A Appendix

B Experimental Setup

B.1 Sampling

Given a pool of M models, for each ensemble size S we sample 100 times with replacement. We then average the accuracy across the 100 samples plus one base model that is shared across all variants. The result at each S is reported until an ensemble of M models is reached.

B.2 CIFAR-100 Training

We use the following architectures: ResNet9 (He et al., 2016a), VGG16 (Simonyan & Zisserman, 2014) and MLP-Mixer (Tolstikhin et al., 2021). We train them as follows:

ResNet-9 We train the model for 24 steps using Stochastic Gradient Descent (SGD). We implemented standard data augmentation by applying Random Horizontal Flip, Random Translate, and Cutout. We use a Slanted Triangular Learning Rate (SLTR) (Howard & Ruder, 2018). The top-1 test set accuracy is 72.24%

ResNet18/34/50 For these 3 ResNet architectures, we train the model for 50 epochs using Stochastic Gradient Descent (SGD), batch size of 512, momentum=0.9, and weight decay=0.0005. We implemented standard data augmentation by applying Random Horizontal Flip, Random Crop, Random Affine, and Cutout. We use a combination of warmup for the first 5 epoch and cosine annealing for scheduler. The top-1 test set accuracy for ResNet-18 is 73.56%, ResNet-34 is 74.24%, and ResNet-50 is 74.89%

VGG16 We train the model for 130 epochs using Stochastic Gradient Descent (SGD). We implemented standard data augmentation by applying Random Horizontal Flip, Random Crop, and Random Rotation. We use a combination of warmup for 1 epoch and a multi-step scheduler with milestones at steps 60 and 120. The top-1 test set accuracy is 71.23%

MLP-Mixer We train the model for 300 steps using Adaptive Moment Estimation (Adam) (Kingma & Ba, 2014). We implemented standard data augmentation by applying Random Crop, AutoAugment (CIFAR10 Policy) (Cubuk et al., 2018), and CutMix (Yun et al., 2019). We use a combination of warmup for the first 5 epoch and cosine annealing for scheduler. The top-1 test set accuracy is 60.28%

B.3 TinyImageNet Training

We use the following architectures: ResNets (He et al., 2016a), VGG-16 (Simonyan & Zisserman, 2014) and ViT (Dosovitskiy et al., 2020). We train them as follows:

ResNets We train 3 different architectures from the ResNet family (ResNet18, 34, 50) for 100 steps using Stochastic Gradient Descent (SGD). We implemented standard data augmentation by applying Random Resized Crop and Random Horizontal Flip. We use a Slanted Triangular Learning Rate (SLTR) (Howard & Ruder, 2018). The top-1 test set accuracy for ResNet-18 is 49.27%, ResNet-34 is 52.18%, and ResNet-50 is 54.99%

VGG16 We train the model for 100 steps using Stochastic Gradient Descent (SGD). We implemented standard data augmentation by applying Random Resized Crop and Random Horizontal Flip. We use a Slanted Triangular Learning Rate (SLTR) (Howard & Ruder, 2018). The top-1 test set accuracy is 60.37%

ViT We train the model for 100 steps using Adaptive Moment Estimation with decoupled weight decay (AdamW) (Loshchilov & Hutter, 2017). We implemented standard data augmentation by applying Random Horizontal Flip, Random Resized Crop, AutoAugment (Cubuk et al., 2018), Random Erasing (Zhong et al., 2020), Cutmix (Yun et al., 2019), and Mixup(Zhang et al., 2017). We use a combination of warmup for the first 10 epoch and cosine annealing (Loshchilov & Hutter, 2016) for scheduler. The top-1 test set accuracy is 51.21%

C FAIR-ENSEMBLE: WHEN HOMOGENEOUS ENSEMBLE DISPROPORTIONATELY BENEFIT MINORITY GROUPS

C.1 EXPERIMENTAL SETUP

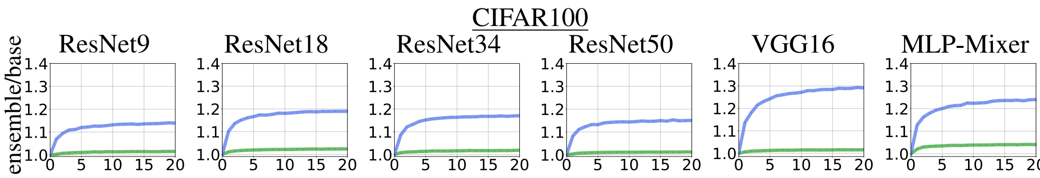
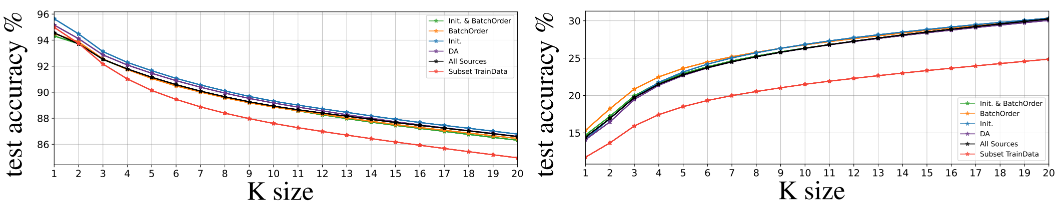


Figure 8: Depiction of the accuracy gain as a ratio of ensemble accuracy % over the singular base model (**y-axis**) by per-group (top-k and bottom-k) test set accuracies for CIFAR100.

C.2 BALANCED DATASET SUB-GROUPS



(a) ResNet-50 Top-K classes (b) ResNet-50 Bottom-K classes

Figure 9: Average Top and Bottom-K accuracy as number of K-classes increase. We observe that **DA** and **Init.** outperforms **All Sources** baseline performance in Top-K classes, whereas **BatchOrder** and **Init.** outperfroms **All Sources** on Bottom-K classes. In both top and bottom groups, only the **TrainSubsetData** variant underperforms **All Sources**.

