Enhancing Simple Models by Exploiting What They Already Know

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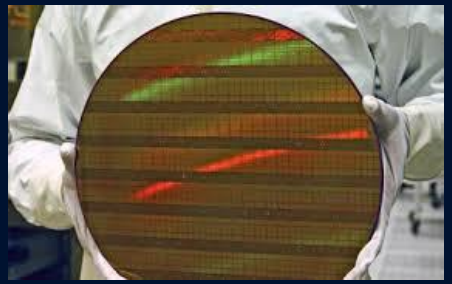
Use Case: Fabrication engineers need to measure the amount of metal etched on each manufactured wafer (collection of chips).



Modeling: The engineers are comfortable using decision trees (e.g. CART) to model their problem because they understand the tool and know how to derive insights from the solution.

Challenge: Transfer information from complex models with higher accuracy to the decision trees in a manner that enhances performance and adds valuable insight to the engineers that is easily consumable by them.

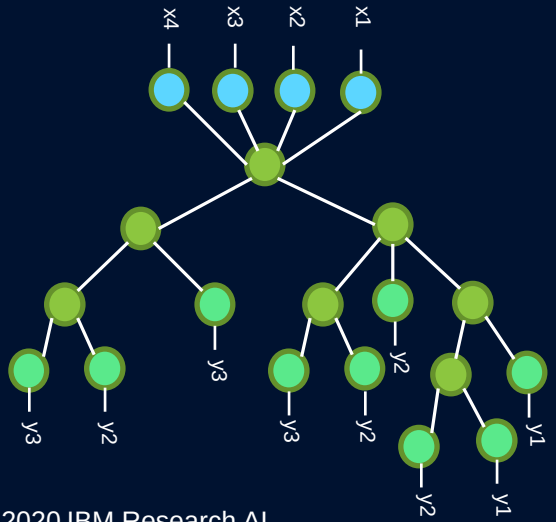
General Idea

Low performing

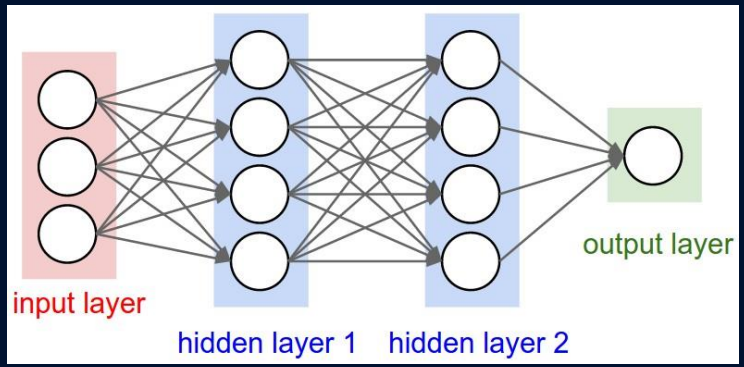
Simple Model
(Decision Tree, SVM, smaller neural network)

Training Data set

Complex Model
(Deep Neural Network, Boosted Trees)



Can you transfer information from a pre-trained neural network to this simple model ?



Applications

Domain experts preference: SMEs many times want to use a model they understand and hence trust. Our methods try to get the most out of these models by significantly enhancing their performance.

Small Data settings: Small client data where complex neural networks might overfit so simple models are preferred. However, possible to improve performance if we have a pretrained network on a large public or private corpora belonging to the same feature space.

Resource Constrained Settings: In memory and power constrained settings only small models can be deployed. Here improving small neural networks with the help of larger neural network can be useful.

Main Contributions

Conceptual Contribution: Simple models can be useful to improve themselves (without increasing complexity).

Algorithmic Contribution: Proposed a method, called SRatio, based on the above conceptual idea that actually accomplishes that.

Theoretical Contribution: We show that our weighting scheme is principled as it is a (tight) upper bound on the simple models expected loss.

Formalization: We propose a notion of delta-graded classifiers which is a formalization and generalization of the idea of probes.

