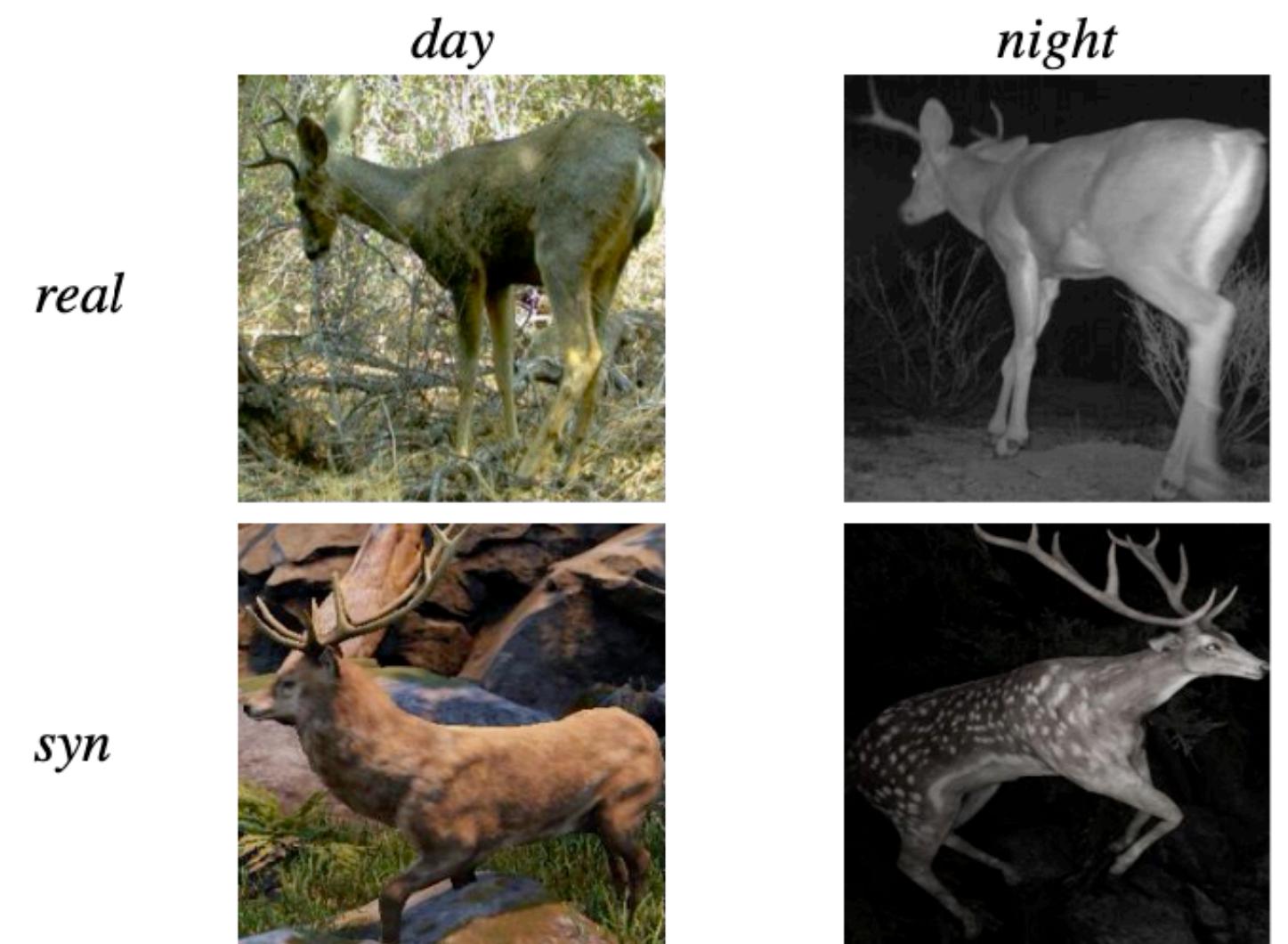


Image-to-Image Translation of Synthetic Samples for Rare Classes

I. Using synthetic data

- Camera-trap domain exhibits long-tailed distribution
- Rare classes are hard to classify
- Augment data with synthetic samples [1]
- Classification improves but there is still a visual gap
- Use *syn2real* image-to-image translation for a rare class to bridge this gap and measure the impact on classification.