C.3 CIFAR-100

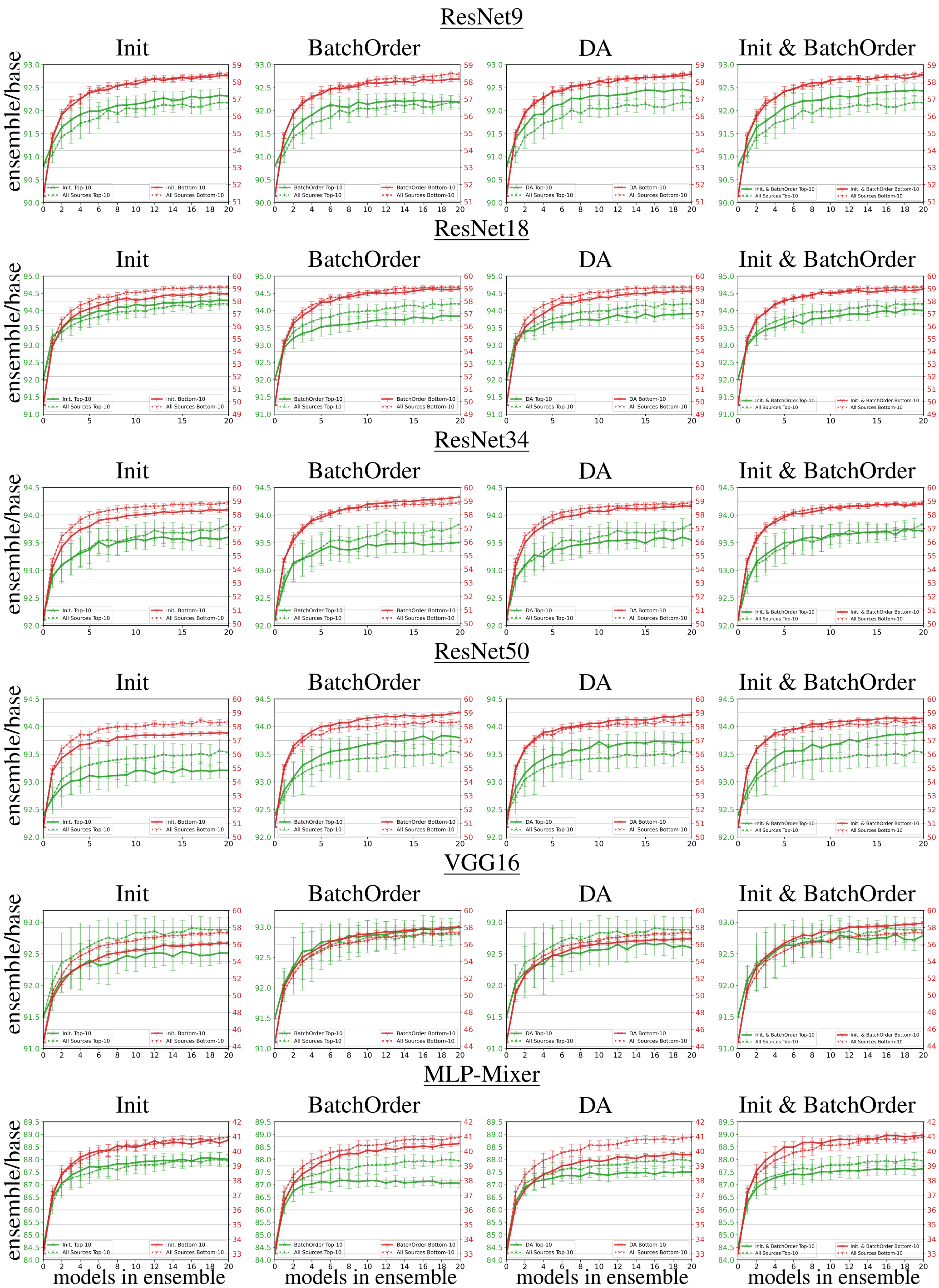


Figure 10: Accuracy for Top-K and Bottom-K across models added to ensemble on CIFAR100