Comparison with other transfer methods

Method	Complex Model	Simple Model	Models Leveraged
Distillation	NN	NN	Complex
ProfWeight	NN	Any	Complex
SRatio	Any	Any	Complex and Simple

Intuition

Covariate Shift

p is source, q is target

$p(y|x) = q(y|x)$

But $p(x) \neq q(x)$

Typical Soln:
Weight by $q(x)/p(x)$

Classifiers

p is simple, q is complex

$p(x) = q(x)$

But $p(y|x) \neq q(y|x)$

Our (analogous) Soln:
Weight by $q(y|x)/p(y|x)$

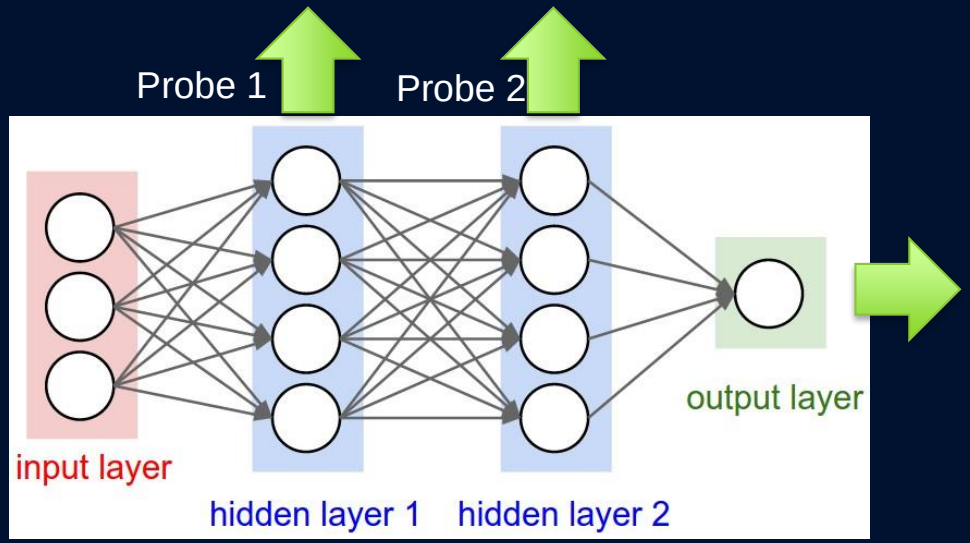
(Inverse covariate shift?)

Theory

Lemma 3.1. *Let $p_\theta(y|x)$ be the softmax scores on a specific model θ from simple model space Θ. Let $\theta^* \in \Theta$ be the set of simple model parameters that is obtained from a given learning algorithm for the simple model on a training dataset. Let $p_c(y|x)$ be a pre-trained complex classifier whose loss is smaller than θ^* on the training distribution. Let $\beta \geq 1$ be a scalar clip level for the ratio $p_c(y|x)/p_{\theta^*}(y|x)$. Then we have:*

$$\mathbb{E}[-\log p_\theta(y|x)] \leq \mathbb{E}\left[\max\left(1, \min\left(\frac{p_c(y|x)}{p_{\theta^*}(y|x)}, \beta\right)\right)\log\left(\frac{1}{p_\theta(y|x)}\right)\right] - \mathbb{E}\left[\log\left(\min\left(\frac{p_c(y|x)}{p_{\theta^*}(y|x)}, \beta\right)\right)\right] + \log(\beta). \quad (1)$$

Probes: To judge hardness of examples in NNs



Improving Simple Models with Confidence Profiles. Dhurandhar et. al. NeurIPS 2018

Generalization of Probes: Graded Classifiers

Definition (δ**-graded**) Let $X \times Y$ denote the input-output space and $p(x, y)$ the joint distribution over this space. Let $\zeta_1, \zeta_2, ..., \zeta_n$ denote classifiers that output the prediction probabilities for a given input $x \in X$ for the most probable (or true) class $y \in Y$ determined by $p(y|x)$. We then say that classifiers $\zeta_1, \zeta_2, ..., \zeta_n$ are δ-graded for some $\delta \in (0, 1]$ and a (measurable) set $Z \subseteq X$ if $\forall x \in Z$, $\zeta_1(x) \leq \zeta_2(x) \leq \cdots \leq \zeta_n(x)$, where $\int_{x \in Z} p(x) \geq \delta$.

