Customizing Student Networks From Heterogeneous Teachers via Adaptive Knowledge Amalgamation – *Supplementary Material* –

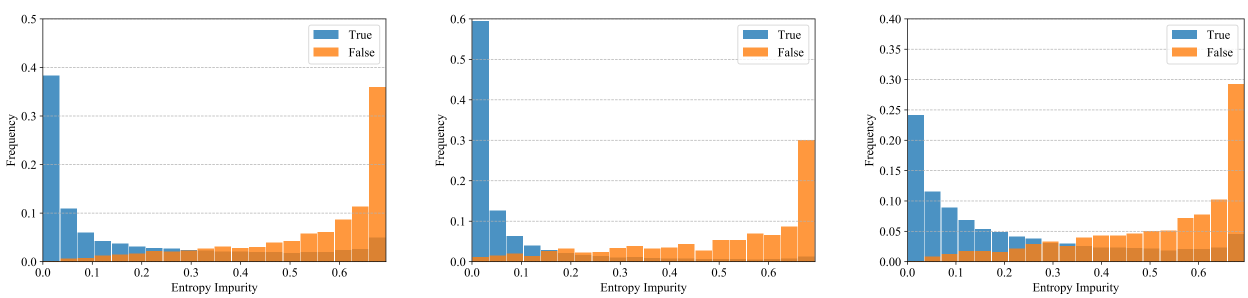
Chengchao Shen[1,*], Mengqi Xue[1,*], Xinchao Wang[2], Jie Song[1,3], Li Sun[1], Mingli Song[1,3]
[1]Zhejiang University, [2]Stevens Institute of Technology,
[3]Alibaba-Zhejiang University Joint Institute of Frontier Technologies
{chengchaoshen,mqxue,sjie,lsun,brooksong}@zju.edu.cn,xinchao.w@gmail.com

We provide in this document additional details and results of the proposed adaptive knowledge amalgamation approach. In what follows, we show the effectiveness of the entropy impurity as a guidance for selective learning, the details of our network architecture, the tasks handled by source nets from different datasets, as well as additional quantitative results.

1. Effectiveness of Entropy Impurity

Here we conduct experiments to show that, the prediction from the teacher with the least ambiguity, is a plausible approximation for the ground-truth label and thus an effective way to guide the selective learning.

To this end, we analyze the entropy distribution of teachers' predictions on three attributes using the validation set of CelebA. For each attribute, the predictions of teacher are categorized into two groups: true prediction and false prediction. The results shown in Fig. 1 demonstrate that entropy impurity of true predictions tends to be lower than the one of false predictions. In other words, the predictions with less ambiguity are more likely to be correct, and thus learning from such predictions is indeed justifiable in the absence of the human-annotated labels.



(a) Black Hair (b) Pale Skin (c) Smiling

Figure 1. The entropy impurity distributions of true and false predictions on three attribute recognition tasks: black hair, pale skin, and smiling.

2. Network Architecture

We show in Tab. 1 the details of our network architecture. For the source net and the component net, we adopt the regular resnet-18; for the target net, we apply more channels in each layer to accommodate more information, since the knowledge from more teachers is amalgamated. The transfer bridge between the source net and the component net is implemented as 1×1 convolutions, with different numbers of channels for different layers as shown in Tab. 1. It is noteworthy that for