C.4 TinyImageNet

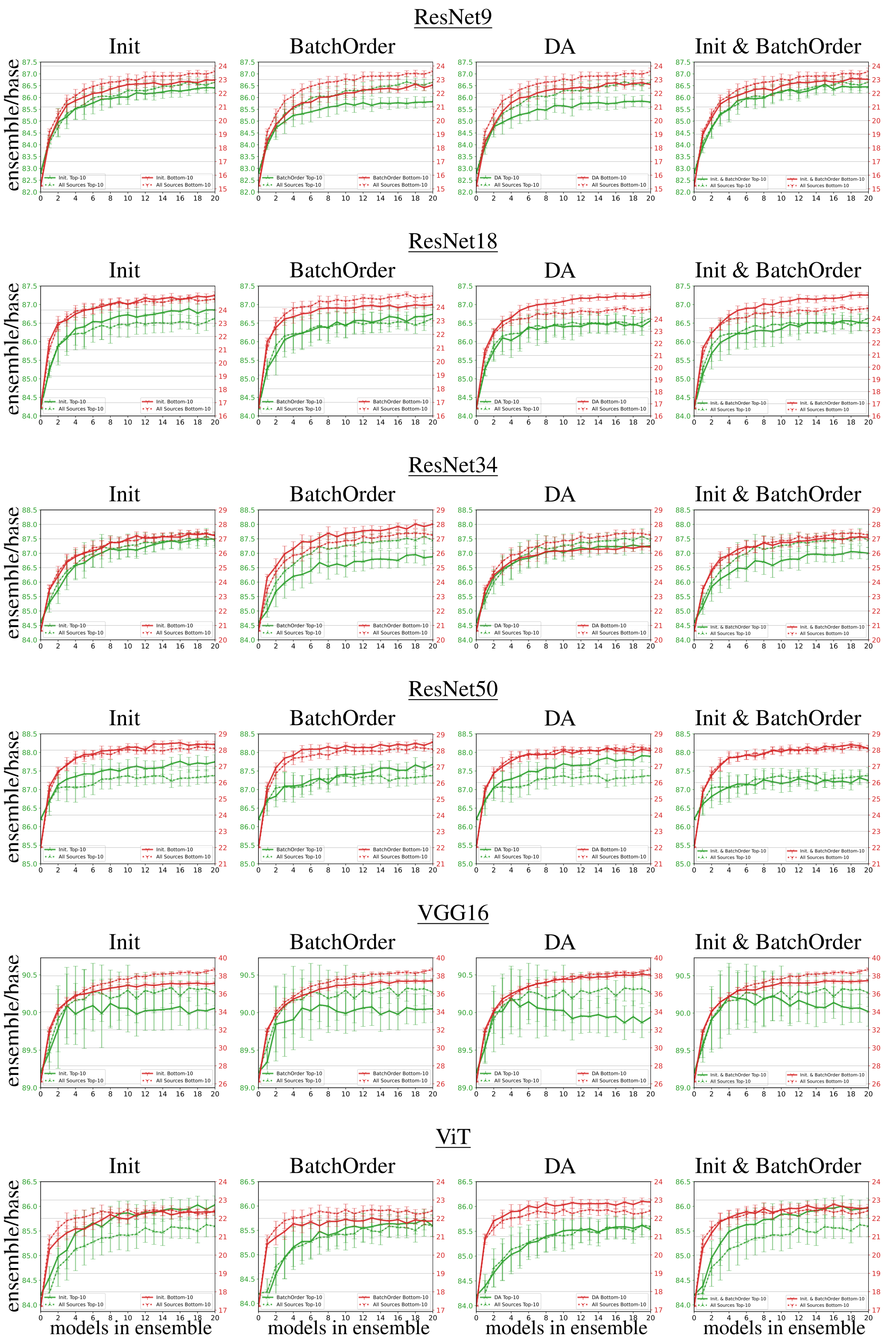


Figure 11: Accuracy for Top-K and Bottom-K across models added to ensemble on TinyImageNet

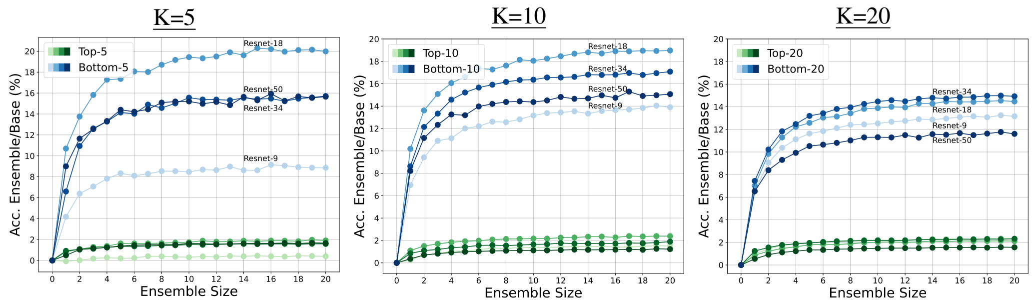
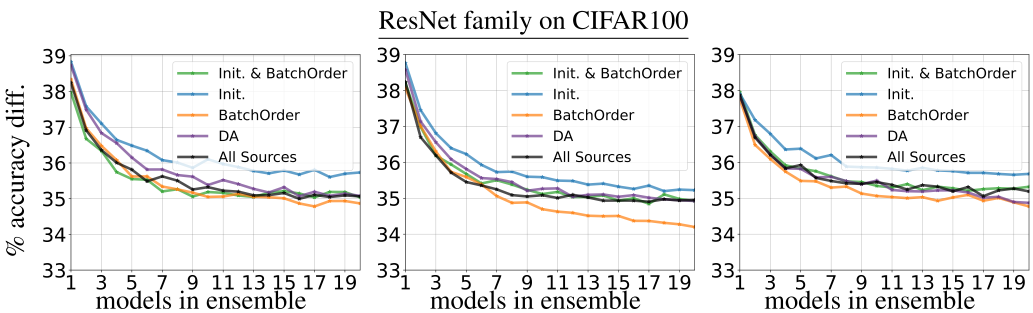


Figure 12: Top/Bottom-K performance for K = {5,10,20} in CIFAR100

D Controlling for the Sources of Stochasticity in Homogeneous Ensembles

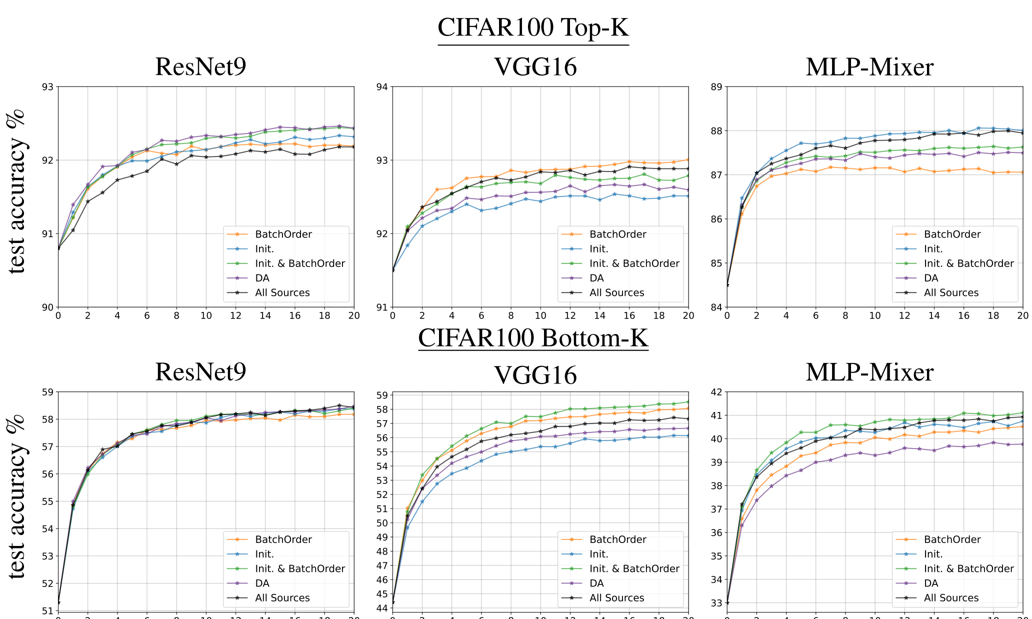
D.1 CIFAR100 Accuracy % difference for ResNet 18, 34, 50



(a) ResNet18, 20 models
(b) ResNet34, 20 models
(c) ResNet50, 20 models

Figure 13: Accuracy % difference between top and bottom 10 classes, for ResNet18, 34, and 50 for CIFAR100.