Deep Neural Networks: (Linear) probes to intermediate representations.

Boosted Trees: Average predictions of first k trees, first 2k trees, …

Random Forests: Order trees by accuracy and average predictions of first k trees, first 2k trees, …

Other Models: Taking increasing order Taylor approximations or do functional decomposition.

SRatio Algorithm

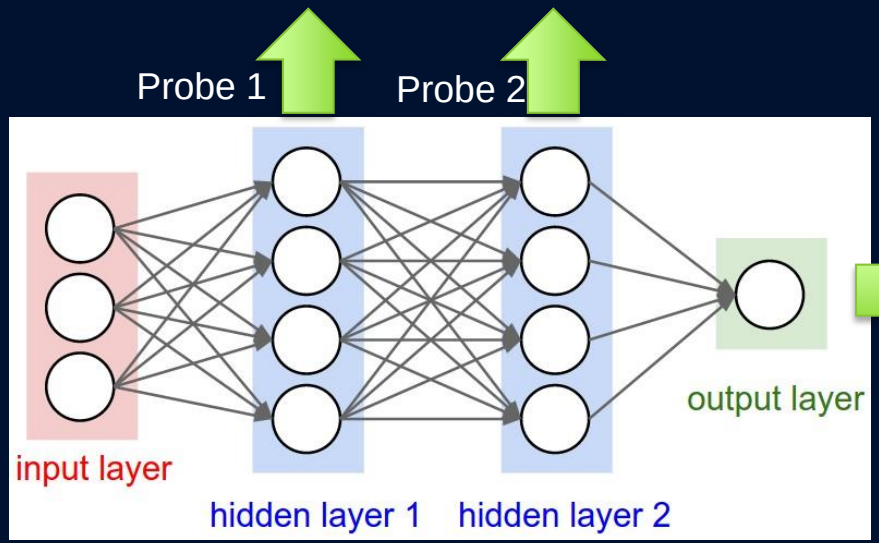
Algorithm 1 Our proposed method SRatio.

Input: n (graded) classifiers $\zeta_1, ..., \zeta_n$, learning algorithm for simple model $\mathcal{L}_\mathcal{S}$, dataset D_S of cardinality N, performance gap parameter γ and maximum allowed ratio parameter β.

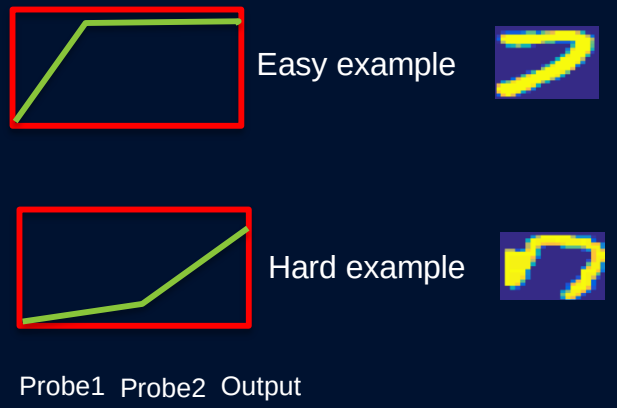
1) Train simple model on D_S, $\mathcal{S} \leftarrow \mathcal{L}_\mathcal{S}(D_S, \vec{1}_N)$ and compute its (average) prediction error ϵ_S.{Obtain initial simple model where each input is given a unit weight.}
2) Compute (average) prediction errors $\epsilon_1, ..., \epsilon_n$ for the n graded classifiers and store the ones that are at least γ more accurate than the simple model i.e. $I \leftarrow \{i \in \{1, ..., n\} \mid \epsilon_S - \epsilon_i \geq \gamma\}$
3) Compute weights for all inputs x as follows: $w(x) = \frac{\sum_{i \in I} \zeta_i(x)}{m\mathcal{S}(x)}$, where m is the cardinality of set I and $\mathcal{S}(x)$ is the prediction probability/score for the true class of the simple model.
4) Set $w(x) \leftarrow 0$, if $w(x) > \beta$ {Limit the importance of extremely hard examples for the simple model.}
5) Retrain the simple model on the dataset D_S with the corresponding learned weights $\mathbf{w}$, $\mathcal{S}_w \leftarrow \mathcal{L}_\mathcal{S}(D_S, \mathbf{w})$
6) **Return** $\mathcal{S}_w$

