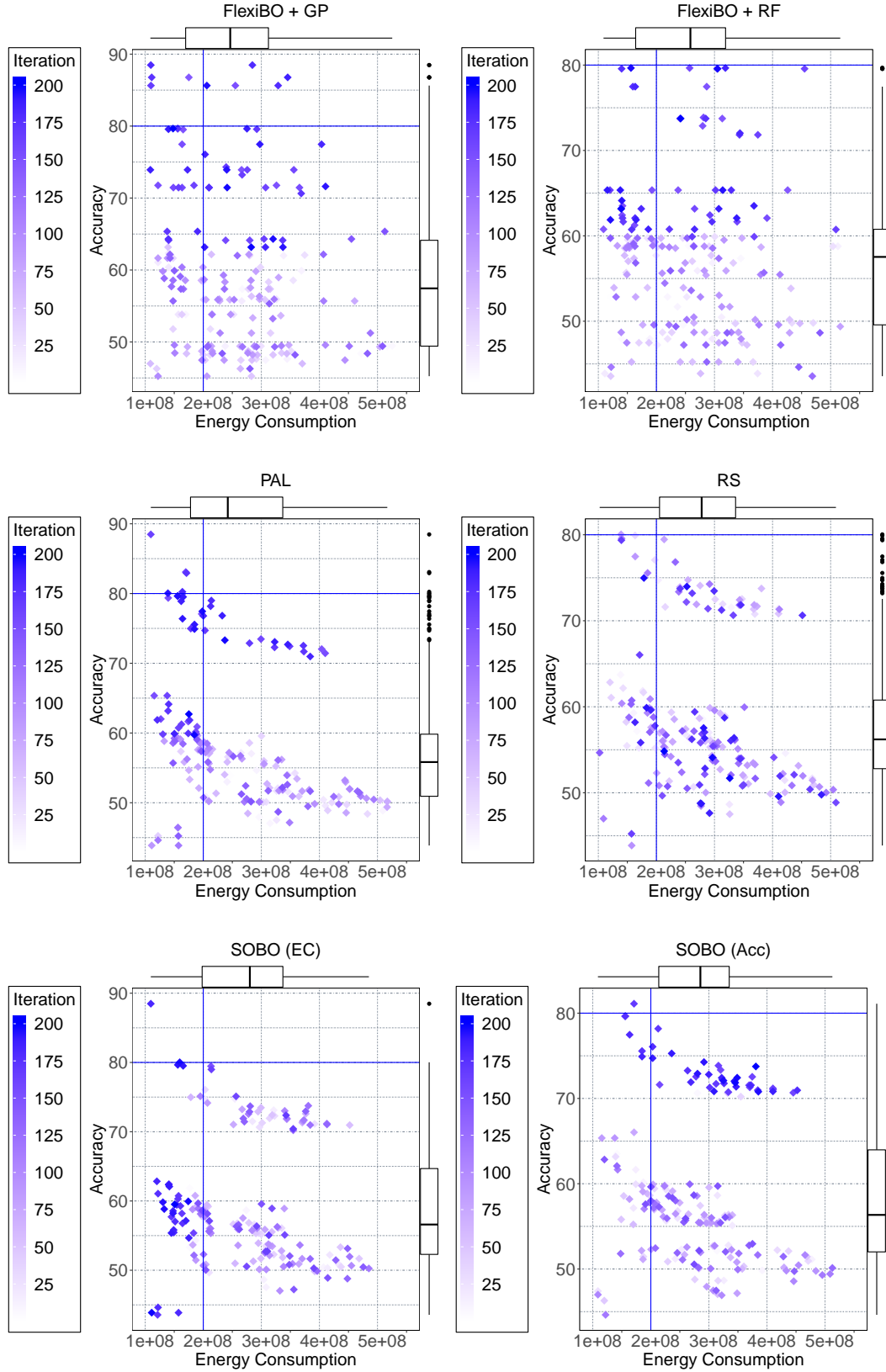


Figure 10: Exploration results in BERT-SQuAD. It is desirable to have more evaluations to the top left half of the figure for optimization. FlexiBO outperforms other methods, finding more accurate and more efficient DNN architectures.