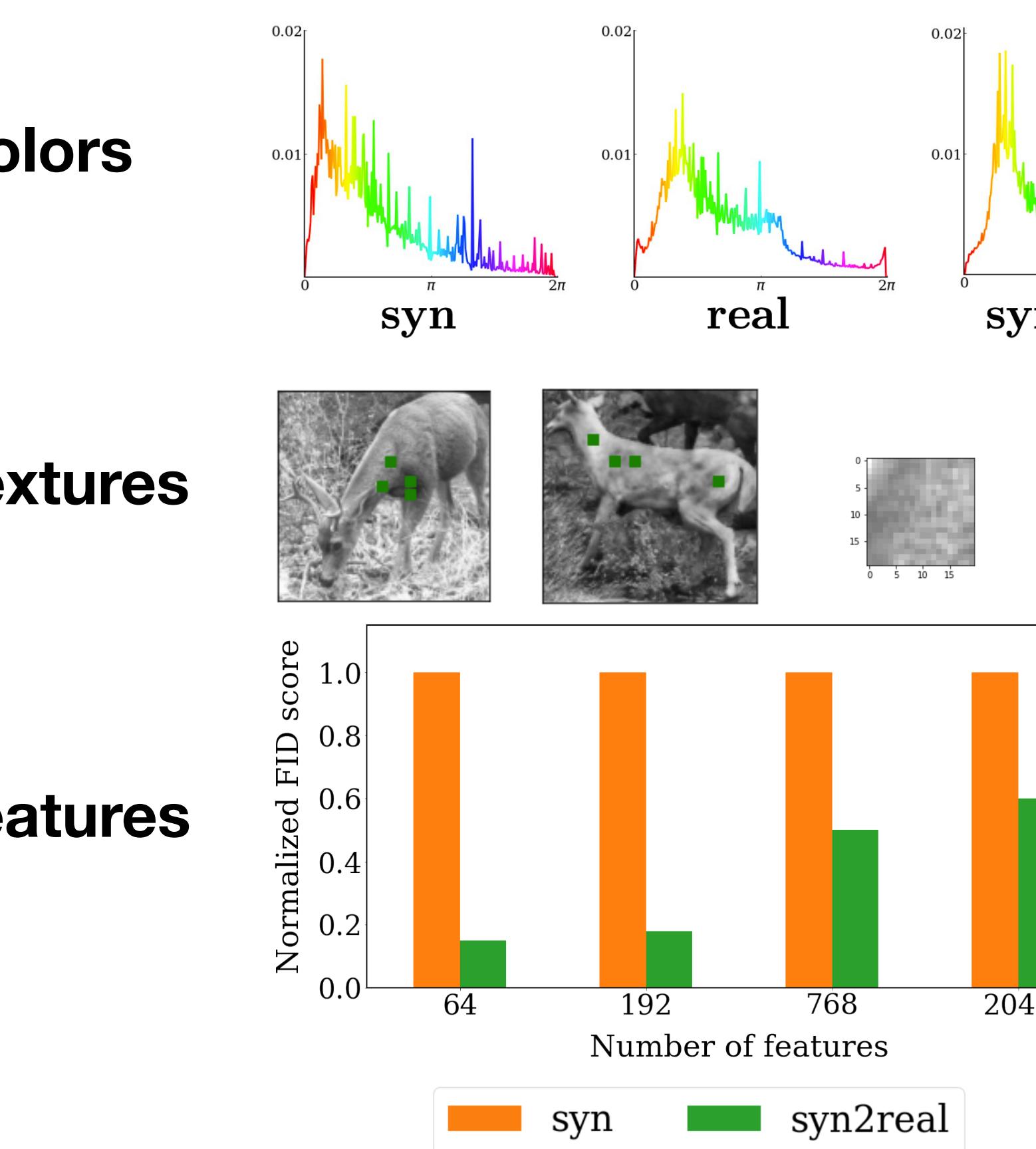


II. Learn the color statistics of different locations



We train UNIT [3] separately for day and night using the entire deer population (~5k samples) as target.