[*]Equal contribution

Layer	Output Size	Source Net	Component Net	Target Net	Transfer Bridge (source to comp)	Transfer Bridge (comp to target)
conv1	112×112	7×7, 64, stride 2	7×7, 64, stride 2	7×7, 90, stride 2	1×1, 32, stride 1	1×1, 64, stride 1
conv2_x	56×56	3×3 max pool, stride 2			/	/
		$\begin{bmatrix}3\times3, 64\\3\times3, 64\end{bmatrix}\times2$	$\begin{bmatrix}3\times3, 64\\3\times3, 64\end{bmatrix}\times2$	$\begin{bmatrix}3\times3, 90\\3\times3, 90\end{bmatrix}\times2$	1×1, 32, stride 1	1×1, 64, stride 1
conv3_x	28×28	$\begin{bmatrix}3\times3, 128\\3\times3, 128\end{bmatrix}\times2$	$\begin{bmatrix}3\times3, 128\\3\times3, 128\end{bmatrix}\times2$	$\begin{bmatrix}3\times3, 180\\3\times3, 180\end{bmatrix}\times2$	1×1, 64, stride 1	1×1, 128, stride 1
conv4_x	14×14	$\begin{bmatrix}3\times3, 256\\3\times3, 256\end{bmatrix}\times2$	$\begin{bmatrix}3\times3, 256\\3\times3, 256\end{bmatrix}\times2$	$\begin{bmatrix}3\times3, 360\\3\times3, 360\end{bmatrix}\times2$	1×1, 128, stride 1	1×1, 256, stride 1
conv5_x	7×7	$\begin{bmatrix}3\times3, 512\\3\times3, 512\end{bmatrix}\times2$	$\begin{bmatrix}3\times3, 512\\3\times3, 512\end{bmatrix}\times2$	$\begin{bmatrix}3\times3, 720\\3\times3, 720\end{bmatrix}\times2$	1×1, 256, stride 1	1×1, 512, stride 1
	1×1	average pool, 2-d fc, softmax			/	/

Table 1. Network architectures. Residual blocks are shown in brackets with the numbers of blocks stacked. Downsample is implemented by conv3_1, conv4_1, and conv5_1 with a stride of 2. *source*, *comp*, and *target* denote source net, component net, and target net, respectively.

each layer, the number of channels of the transfer bridge is set smaller than that of source net, as the source net, which may be multi-task, is expected to transfer only the related knowledge to the component. For the transfer bridge between the component net and the target net, we set its number of channels to be equal to that of the component net, as the target net is expected to "absorb" as much as possible knowledge from the components.

3. Tasks of Source Nets

We show in Tab. 2 the tasks handled by the source nets of the CelebA dataset. Apart from the *mouth-related* source nets as described in Tab. 2 of the main manuscript, we show here the *hair-related*, *eye-related*, and *face-related* source nets. The experimental results of the mouth- and hair-related attributes are demonstrated in Tab. 3 of the main manuscript, while the ones of eye- and face-related are presented in Tab. 3 here.

We also show the category partitions of the Standford Dogs and CUB-200-2011 dataset in Tab. 6, and those of FGVC-Aircraft and Cars dataset in Tab. 7. The remaining category sets that are referred to in the main manuscript, are defined as follows: $\mathcal{D}_1 = \mathcal{D}'_1 \cup \mathcal{D}'_2$, $\mathcal{D}_2 = \mathcal{D}'_3 \cup \mathcal{D}'_4$, $\mathcal{B}_1 = \mathcal{B}'_1 \cup \mathcal{B}'_2$, $\mathcal{B}_2 = \mathcal{B}'_3 \cup \mathcal{B}'_4$, $\mathcal{A}_1 = \mathcal{A}'_1 \cup \mathcal{A}'_2$, $\mathcal{A}_2 = \mathcal{A}'_3 \cup \mathcal{A}'_4$, $\mathcal{C}_1 = \mathcal{C}'_1 \cup \mathcal{C}'_2$, $\mathcal{C}_2 = \mathcal{C}'_3 \cup \mathcal{C}'_4$.

4. More Results of Network Customization

To further validate the effectiveness of the proposed approach, we conduct more experiments on network customization and show the results in Tab. 3. Again, we observe that the derived component nets yield consistent improvements over the source nets. Meanwhile, the target nets, despite their compact sizes, achieve performances on par with those of the component nets.

Besides customizing networks for attributes in the one group, we also conduct experiments to customize networks that handle attribute categorizations across different groups. We show the experimental results in Tab. 4. In the first sub-table, for example, we have multi-task sources working on both hair-related attributes including "black hair" and "blond hair" and mouth-related attributes including "mouth slightly open" and "wearing lipstick". In the third sub-table, we have source nets handling mouth-related attribute "smiling", hair-related attribute "bangs", and face-related ones including "oval face" and "heavy makeup". Results demonstrate that such network customization across different attribute groups can also achieve very encouraging performances.

