Performance Variability in Zero-shot Classification

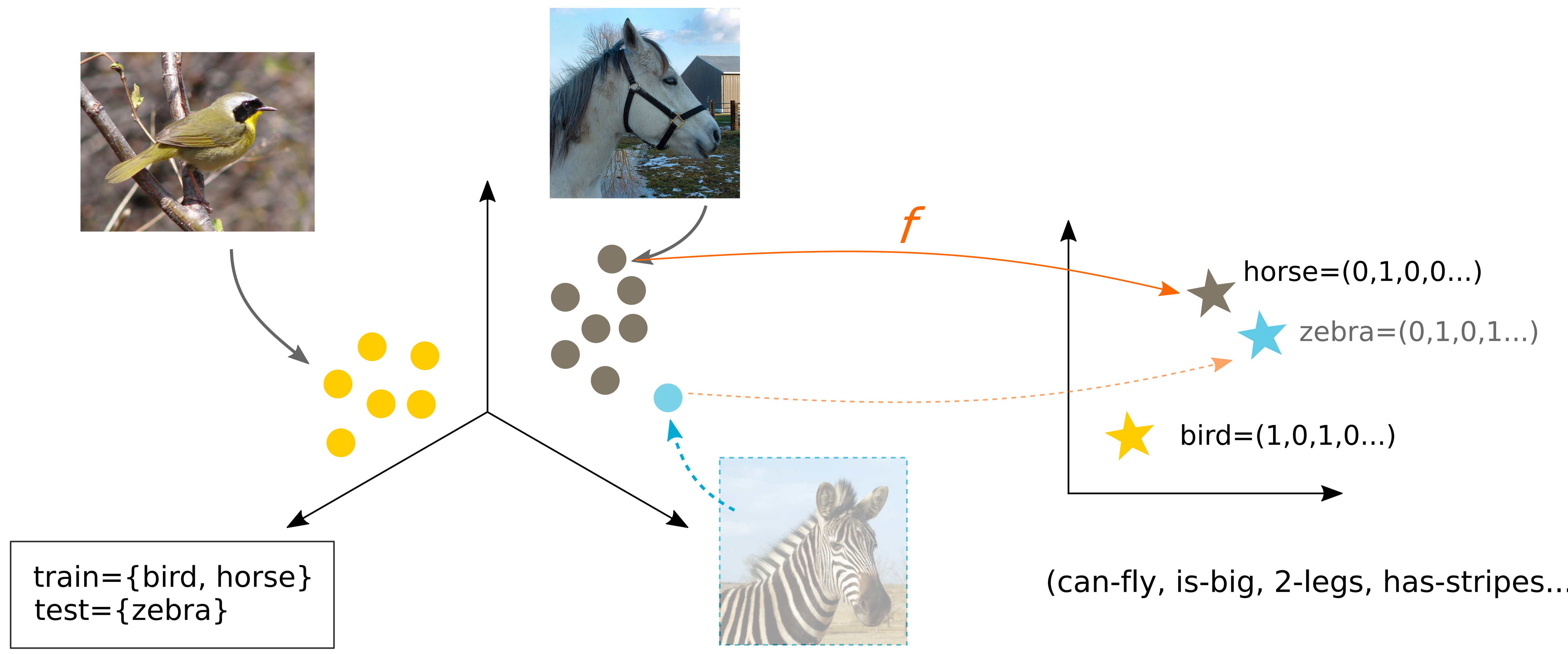
Matías Molina[1] · Jorge Sánchez[1,2]

[1] Universidad Nacional de Córdoba, Argentina. [2]CONICET

Motivation

Zero-shot classification (ZSC) is the task of learning predictors for classes not seen during training.

- How much does the ZSC performance vary over different class partitions?
- Is it enough to compare only the precisions to choose between one method or another?