D.2 CIFAR100 and TinyImageNet Results



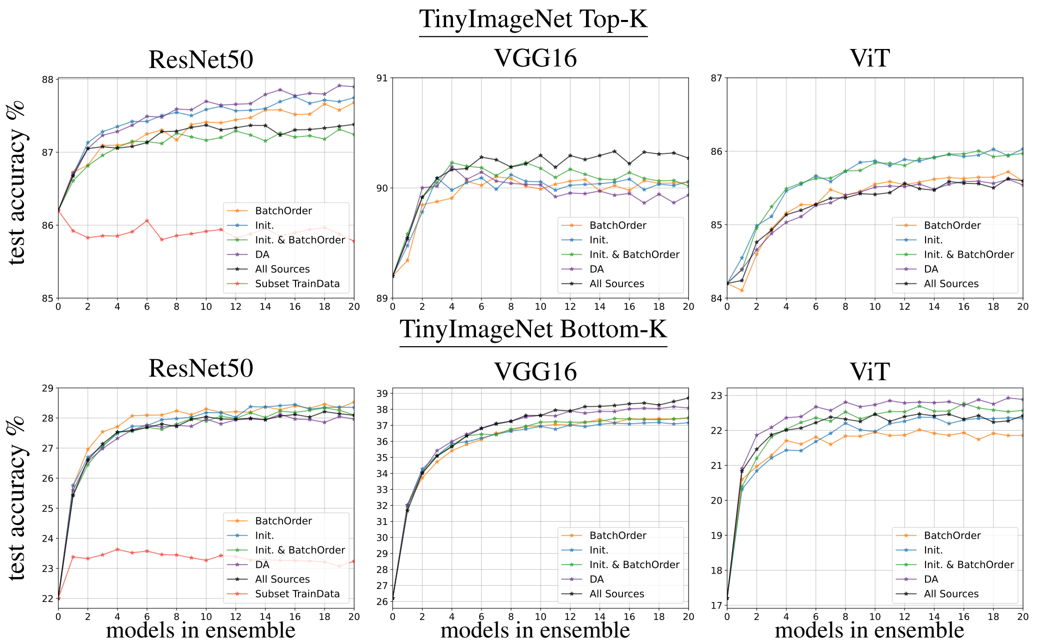


Figure 14: Average Test Accuracy on CIFAR100 and TinyImageNet for Top-K and Bottom-K ($K = 10$) Performing Classes

D.3 Dominant sources of stochasticity

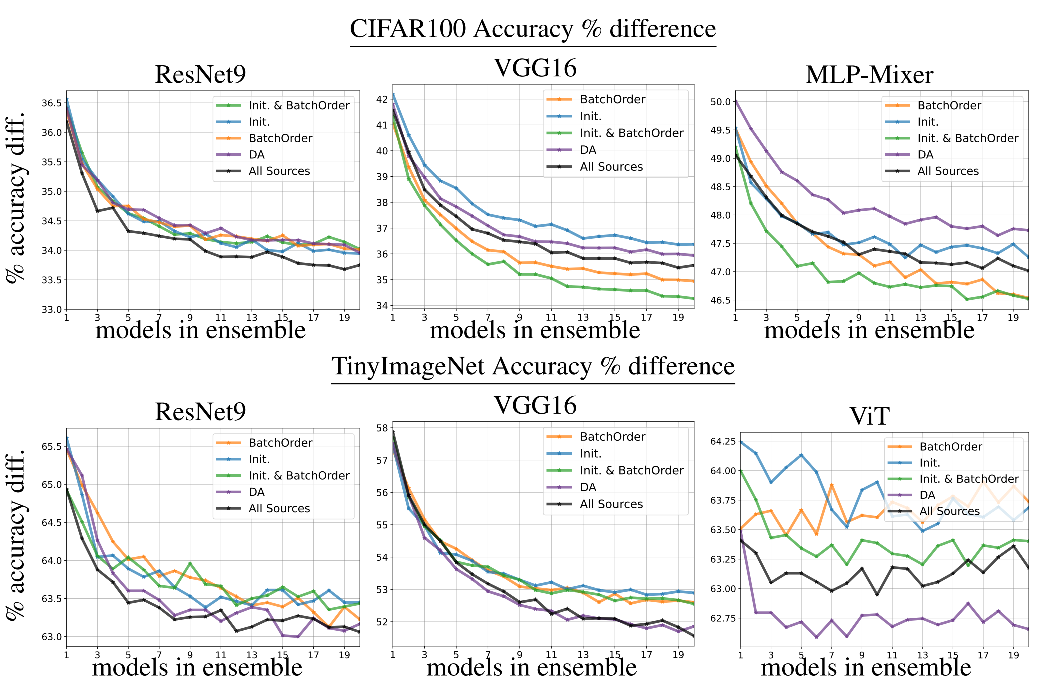


Figure 15: Accuracy % difference between top and bottom 10 classes for ResNet-9, VGG16, and MLPMixer trained on CIFAR100 and TinyImageNet