We also conduct experiments to explore network customization from groups of different categories. In this experiment, two dog-related source nets and two bird-related source nets are amalgamated into the final target net. The experimental results are shown in Tab. 5. It is noteworthy that the performance of the target net is slightly worse than the one achieved

Source Net	Attributes	Source Net	Attributes
$\mathcal{S}_1^{\text{hair}}$	black hair, arched eyebrows, attractive, big lips	$\mathcal{S}_6^{\text{hair}}$	brown hair, oval face, bushy eyebrows
$\mathcal{S}_2^{\text{hair}}$	black hair, bags under eyes, blurry	$\mathcal{S}_7^{\text{hair}}$	brown hair, narrow eyes, chubby
$\mathcal{S}_3^{\text{hair}}$	blond hair, pale skin, receding hairline	$\mathcal{S}_8^{\text{hair}}$	bangs, attractive, receding hairline, big nose
$\mathcal{S}_4^{\text{hair}}$	blond hair, high cheekbones	$\mathcal{S}_9^{\text{hair}}$	bangs, blurry, pale skin
$\mathcal{S}_5^{\text{hair}}$	brown hair, double chin		

$\mathcal{S}_1^{\text{eye}}$	bags under eyes, rosy cheeks, oval face, s-miling	$\mathcal{S}_5^{\text{eye}}$	bushy eyebrows, heavy makeup, wearing necklace
$\mathcal{S}_2^{\text{eye}}$	bags under eyes, heavy makeup	$\mathcal{S}_6^{\text{eye}}$	narrow eyes, wearing lipstick
$\mathcal{S}_3^{\text{eye}}$	bushy eyebrows, big lips, pale skin	$\mathcal{S}_7^{\text{eye}}$	narrow eyes, mouth slightly open, wearing necktie
$\mathcal{S}_4^{\text{eye}}$	bushy eyebrows, young		

$\mathcal{S}_1^{\text{face}}$	oval face, male	$\mathcal{S}_5^{\text{face}}$	young, gray hair, receding hairline, goatee
$\mathcal{S}_2^{\text{face}}$	oval face, big lips, pointy nose	$\mathcal{S}_6^{\text{face}}$	heavy makeup, male
$\mathcal{S}_3^{\text{face}}$	young, wearing lipstick	$\mathcal{S}_7^{\text{face}}$	heavy makeup, sideburns, double chin, at-tractive
$\mathcal{S}_4^{\text{face}}$	young, wearing lipstick		

Table 2. Source nets that work on hair-related, eye-related, and face-related attribute recognition tasks from the CelebA dataset.

Model	**Eye-Related Attributes**		
	Bags Under Eyes	Bushy Eyebrows	Narrow Eyes
Source Net	$\mathcal{S}_1^{\text{eye}}$(81.6), $\mathcal{S}_2^{\text{eye}}$(81.7)	$\mathcal{S}_3^{\text{eye}}$(87.5), $\mathcal{S}_4^{\text{eye}}$(87.8), $\mathcal{S}_5^{\text{eye}}$(88.2)	$\mathcal{S}_6^{\text{eye}}$(85.8), $\mathcal{S}_7^{\text{eye}}$(85.9)
Component Net	$82.2^{\uparrow\mathbf{0.6,0.5}}$	$88.8^{\uparrow\mathbf{1.3,1.0,0.6}}$	$86.3^{\uparrow\mathbf{0.5,0.4}}$
Target Net	$82.2^{\uparrow\mathbf{0.6,0.5}}$	$88.7^{\uparrow\mathbf{1.2,0.9,0.5}}$	$86.1^{\uparrow\mathbf{0.3,0.2}}$

Model	**Face-Related Attributes**		
	Oval Face	Young	Heavy Makeup
Source Net	$\mathcal{S}_1^{\text{face}}$(72.3), $\mathcal{S}_2^{\text{face}}$(71.6)	$\mathcal{S}_3^{\text{face}}$(83.7), $\mathcal{S}_4^{\text{face}}$(83.7)	$\mathcal{S}_6^{\text{face}}$(87.5), $\mathcal{S}_7^{\text{face}}$(88.1)
Component Net	$72.6^{\uparrow\mathbf{0.3,1.0}}$	$84.1^{\uparrow\mathbf{0.4,0.4}}$	$88.8^{\uparrow\mathbf{1.3,0.7}}$
Target Net	$72.4^{\uparrow\mathbf{0.1,0.8}}$	$84.0^{\uparrow\mathbf{0.3,0.3}}$	$88.7^{\uparrow\mathbf{1.2,0.6}}$

$\uparrow$ denotes the performance improvement with respect to the corresponding source net.