ProfWeight

- Find area under curve (AUC) based on confidence scores at each probe whose accuracy > α of the simple model for each example based on complex neural network.
- Weight each training example by corresponding AUC and retrain simple model such as a decision tree.



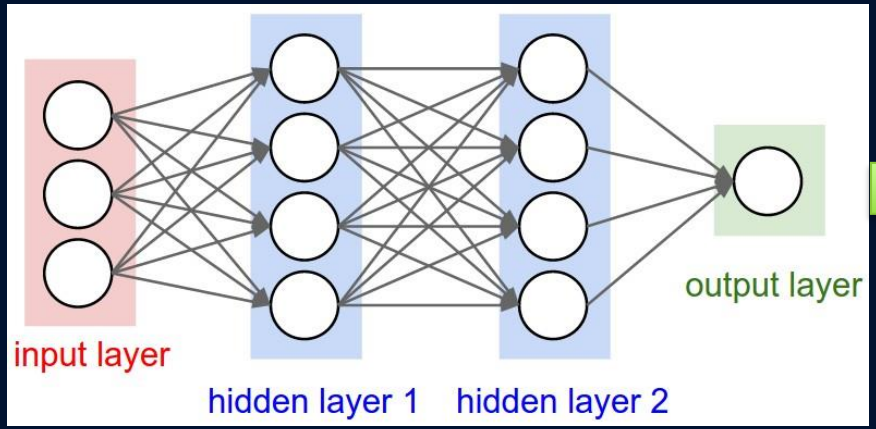
Confidence profiles



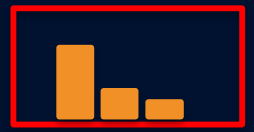
Improving Simple Models with Confidence Profiles. Dhurandhar et. al. NeurIPS 2018

Knowledge Distillation

- Obtain soft predictions from a complex neural network.
- Use them to regress a simpler neural network with cross-entropy loss.



Soft Prediction



Distilling the Knowledge in a Neural Network. Hinton et. Al. NeurIPS 2014

Results

Complex Models

- Boosted Trees
- Random Forests
- ResNet 18

Simple Models

- Decision tree
- SVM
- ResNet 3, 5, 7

Table 1. Dataset characteristics, where N denotes dataset size and d is the dimensionality.

Dataset	N	d	# of Classes
Ionosphere	351	34	2
Ovarian Cancer	216	4000	2
Heart Disease	303	13	2
Waveform	5000	40	3
Human Activity	10299	561	6
Musk	6598	166	2
CIFAR-10	60000	32×32	10