III. Measuring distance between synthetic and real



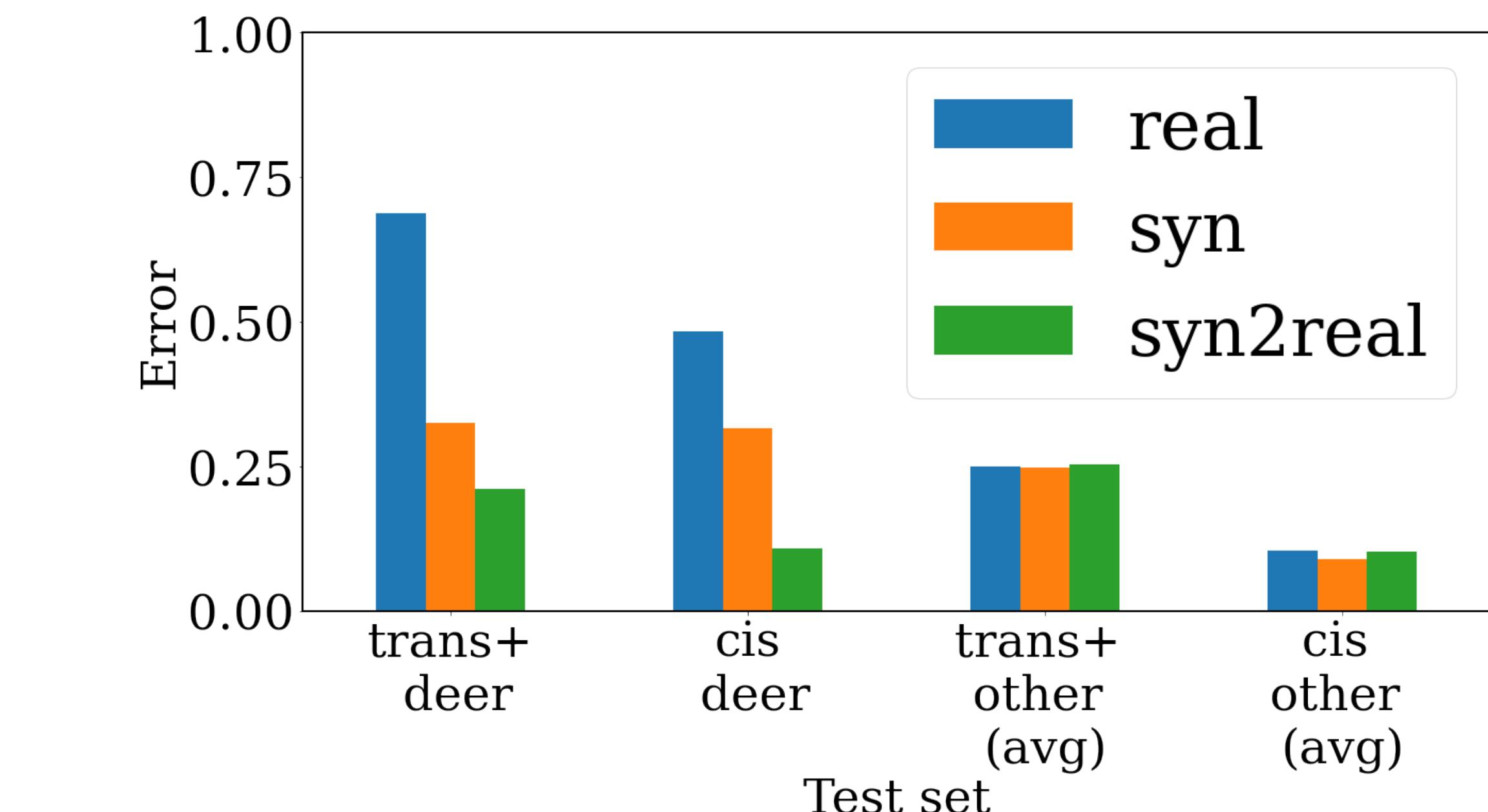
- The color distribution significantly changes while textures are slightly altered.
- The low-level features are more aligned after the translation.
- We can use the real training data from **other** categories to transfer *realness*.

IV. Transfer *realness* from other categories



With only 44 deer samples, we transfer *realness* using the entire training set, including all categories as our target domain.

V. Classification improvements



trans(+) : unseen locations (+ all deer)
cis : seen locations

- We augment with 10k *syn* samples, refine them in *syn2real*
- ***syn2real* compared to *syn* error rates:**
 - - 21% on *cis* test set on deer class
 - - 12% on *trans+* test set on deer class.
 - ± <1% in the average error rate of the other classes.

VI. Conclusion

- “Realness” can be learned using data from other categories
- Combining synthetic data augmentation with a *syn2real* step can considerably help the classification of the rare class

VII. References

- [1] Beery, Sara, et al. "Synthetic examples improve generalization for rare classes." WACV. 2020.
- [2] Beery, Sara, Grant Van Horn, and Pietro Perona. "Recognition in terra incognita." ECCV. 2018.
- [3] Liu, Ming-Yu, Thomas Breuel, and Jan Kautz. "Unsupervised image-to-image translation networks." NeurIPS. 2017.