Table 3. The performance (%) of knowledge amalgamation from source nets to component nets and from component nets to target net on the CelebA dataset. Numbers in parentheses denote the accuracies of the corresponding source nets. Unlike a component net that handles only one task, the target net handles three tasks simultaneously.

by amalgamating only two source nets within the one category group, as shown in Tab. 7 of the main manuscript. This is potentially due to the fact that, there is a large visual gap between the two category groups (dogs and birds), and thus the network, which is compact in size, can not accommodate sufficient information for all these lightly-correlated tasks.

Model	**Attributes**			
	Black Hair	Blond Hair	Mouth Slightly Open	Wearing Lipstick
Source Net	$\mathcal{S}_1^{\text{hair}}(85.2)$, $\mathcal{S}_2^{\text{hair}}(86.9)$	$\mathcal{S}_3^{\text{hair}}(94.0)$, $\mathcal{S}_4^{\text{hair}}(94.2)$	$\mathcal{S}_6^{\text{mouth}}(89.6)$, $\mathcal{S}_7^{\text{mouth}}(89.5)$	$\mathcal{S}_8^{\text{mouth}}(90.4)$, $\mathcal{S}_9^{\text{mouth}}(90.4)$, $\mathcal{S}_{10}^{\text{mouth}}(90.3)$
Component Net	$87.8^{\uparrow 2.6,0.9}$	$95.0^{\uparrow 1.0,0.8}$	$91.4^{\uparrow 1.8,1.9}$	$91.7^{\uparrow 1.3,1.3,1.4}$
Target Net	$87.8^{\uparrow 2.6,0.9}$	$95.1^{\uparrow 1.1,0.9}$	$91.4^{\uparrow 1.8,1.9}$	$91.8^{\uparrow 1.4,1.4,1.5}$

Model	**Attributes**			
	Bags Under Eyes	Bushy Eyebrows	Mouth Slightly Open	Wearing Lipstick
Source Net	$\mathcal{S}_1^{\text{eye}}(81.6)$, $\mathcal{S}_2^{\text{eye}}(81.7)$	$\mathcal{S}_3^{\text{eye}}(87.5)$, $\mathcal{S}_4^{\text{eye}}(87.8)$, $\mathcal{S}_5^{\text{eye}}(88.2)$	$\mathcal{S}_6^{\text{mouth}}(89.6)$, $\mathcal{S}_7^{\text{mouth}}(89.5)$	$\mathcal{S}_8^{\text{mouth}}(90.4)$, $\mathcal{S}_9^{\text{mouth}}(90.4)$, $\mathcal{S}_{10}^{\text{mouth}}(90.3)$
Component Net	$82.2^{\uparrow 0.6,0.5}$	$88.8^{\uparrow 1.3,1.0,0.6}$	$91.4^{\uparrow 1.8,1.9}$	$91.7^{\uparrow 1.3,1.3,1.4}$
Target Net	$82.5^{\uparrow 0.9,0.8}$	$88.7^{\uparrow 1.2,0.9,0.5}$	$91.5^{\uparrow 1.9,2.0}$	$91.8^{\uparrow 1.4,1.4,1.5}$

Model	**Attributes**			
	Smiling	Bangs	Oval Face	Heavy Makeup
Source Net	$\mathcal{S}_3^{\text{mouth}}(88.6)$, $\mathcal{S}_4^{\text{mouth}}(88.6)$, $\mathcal{S}_5^{\text{mouth}}(87.5)$	$\mathcal{S}_8^{\text{hair}}(94.5)$, $\mathcal{S}_9^{\text{hair}}(94.4)$	$\mathcal{S}_1^{\text{face}}(72.3)$, $\mathcal{S}_2^{\text{face}}(71.6)$	$\mathcal{S}_6^{\text{face}}(87.5)$, $\mathcal{S}_7^{\text{face}}(88.1)$
Component Net	$90.5^{\uparrow 1.9,1.9,3.0}$	$95.2^{\uparrow 0.7,0.8}$	$72.6^{\uparrow 0.3,1.0}$	$88.8^{\uparrow 1.3,0.7}$
Target Net	$90.3^{\uparrow 1.7,1.7,2.8}$	$95.1^{\uparrow 0.6,0.7}$	$72.3^{\uparrow 0.0,0.7}$	$88.9^{\uparrow 1.4,0.8}$