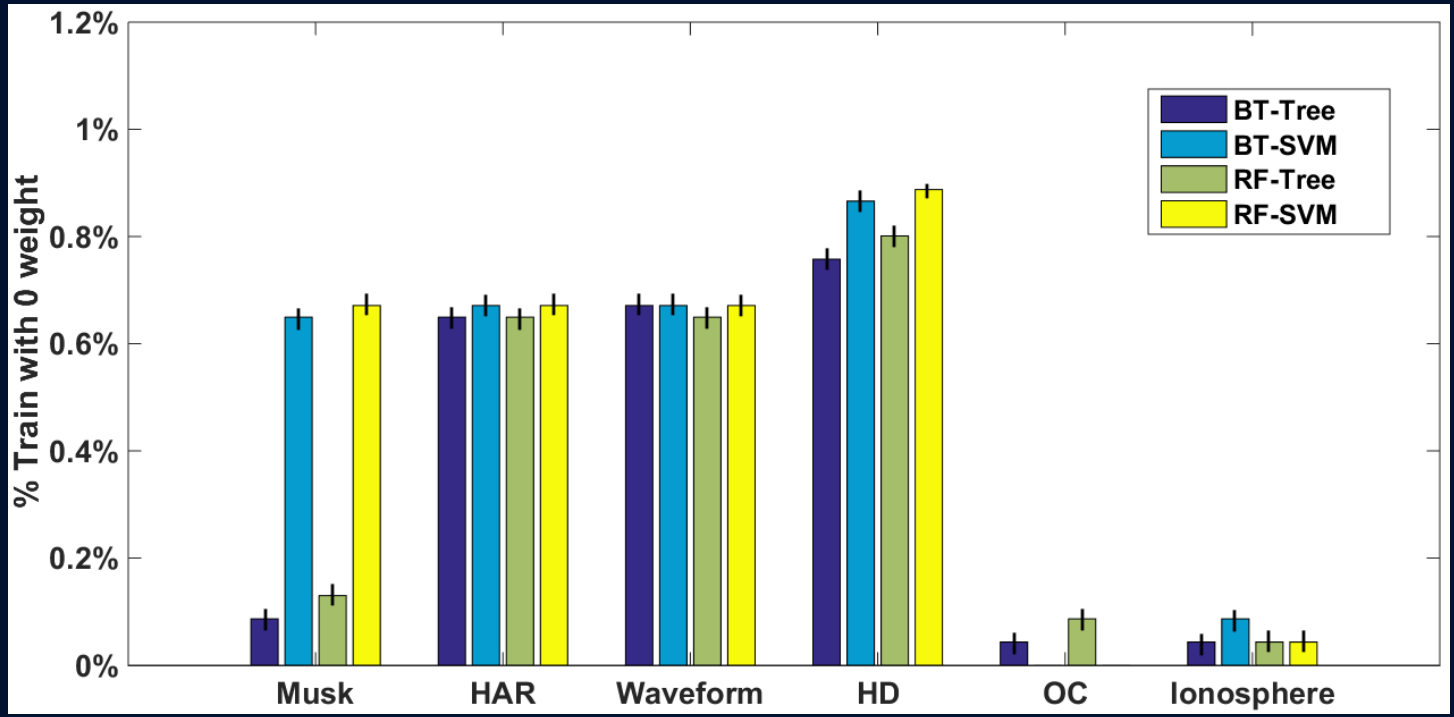
Results

Dataset	Complex Model	CM Error	Simple Model	SM Error	Distill-proxy 1 Error (SM)	ConfWeight Error (SM)	SRatio Error (SM)
Ionosphere	Boosted Trees	8.10 ±0.4	Tree	10.95 ±0.4	10.95 ±0.4	11.42 ±0.8	**8.57*** **±0.5**
			SVM	12.38 ±0.6	11.90 ±0.6	11.90 ±0.6	**10.47 ±0.5**
	Random Forest	6.19 ±0.4	Tree	10.95 ±0.4	10.95 ±0.4	11.42 ±0.4	**10.42 ±0.1**
			SVM	12.38 ±0.6	12.38 ±0.6	12.38 ±0.6	**11.42 ±0.3**
Ovarian Cancer	Boosted Trees	4.68 ±0.4	Tree	**15.62 ±0.8**	**15.62 ±0.8**	**15.62 ±1.0**	**15.62 ±0.5**
			SVM	**1.56 ±0.4**	**1.56 ±0.4**	**1.56 ±0.4**	**1.56 ±0.4**
	Random Forest	6.25 ±0.8	Tree	15.62 ±0.8	15.62 ±0.8	**14.06 ±0.1**	**14.04 ±0.1**
			SVM	**1.56 ±0.4**	**1.56 ±0.4**	**1.56 ±0.4**	**1.56 ±0.4**
Heart Disease	Boosted Trees	15.55 ±0.6	Tree	23.88 ±0.7	**22.77 ±0.1**	23.33 ±0.3	**22.77 ±0.2**
			SVM	17.22 ±0.2	**16.67 ±0.3**	17.22 ±0.2	**16.77 ±0.2**
	Random Forest	15.88 ±0.6	Tree	23.88 ±0.7	23.88 ±0.7	25.55 ±0.5	**22.77 ±0.3**
			SVM	17.22 ±0.2	17.22 ±0.2	**16.67 ±0.3**	**16.67 ±0.2**