E RESULTS AND DISCUSSION

E.1 COMPARISON BETWEEN RESNET ARCHITECTURES

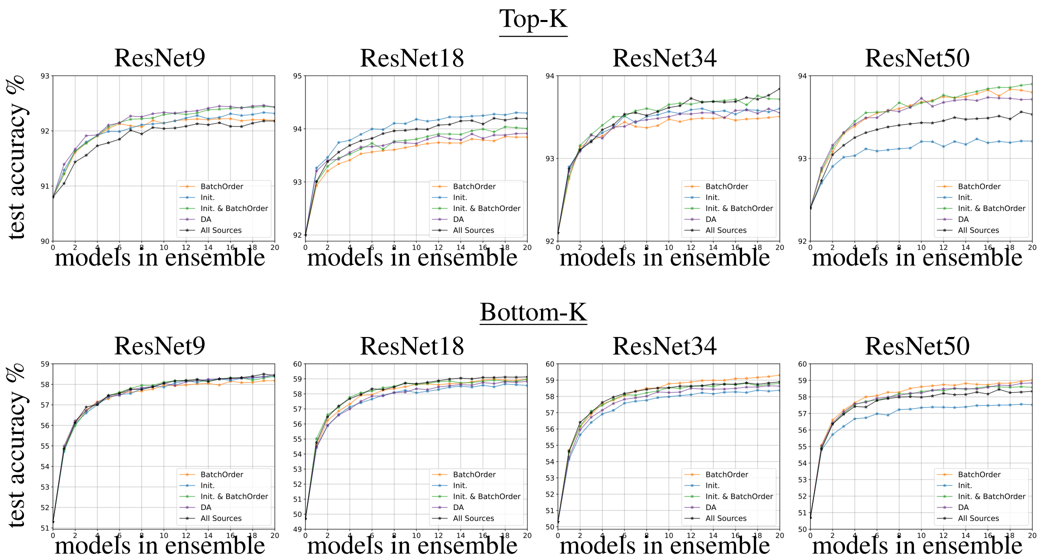
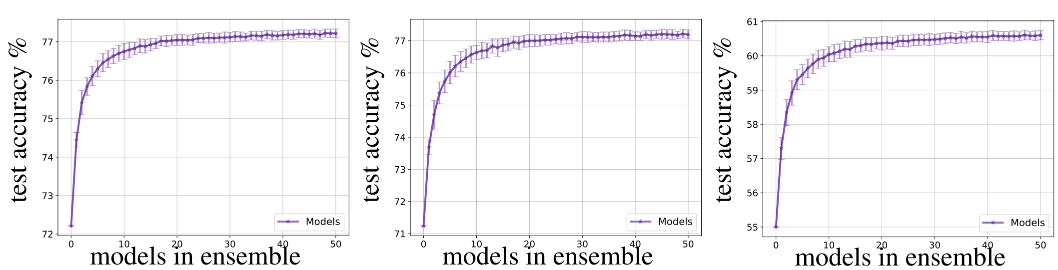


Figure 16: Average Test Accuracy on CIFAR100 for Top-K and Bottom-K classes across different sizes of ResNets.

E.2 BENEFITS OF EVEN LARGER HOMOGENEOUS ENSEMBLES



(a) ResNet9 on CIFAR100 (b) VGG16 on CIFAR100 (c) ResNet50 on TinyImageNet

Figure 17: Average Accuracy per size of homogeneous ensemble. The average accuracy for each model added is calculated by averaging 100 random samples from a population of 50 models. We can see that the average accuracy starts to slowly plateau as the ensemble grows to 50 models.