Model	**Attributes**			
	Brown Hair	Bangs	Narrow Eyes	Young
Source Net	$\mathcal{S}_5^{\text{hair}}(86.4)$, $\mathcal{S}_6^{\text{hair}}(86.3)$, $\mathcal{S}_7^{\text{hair}}(86.7)$	$\mathcal{S}_8^{\text{hair}}(94.5)$, $\mathcal{S}_9^{\text{hair}}(94.4)$	$\mathcal{S}_6^{\text{eye}}(85.8)$, $\mathcal{S}_7^{\text{eye}}(85.9)$	$\mathcal{S}_3^{\text{face}}(83.7)$, $\mathcal{S}_4^{\text{face}}(83.7)$
Component Net	$88.0^{\uparrow 1.6,1.7,1.3}$	$95.2^{\uparrow 0.7,0.8}$	$86.3^{\uparrow 0.5,0.4}$	$84.1^{\uparrow 0.4,0.4}$
Target Net	$87.9^{\uparrow 1.5,1.6,1.2}$	$95.2^{\uparrow 0.7,0.8}$	$86.0^{\uparrow 0.2,0.1}$	$83.9^{\uparrow 0.2,0.2}$

$\uparrow$ denotes the performance improvement with respect to the corresponding source net.

Table 4. The performance (%) of knowledge amalgamation on attributes of different attribute groups. In the first row, we customize the target net from source nets of a pair of attribute groups: hair-related and mouth-related groups; in the second, we customize from another pair: eye-related and mouth-related groups; in the third row, we customize the target from three different groups: mouth-related, hair-related, and face-related groups; in the last row, we conduct customization from a different combination of three groups: hair-related, eye-related, and face-related groups.

Model	**Category Sets**			
	Stanford Dogs $\mathcal{D}_1$	Stanford Dogs $\mathcal{D}_2$	CUB-200-2011 $\mathcal{B}_1$	CUB-200-2011 $\mathcal{B}_2$
Source Net	$\mathcal{S}_1^{\text{dog}}(87.4)$, $\mathcal{S}_2^{\text{dog}}(87.3)$	$\mathcal{S}_3^{\text{dog}}(87.9)$, $\mathcal{S}_4^{\text{dog}}(87.7)$	$\mathcal{S}_1^{\text{cub}}(74.5)$, $\mathcal{S}_2^{\text{cub}}(74.8)$	$\mathcal{S}_3^{\text{cub}}(73.9)$, $\mathcal{S}_4^{\text{cub}}(74.0)$
Component Net	$88.2^{\uparrow 0.8,0.9}$	$88.5^{\uparrow 0.6,0.8}$	$75.4^{\uparrow 0.9,0.6}$	$74.8^{\uparrow 0.9,0.8}$
Target Net	$88.1^{\uparrow 0.7,0.8}$	$88.6^{\uparrow 0.7,0.9}$	$75.4^{\uparrow 0.9,0.6}$	$75.1^{\uparrow 1.2,1.1}$

$\uparrow$ denotes performance improvement compared with the corresponding source network.

Table 5. The performance (%) of knowledge amalgamation from source nets to component net and from component nets to target net on Stanford Dogs and CUB-200-2011. Note that the target net can handle the classification task on $\mathcal{D}_1 \cup \mathcal{D}_2 \cup \mathcal{B}_1 \cup \mathcal{B}_2$.