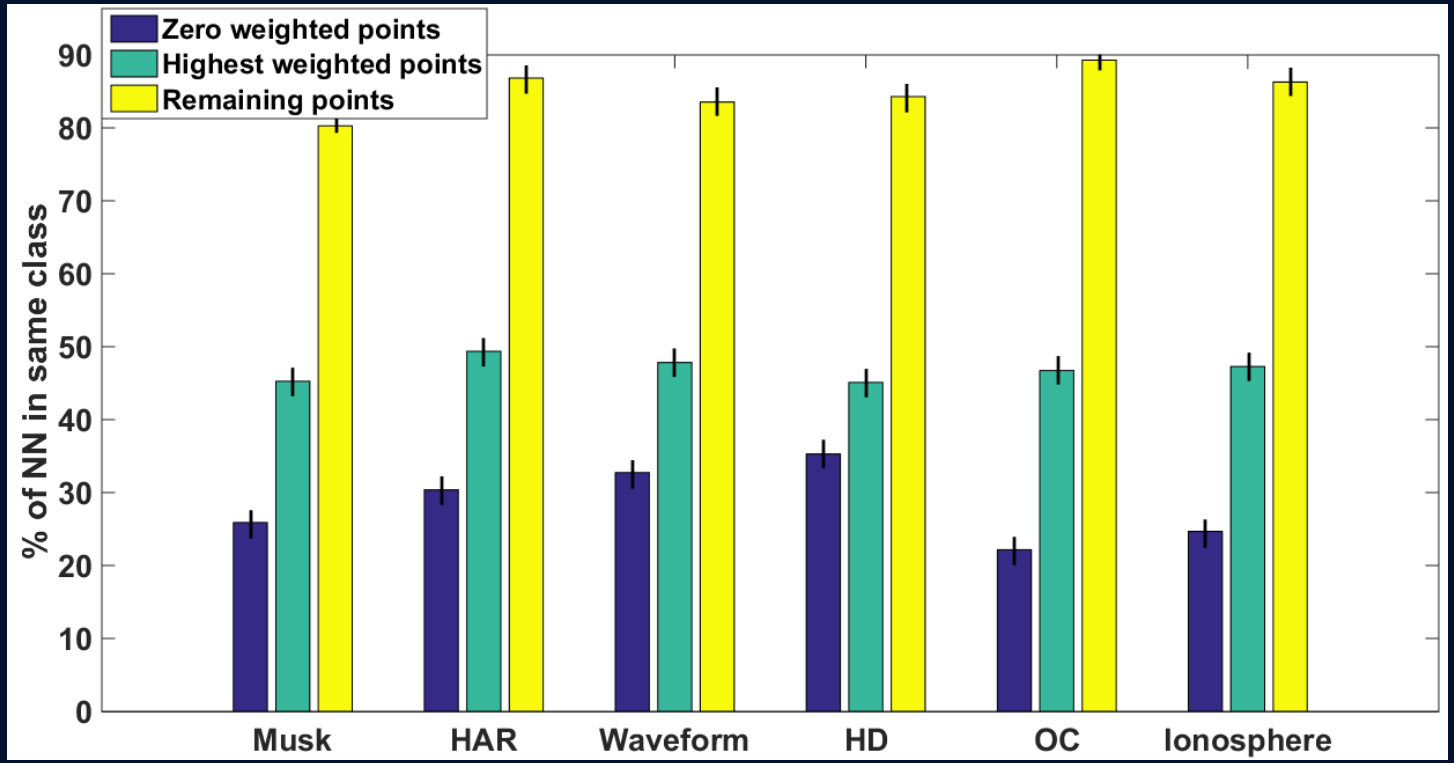
Results

Waveform	Boosted Trees	12.96 ±0.1	Tree	25.43 ±0.2	**25.06 ±0.1**	**25.10 ±0.1**	**25.06 ±0.1**
			SVM	14.70 ±0.2	15.33 ±0.0	14.70 ±0.2	**13.72 ±0.2**
	Random Forest	10.90 ±0.1	Tree	25.43 ±0.2	25.43 ±0.2	25.43 ±0.2	**25.06 ±0.1**
			SVM	14.70 ±0.2	14.33 ±0.0	14.30 ±0.2	**12.72 ±0.5**
Human Activity Recognition	Boosted Trees	6.32 ±0.0	Tree	7.93 ±0.2	7.93 ±0.1	7.86 ±0.2	**7.15 ±0.1**
			SVM	14.56 ±0.1	15.85 ±0.1	**13.92 ±0.1**	**13.92 ±0.2**
	Random Forest	2.34 ±0.0	Tree	7.93 ±0.2	7.23 ±0.1	7.21 ±0.1	**6.67 ±0.0**
			SVM	14.56 ±0.1	**13.92 ±0.1**	14.24 ±0.1	**13.92 ±0.1**
Musk	Boosted Trees	4.06 ±0.1	Tree	4.49 ±0.1	6.11 ±0.1	4.45 ±0.1	**4.06* ±0.1**
			SVM	6.11 ±0.1	6.29 ±0.1	6.41 ±0.1	**5.48 ±0.1**
	Random Forest	2.45 ±0.1	Tree	4.49 ±0.1	4.49 ±0.1	4.47 ±0.1	**3.89 ±0.1**
			SVM	6.11 ±0.1	6.16 ±0.1	5.96 ±0.1	**5.53 ±0.1**

Results



Results



Results

Table 3. Below we see the % of training points whose weights based on SRatio have changed by $> 1\%$ compared to just considering the complex model, i.e., ignoring simple model confidences in Step 3 of algorithm 1. This depicts the impact of considering the simple models confidences in the weighting, which is our main conceptual contribution. Results are averaged over both complex models.

Ionosphere		OC		HD		Waveform		HAR		Musk	