E.3 CIFAR-100

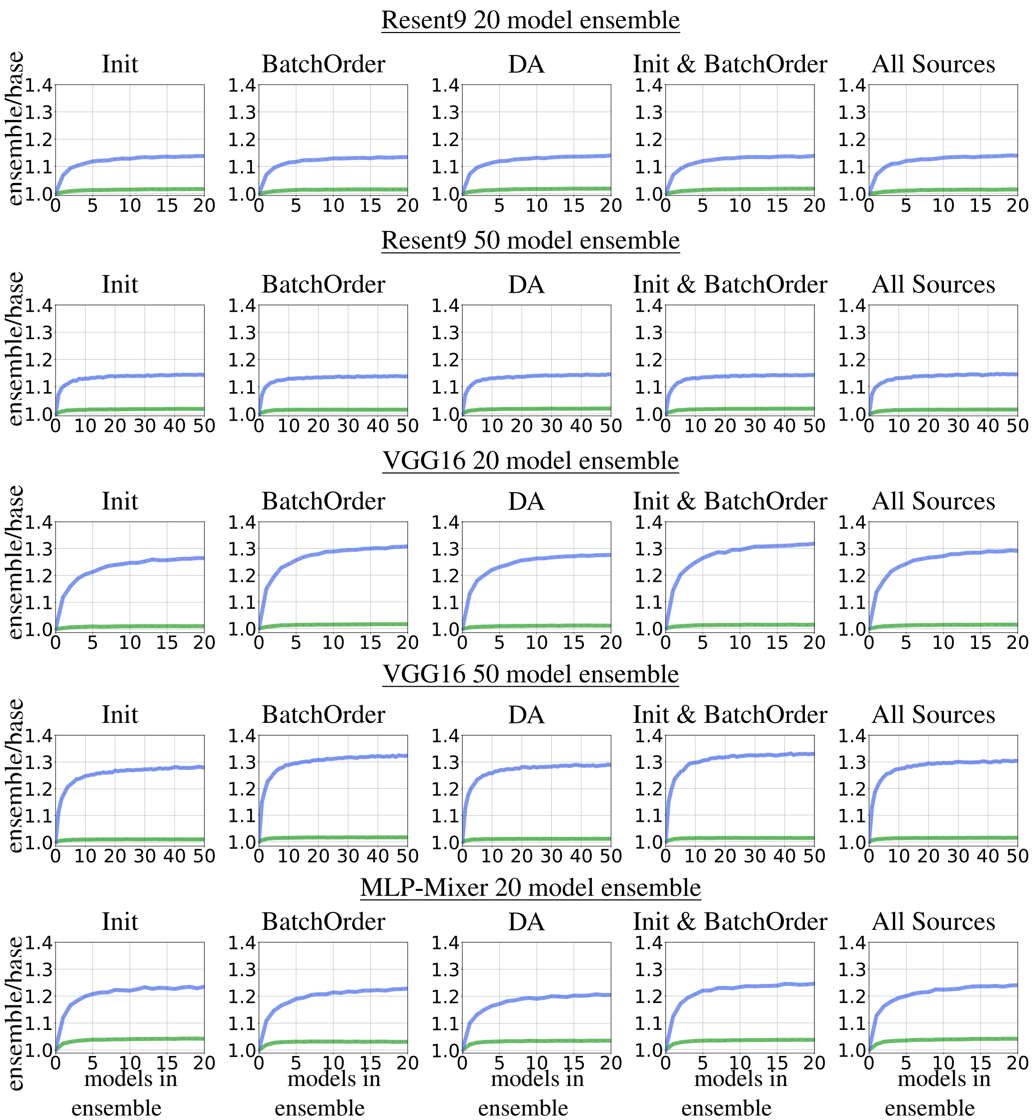


Figure 18: Ratio of Top & Bottom K ensemble accuracy for different model architectures and ensemble sizes on CIFAR100

E.4 TinyImageNet

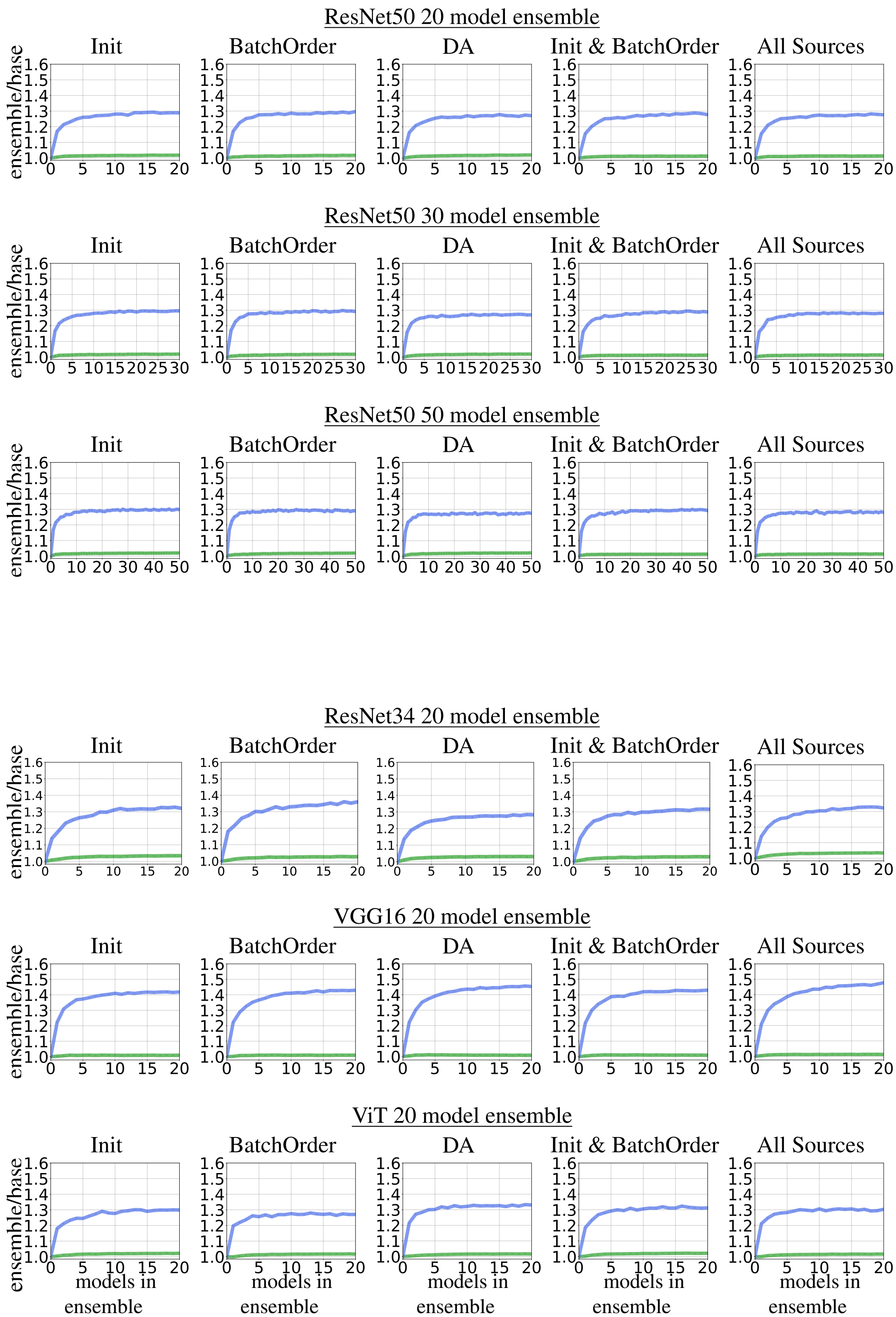
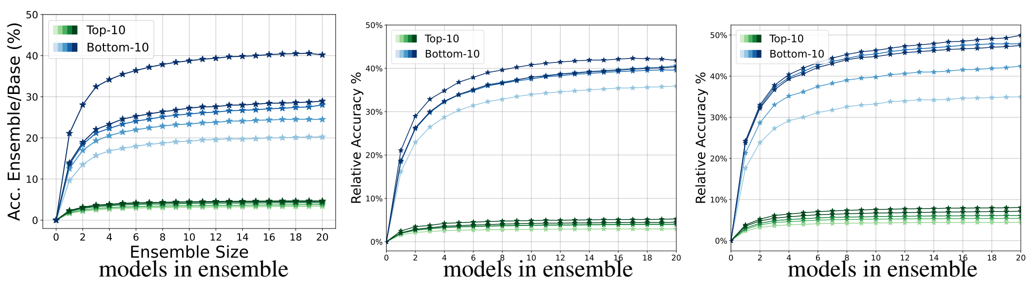


Figure 19: Ratio of Top & Bottom K ensemble accuracy for different model architectures and ensemble sizes on TinyImageNet

F FAIR ENSEMBLE: IMPROVED ROBUSTNESS

Figure 20: For each **row** we depict three of the different types of corruptions from the CIFAR100-C dataset (`elastic_transform`, `snow`, and `impulse_noise` respectively), and for each **column** we depict the corruption severity levels ($1 \mapsto 5$). The image belongs to the `lion` class.