Set	Category
Dogs $\mathcal{D}'_1$	chow, scotch terrier, tibetan terrier, dhole, labrador retriever, old english sheepdog, whippet, lakeland terrier, appenzeller, leonberg, pomeranian, bluetick, redbone, haired pointer, australian terrier, dingo, blenheim spaniel, collie, german shepherd, bull mastiff, eskimo dog, boxer, entlebucher, basenji, rhodesian ridgeback, scottish deerhound, brittany spaniel, african hunting dog, samoyed, clumber
Dogs $\mathcal{D}'_2$	miniature pinscher, giant schnauzer, chihuahua, tzu, borzoi, basset, weimaraner, norwegian elkhound, irish setter, tibetan mastiff, pembroke, standard schnauzer, border terrier, boston bull, miniature schnauzer, siberian husky, coated retriever, irish water spaniel, briard, haired fox terrier, cairn, schipperke, toy poodle, mexican hairless, bloodhound, staffordshire bullterrier, airedale, border collie, brabancon griffon, pug
Dogs $\mathcal{D}'_3$	irish wolfhound, greater swiss mountain dog, irish terrier, doberman, yorkshire terrier, beagle, walker hound, cocker spaniel, great pyrenees, sealyham terrier, american staffordshire terrier, bernese mountain dog, gordon setter, west highland white terrier, papillon, cardigan, shetland sheepdog, saluki, kuvasz, pekinese, japanese spaniel, sussex spaniel, coated retriever, french bulldog, toy terrier, great dane, italian greyhound, english setter, welsh springer spaniel, rottweiler
Dogs $\mathcal{D}'_4$	norwich terrier, groenendael, lhasa, miniature poodle, bedlington terrier, komondor, english foxhound, coated wheaten terrier, kerry blue terrier, standard poodle, keeshond, saint bernard, chesapeake bay retriever, norfolk terrier, silky terrier, ibizan hound, maltese dog, newfoundland, malamute, vizsla, affenpinscher, tan coonhound, english springer, golden retriever, dandie dinmont, bouvier des flandres, otterhound, kelpie, malinois, afghan hound
CUB $\mathcal{B}'_1$	clay colored sparrow, yellow bellied flycatcher, gray crowned rosy finch, common raven, hooded oriole, white crowned sparrow, northern fulmar, chestnut sided warbler, warbling vireo, prothonotary warbler, philadelphia vireo, le conte sparrow, chipping sparrow, pacific loon, rhinoceros auklet, bay breasted warbler, dark eyed junco, bewick wren, pine warbler, ruby throated hummingbird, bank swallow, field sparrow, belted kingfisher, gray kingbird, fox sparrow, white breasted nuthatch, tree swallow, fish crow, frigatebird, house wren, artic tern, rose breasted grosbeak, black capped vireo, marsh wren, ringed kingfisher, wilson warbler, black tern, western meadowlark, european goldfinch, nashville warbler, henslow sparrow, american goldfinch, red winged blackbird, cape may warbler, tree sparrow, louisiana waterthrush, orange crowned warbler, green jay, white throated sparrow, least tern
CUB $\mathcal{B}'_2$	carolina wren, red legged kittiwake, cape glossy starling, magnolia warbler, glaucous winged gull, scarlet tanager, pelagic cormorant, yellow throated vireo, mangrove cuckoo, red breasted merganser, mallard, house sparrow, gadwall, acadian flycatcher, harris sparrow, northern waterthrush, american redstart, orchard oriole, parakeet auklet, swainson warbler, nelson sharp tailed sparrow, sage thrasher, brewer sparrow, tropical kingbird, boat tailed grackle, great crested flycatcher, american three toed woodpecker, bohemian waxwing, blue winged warbler, shiny cowbird, yellow warbler, loggerhead shrike, rock wren, green tailed towhee, white pelican, hooded warbler, winter wren, palm warbler, barn swallow, grasshopper sparrow, herring gull, yellow headed blackbird, crested auklet, common tern, painted bunting, horned grebe, green kingfisher, mourning warbler, nighthawk, california gull
CUB $\mathcal{B}'_3$	black billed cuckoo, brown thrasher, common yellowthroat, seaside sparrow, scissor tailed flycatcher, vesper sparrow, pomarine jaeger, forsters tern, indigo bunting, black footed albatross, brewer blackbird, scott oriole, kentucky warbler, least flycatcher, yellow billed cuckoo, myrtle warbler, song sparrow, laysan albatross, pileated woodpecker, bronzed cowbird, black throated blue warbler, purple finch, cedar waxwing, horned lark, brown creeper, sooty albatross, blue grosbeak, western grebe, ring billed gull, black and white warbler, blue jay, canada warbler, hooded merganser, lincoln sparrow, mockingbird, elegant tern, red bellied woodpecker, chuck will widow, rusty blackbird, baltimore oriole, sayornis, caspian tern, brandt cormorant, pied kingfisher, red cockaded woodpecker, cliff swallow, black throated sparrow, worm eating warbler, great grey shrike, whip poor will
CUB $\mathcal{B}'_4$	horned puffin, white necked raven, blue headed vireo, ovenbird, northern flicker, vermilion flycatcher, pine grosbeak, prairie warbler, pied billed grebe, florida jay, geococcyx, groove billed ani, olive sided flycatcher, western wood pewee, golden winged warbler, least auklet, eared grebe, red eyed vireo, clark nutcracker, tennessee warbler, gray catbird, american crow, bobolink, red headed woodpecker, white breasted kingfisher, baird sparrow, heermann gull, downy woodpecker, green violetear, pigeon guillemot, ivory gull, yellow breasted chat, brown pelican, summer tanager, american pipit, cactus wren, cerulean warbler, rufous hummingbird, long tailed jaeger, lazuli bunting, evening grosbeak, savannah sparrow, eastern towhee, red faced cormorant, anna hummingbird, cardinal, white eyed vireo, slaty backed gull, western gull, spotted catbird

