Counterfactual Attention Learning for Fine-Grained Visual Categorization and Re-identification Supplementary Material

A. More Visual Results

To have an intuitive understanding of our counterfactual attention learning method, we compare the attention maps of our models and the baselines models on CUB [3], Stanford Cars [1] and Aircraft datasets [2]. The more visual results are presented in Figure 1. We see our method helps the attention models make correct predictions by 1) reducing the misleading and scatter attentions and 2) encouraging the model to focus on the main clues for classification and explore more discriminative regions.

B. More Implementation Details

Different types of counterfactual attentions. We compared four different counterfactual attentions in our experiments. The details about how to generate them are described as follows.

- **Random Attention.** We use randomly generated attention maps as the counterfactual attentions. The attention value for each location is sampled from a uniform distribution $\mathcal{U}(0, 2)$.
- Uniform Attention. We simply set the attention value for each location to the average value of the real attention maps.
- **Reversed Attention.** We reverse the attention maps by subtracting the original attention from the maximal attention value of each sample.
- **Shuffle Attention.** We randomly shuffle the attention maps along the batch dimension.

Attention Regularization Strategy. We investigated several regularization strategies on the baseline attention model to verify the effectiveness of our method. The details about these regularization strategies are described as follows.

• Attention Dropout. We apply the Dropout method to the attention maps.

- Entropy Regularization. We add an extra term to the loss function to maximize the entropy of the attention maps.
- Attention Normalization. We add ℓ_2 normalization to the attention maps.

References

- Jonathan Krause, Michael Stark, Jia Deng, and Li Fei-Fei. 3d object representations for fine-grained categorization. In *ICCVW*, pages 554–561, 2013.
- [2] Subhransu Maji, Esa Rahtu, Juho Kannala, Matthew Blaschko, and Andrea Vedaldi. Fine-grained visual classification of aircraft. arXiv preprint arXiv:1306.5151, 2013. 1
- [3] Catherine Wah, Steve Branson, Peter Welinder, Pietro Perona, and Serge Belongie. The caltech-ucsd birds-200-2011 dataset. 2011. 1

Input Image	Baseline Attention	Our Attention	Input Image	Baseline Attention	Our Attention
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Baird Sparrow	Vesper Sparrow	Baird Sparrow	Kentucky Warbler	Blue winged Warbler	Kentucky Warbler
Frigatebird	Long tailed Jaeger	Frigatebird	Marsh Wren	Acadian Flycatcher	Marsh Wren
Mangrove Cuckoo	Gray Kingbird	Mangrove Cuckoo	Eared Grebe	Horned Grebe	Eared Grebe
Pomarine Jacquer	Slaty backed Gull	Pomarine Jaeger	Evening Grosbesk	American Goldfinch	Exercise Crosheak
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BMW X6 SUV 2012	BMW 3 Series Sedan 2012	BMW X6 SUV 2012	BMW Z4 Convertible 2012	BMW 6 Series Convertible 2007	BMW Z4 Convertible 2012
Geo Metro Convertible 1993	Ford Mustang Convertible 2007	Geo Metro Convertible 1993	Dodge Caliber Wagon 2012	Dodge Caliber Wagon 2007	Dodge Caliber Wagon 2012
Convertible 2007	Convertible 2010	Convertible 2007	Reventon Coupe 2008	Aventador Coupe 2012	Reventon Coupe 2008
Audi S5 Coupe 2012	Audi A5 Coupe 2012	Audi S5 Coupe 2012	Audi S5 Coupe 2012	Audi A5 Coupe 2012	Audi S5 Coupe 2012
737-300	737-400	737-300	A300B4	A310	A300B4
737-800	737-400	737-800	737-300	737-500	737-300

Figure 1: Visualization of the attention maps of our models and the baseline models. We see our method helps the attention models make correct predictions by 1) reducing the misleading and scatter attentions and 2) encouraging the model to focus on the main clues for classification and explore more discriminative regions. Best viewed in color.