(a) ResNet-9 (b) VGG-16 (c) MLP-Mixer

Figure 21: Performance on CIFAR-100 Corrupt based on Severity Levels.

G DIFFERENCE IN CHURN BETWEEN MODELS EXPLAINS ENSEMBLE FAIRNESS

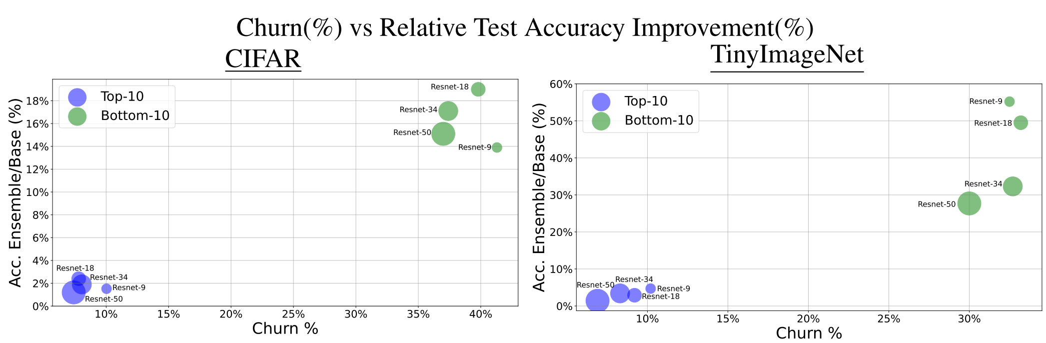


Figure 22: Correlation between Model Disagreement and Ensemble Performance

H Can Different Sources of Stochasticity Improve Homogeneous Deep Ensemble Fairness?

H.1 Contribution of stochasticity in ensembles

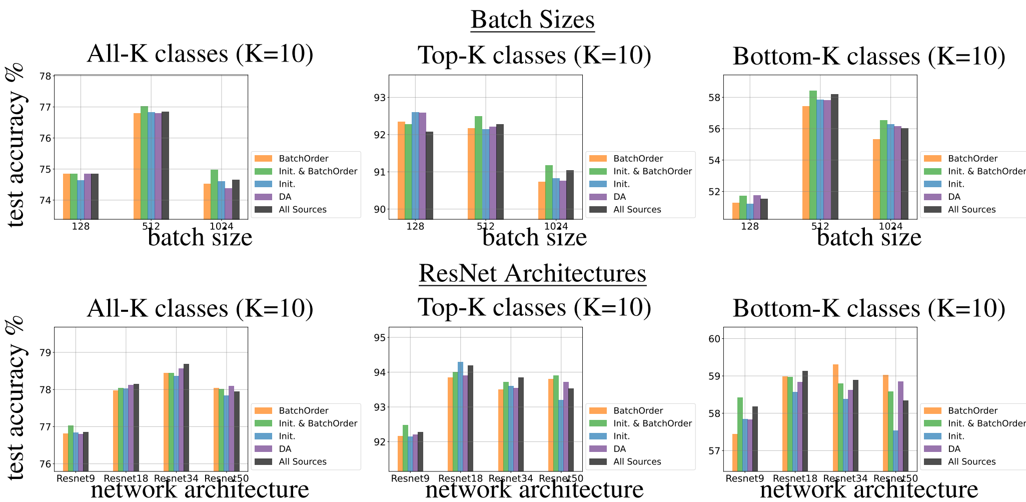


Figure 23: Average Test Accuracy on CIFAR100 as batch and architecture size increases. Batch 512 is default.

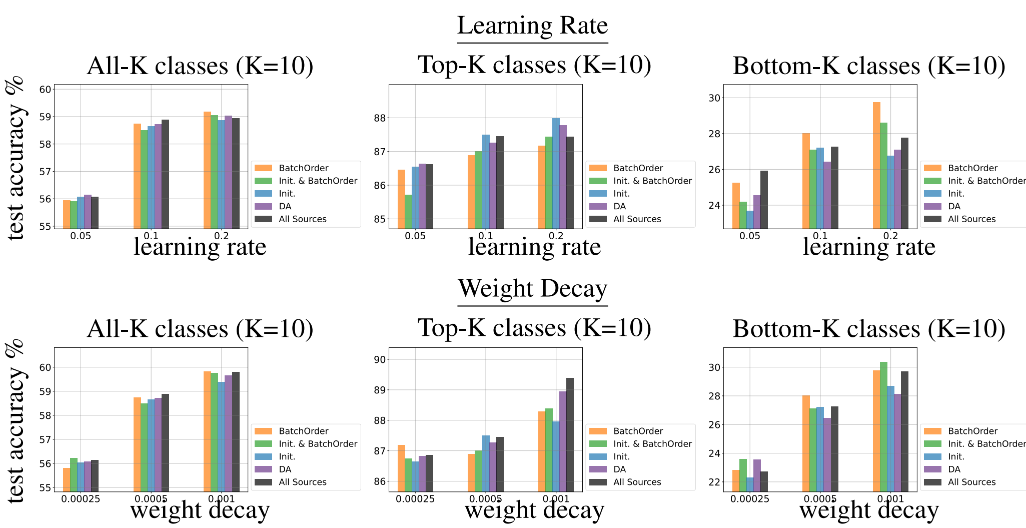


Figure 24: Average Eval Accuracy on TinyImageNet as learning rate and weight decay increases. 0.1 is default learning rate, and 0.0005 is default weight decay.