Table 6. Details of the category partition for the Stanford Dogs and the CUB-200-2011 dataset.

Set	Category
Aircraft $\mathcal{A}'_1$	737-500, MD-11, BAE-146-300, 737-600, Metroliner, EMB-120, 747-200, Challenger-600, ERJ-135, 777-300, Falcon-2000, A340-500, MD-80, Gulfstream-IV, F-A-18, Cessna-172, ATR-72, 737-200, Spitfire, A321, ERJ-145, Saab-340, DHC-1, Boeing-717, An-12
Aircraft $\mathcal{A}'_2$	Fokker-70, Hawk-T1, E-170, A310, BAE-146-200, SR-20, 767-400, Tu-154, DC-9-30, DHC-8-300, CRJ-700, Eurofighter-Typhoon, DC-10, Fokker-100, 737-300, A330-200, Beechcraft-1900, DC-6, BAE-125, Cessna-208, A319, Falcon-900, A380, L-1011, Embraer-Legacy-600
Aircraft $\mathcal{A}'_3$	Cessna-525, 747-400, 767-300, Dornier-328, DR-400, A340-600, 737-800, Gulfstream-V, DC-3, 737-400, F-16A-B, ATR-42, 737-900, 747-100, DH-82, 777-200, A318, DC-8, Fokker-50, 727-200, CRJ-200, DHC-6, DHC-8-100, Model-B200, PA-28
Aircraft $\mathcal{A}'_4$	Tu-134, C-47, Cessna-560, Saab-2000, 757-200, E-190, A330-300, Il-76, A300B4, E-195, Yak-42, 747-300, A340-300, Tornado, 767-200, A340-200, Global-Express, C-130, 737-700, MD-90, 757-300, A320, 707-320, CRJ-900, MD-87