Tree	SVM	Tree	SVM	Tree	SVM	Tree	SVM	Tree	SVM	Tree	SVM
37.40	90.65	8.55	6.57	92.02	99.06	44.9	99.7	5.9	29.45	7.5	13.93
($\pm$ 2.4)	($\pm$ 1.1)	($\pm$ 0.2)	($\pm$ 1)	($\pm$ 1.8)	($\pm$ 0.1)	($\pm$ 2.4)	($\pm$ 0.1)	($\pm$ 0.9)	($\pm$ 1.3)	($\pm$ 0.5)	($\pm$ 0.7)

Results on CIFAR-10

Table 4. Below we observe the averaged accuracies (%) of simple models SM-3 (3 Res units), SM-5 (5 Res units) and SM-7 (7 Res units) trained with various weighting methods and distillation. The complex model achieved 84.5% accuracy. Statistically significant best results are indicated in bold.

	SM-3	SM-5	SM-7
Standard	73.15 (± 0.7)	75.78 (±0.5)	78.76 (±0.35)
ConfWeight	76.27 (±0.48)	78.54 (±0.36)	**81.46** (±0.50)
Distillation	65.84 (±0.60)	70.09 (±0.19)	73.4 (±0.64)
ProfWeight	76.56 (±0.51)	79.25 (±0.36)	**81.34** (±0.49)
SRatio	**77.23** (±0.14)	**80.14** (±0.22)	**81.89** (±0.28)

Conclusion

- We proposed a method to improve simple models using high performing complex models (algorithmic contribution).
- The method leverages the simple models confidences (conceptual contribution).
- Proved that optimizing the (weighted) loss of the simple model based on SRatio is a sound procedure.
- Formalized and generalized the idea of probes for a NN.

Concluding Remark

Even if you desire just a simple model…

build the most accurate model you can
and
transfer information to the simple model

Thank you