I HOMOGENEOUS ENSEMBLES IN NON-DNN MODELS/NON-IMAGE DATASETS

Table 2: MLP ensemble performance over Adult Census Income subgroups with sensitive attributes

		10-model ensemble			
	Base Model	BatchOrder	Initialization	Init & BatchOrder	All Sources
>$50k	**79.93**	79.87 ± 0.03	79.75 ± 0.28	79.57 ± 0.38	79.68 ± 0.21
>$50k Male	25.98	26.75 ± 0.19	26.1 ± 0.49	**27.17 ± 0.83**	26.96 ± 0.51
>$50k Female	27.97	28.63 ± 0.21	28.23 ± 0.41	**28.93 ± 0.81**	28.76 ± 0.4
>$50k White	26.48	27.22 ± 0.17	26.64 ± 0.47	**27.61 ± 0.81**	27.4 ± 0.48
>$50k Nonwhite	24.44	25.2 ± 0.45	24.25 ± 0.6	**25.83 ± 0.88**	25.62 ± 0.62
>$50k Black	24.02	25.29 ± 0.67	23.92 ± 0.74	**25.89 ± 0.66**	25.73 ± 0.57
>$50k Asian-Pac-Islander	23.31	23.64 ± 0.39	22.82 ± 0.52	**24.14 ± 0.96**	23.98 ± 0.7
>$50k Amer-Indian-Eskimo	26.32	26.32 ± 0	27.79 ± 3.5	**28.85 ± 4.73**	27.74 ± 3.14
>$50k Other	32	32 ± 0	31.44 ± 1.39	**32.12 ± 0.68**	32.04 ± 0.4

Table 3: Decision Trees ensemble performance over Adult Census Income subgroups with sensitive attributes

	Base Model	10-Model Ensemble
>$50k	85.85	**85.91 ± 0.02**
>$50k Male	60.26	**60.35 ± 0.04**
>$50k Female	55.59	**56.04 ± 0.09**
>$50k White	59.89	**59.99 ± 0.05**
>$50k Nonwhite	56.18	**56.73 ± 0.05**
>$50k Black	**52.51**	**52.51 ± 0**
>$50k Asian-Pac-Islander	61.65	**62.41 ± 0**
>$50k Amer-Indian-Eskimo	**63.16**	**63.16 ± 0**
>$50k Other	48	**51.84 ± 0.78**

J TOP AND BOTTOM CLASSES FOR CIFAR100 AND TINYIMAGENET

J.1 CIFAR100

Table 4: Top-10 and Bottom-10 class names for CIFAR100. The classes are from the averaged test accuracies from the 20-model ensembles.

ResNet9	ResNet18	ResNet34	ResNet50	VGG16	MLP-Mixer
			Top-10		
wardrobe	skunk	skunk	orange	road	wardrobe
motorcycle	orange	road	wardrobe	wardrobe	motorcycle
orange	motorcycle	orange	motorcycle	sunflower	orange
skunk	road	sunflower	skunk	motorcycle	sunflower
road	wardrobe	motorcycle	road	skyscraper	road
chimpanzee	palm_tree	wardrobe	sunflower	skunk	skyscraper
sunflower	chimpanzee	palm_tree	chimpanzee	palm_tree	keyboard
orchid	sunflower	pickup_truck	palm_tree	orange	palm_tree
mountain	tractor	aquarium_fish	aquarium_fish	chair	plain
apple	skyscraper	skyscraper	lawn_mower	chimpanzee	skunk
			Bottom-10		
man	mouse	shark	girl	possum	mouse
shark	bear	possum	lizard	crocodile	bowl
lizard	shark	crocodile	possum	girl	woman
bowl	girl	lizard	maple_tree	shark	girl
possum	lizard	girl	bear	bear	squirrel
shrew	man	man	otter	lizard	possum
seal	otter	bowl	bowl	seal	lizard
girl	seal	otter	man	boy	boy
otter	bowl	seal	boy	otter	otter
boy	boy	boy	seal	man	seal

J.2 TINYIMAGENET

Table 5: Top-10 and Bottom-10 wnid names for TinyImageNet. The names are from the averaged test accuracies from the 20-model ensembles.

ResNet9	ResNet18	ResNet34	ResNet50	VGG16	ViT
			Top-10		
n02791270	n02791270	n02791270	n02791270	n02791270	n07875152
n02509815	n02509815	n02509815	n02509815	n03042490	n03814639
n03976657	n02906734	n02906734	n02906734	n02509815	n03983396
n02124075	n03042490	n03814639	n03042490	n03814639	n03042490
n03814639	n03814639	n01950731	n01950731	n02906734	n02823428
n03089624	n03976657	n03599486	n04067472	n01950731	n03599486
n03983396	n01950731	n03042490	n03599486	n04398044	n02509815
n02002724	n04560804	n03976657	n03976657	n02124075	n02791270
n03126707	n03599486	n04067472	n07579787	n03089624	n03126707
n03447447	n02002724	n03126707	n03126707	n04067472	n02906734
			Bottom-10		
n02437312	n04532670	n03160309	n03544143	n02085620	n02927161
n04070727	n03544143	n01945685	n03617480	n04417672	n03544143
n02268443	n04486054	n04417672	n04070727	n02268443	n04070727
n01945685	n02268443	n04532670	n03804744	n04486054	n01641577
n02226429	n03160309	n03617480	n03160309	n01945685	n02094433
n02233338	n03617480	n01855672	n01945685	n02094433	n02480495
n02480495	n01855672	n03804744	n02268443	n04070727	n02410509
n02410509	n02480495	n02480495	n02480495	n02480495	n04532670
n03617480	n02123394	n02123394	n02123394	n02410509	n02950826
n02123394	n02410509	n02410509	n02410509	n02123394	n02123394