Cars $\mathcal{C}'_1$	buick verano sedan, chevrolet trailblazer ss, hyundai elantra touring hatchback, isuzu ascender suv, geo metro convertible, bentley continental gt coupe, bentley continental gt coupe, hummer h2 sut crew cab, dodge ram pickup 3500 crew cab, bmw x6 suv, hyundai accent sedan, land rover lr2 suv, mercedes benz sprinter van, lamborghini gallardo lp 570 4 superleggera, lamborghini reventon coupe, chevrolet sonic sedan, bmw activehybrid 5 sedan, chevrolet silverado 2500hd regular cab, toyota sequoia suv, dodge challenger srt8, hummer h3t crew cab, audi s4 sedan, hyundai elantra sedan, bmw 3 series sedan, jeep patriot suv, ford e series wagon van, jeep wrangler suv, mini cooper roadster convertible, dodge charger sedan, dodge caliber wagon, jeep compass suv, bmw 1 series coupe, audi tts coupe, chevrolet traverse suv, fiat 500 convertible, cadillac cts v sedan, toyota corolla sedan, mitsubishi lancer sedan, chrysler 300 srt 8, aston martin v8 vantage convertible, mercedes benz c class sedan, dodge journey suv, chevrolet tahoe hybrid suv, nissan leaf hatchback, jeep grand cherokee suv, chevrolet malibu sedan, bmw 1 series convertible, suzuki aerio sedan, spyker c8 coupe
Cars $\mathcal{C}'_2$	ford f 150 regular cab, bmw 6 series convertible, chevrolet corvette convertible, ford gt coupe, audi rs 4 convertible, acura rl sedan, infiniti qx56 suv, dodge magnum wagon, bmw m6 convertible, volvo c30 hatchback, bmw z4 convertible, tesla model s sedan, ford focus sedan, dodge dakota club cab, hyundai veracruz suv, gmc yukon hybrid suv, ferrari california convertible, eagle talon hatchback, fiat 500 abarth, toyota 4runner suv, bmw 3 series wagon, audi tt rs coupe, aston martin virage convertible, dodge durango suv, volkswagen golf hatchback, gmc canyon extended cab, spyker c8 convertible, volvo 240 sedan, bugatti veyron 16.4 coupe, rolls royce ghost sedan, chevrolet impala sedan, smart fortwo convertible, hyundai genesis sedan, mercedes benz s class sedan, acura tl sedan, chevrolet silverado 1500 classic extended cab, bugatti veyron 16.4 convertible, dodge caravan minivan, honda accord sedan, ford f 450 super duty crew cab, bentley arnage sedan, ford ranger supercab, audi s6 sedan, chrysler town and country minivan, bentley continental supersports conv. convertible, toyota camry sedan, mazda tribute suv, suzuki sx4 hatchback, dodge caliber wagon
Cars $\mathcal{C}'_3$	audi s4 sedan, chevrolet camaro convertible, nissan nv passenger van, chevrolet express cargo van, nissan juke hatchback, chrysler aspen suv, bmw x5 suv, bentley mulsanne sedan, hyundai tucson suv, volkswagen beetle hatchback, am general hummer suv, chevrolet avalanche crew cab, audi v8 sedan, dodge charger srt 8, mercedes benz 300 class convertible, chevrolet corvette zr1, gmc terrain suv, hyundai azera sedan, infiniti g coupe ipl, porsche panamera sedan, audi r8 coupe, fisker karma sedan, mercedes benz sl class coupe, hyundai sonata sedan, chevrolet express van, chevrolet hhr ss, ferrari 458 italia coupe, buick enclave suv, ram c v cargo van minivan, chevrolet corvette ron fellows edition z06, chevrolet silverado 1500 regular cab, hyundai veloster hatchback, nissan 240sx coupe, chevrolet cobalt ss, chevrolet silverado 1500 hybrid crew cab, aston martin v8 vantage coupe, ford mustang convertible, audi 100 wagon, ford freestar minivan, audi a5 coupe, bmw m3 coupe, ford expedition el suv, chevrolet monte carlo coupe, cadillac escalade ext crew cab, cadillac srx suv, dodge dakota crew cab, chevrolet silverado 1500 extended cab, dodge ram pickup 3500 quad cab, rolls royce phantom sedan
Cars $\mathcal{C}'_4$	ferrari ff coupe, volkswagen golf hatchback, volvo xc90 suv, lamborghini diablo coupe, audi s5 coupe, honda odyssey minivan, scion xd hatchback, chrysler sebring convertible, acura zdx hatchback, bmw m5 sedan, suzuki kizashi sedan, maybach landaulet convertible, bentley continental flying spur sedan, gmc savana van, suzuki sx4 sedan, audi 100 sedan, gmc acadia suv, ford edge suv, daewoo nubira wagon, hyundai santa fe suv, mclaren mp4 12c coupe, buick rainier suv, chrysler crossfire convertible, dodge durango suv, ferrari 458 italia convertible, aston martin virage coupe, ford fiesta sedan, chrysler pt cruiser convertible, plymouth neon coupe, honda accord coupe, acura tsx sedan, acura tl type s, hyundai sonata hybrid sedan, bmw x3 suv, lamborghini aventador coupe, rolls royce phantom drophead coupe convertible, buick regal gs, ford f 150 regular cab, mercedes benz e class sedan, audi tt hatchback, land rover range rover suv, dodge sprinter cargo van, acura integra type r, audi s5 convertible, jaguar xk xkr, honda odyssey minivan, lincoln town car sedan, jeep liberty suv, chevrolet malibu hybrid sedan

Table 7. Details of the category partition for the FGVC-Aircraft and the Cars dataset.