Problem setup

Given a training set

$$\mathcal{D}^{tr} = \{(x_i, y_i) \mid x_i \in \mathcal{X}^{tr}, y_i \in \mathcal{Y}^{tr}\}$$

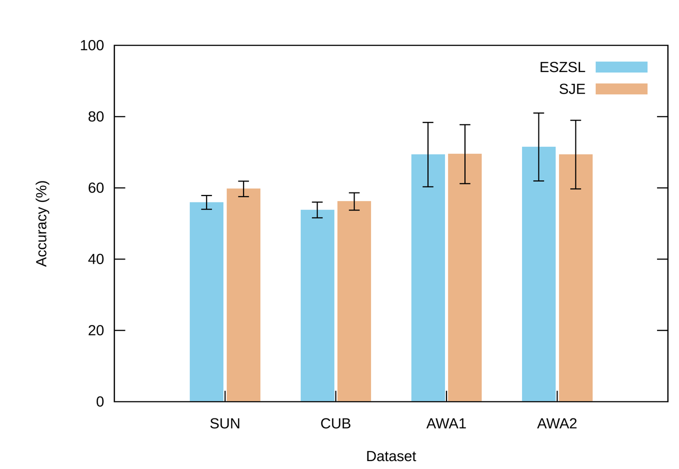
Goal:

- Learn $f : \mathcal{X} \to \mathcal{Y}$ from $\mathcal{D}^{tr}$
- Use f to classify images from a different set of categories $\mathcal{Y}^{ts}$. Where $\mathcal{Y}^{tr} \cap \mathcal{Y}^{ts} = \emptyset$

Variability Problem

Two ZSC methods: SJE and EZSL over 20+ train-test random partitions:

		SUN	CUB	AWA1	AWA2
Avg. acc.	ESZSL	55.90 (1.95)	53.49 (2.10)	69.66 (9.94)	71.10 (10.94)
	SJE	59.16 (2.37)	56.08 (3.03)	68.85 (7.96)	68.84 (11.16)
	p-value	0.000001	0.0012	0.7024	0.5028
Avg. per-class acc.	ESZSL	55.92 (1.94)	53.81 (2.20)	69.34 (9.02)	71.48 (9.54)
	SJE	59.73 (2.17)	56.19 (2.44)	69.48 (8.27)	69.34 (9.63)
	p-value	0.0000005	0.0000024	0.8736	0.1762

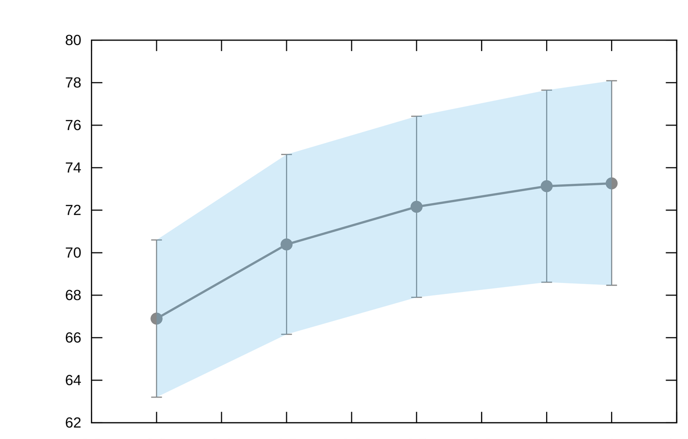


1. Strong performance variability (less in fine-grained datasets (CUB, SUN)).
2. The accuracy difference might bias the selection between the methods:
3. p-values (*Wilcoxon signed-rank test)*: for the fine-grained cases we can reject the null hypothesis.

Ensemble learning

Ensemble of n ESZSL models trained with a proportion s of the original training set. For $n = 90$:

	s 0.3	0.5	0.7	0.9	baseline
SUN	55.61 (2.16)	56.81 (2.02)	56.77 (1.98)	57.03 (1.73)	56.91 (1.63)
CUB	50.89 (2.92)	53.45 (2.84)	54.39 (2.84)	54.83 (2.72)	54.80 (2.82)
AWA1	65.35 (6.52)	68.38 (7.49)	69.70 (7.63)	70.52 (7.31)	70.62 (7.32)
AWA2	66.90 (3.70)	70.39 (4.23)	72.16 (4.26)	73.13 (4.52)	73.26 (4.81)



1. As the proportion s increases, the result approaches to the baseline.
2. The standard deviation may marginally decrease but with a considerable loss in performance (more noticeable in coarse-grained cases)
3. The use of ensemble does not lead to an increase on the overall ZSC performance.

Conclusions

1. The ZSC task suffers the problem of performance variability w.r.t the class partitions.
2. The accuracy difference might bias the selection between one model or another.
3. It is important to consider the variability to compare different methods.
4. The ensemble learning is not enough to reduce the variability without losing precision.
5. As general conclusion, we suggest to incorporate the variability to obrain a more comprehensive evaluation protocol in ZSC.

References

[1] Z. Akata, S. Reed, D. Walter, H. Lee, and B. Schiele. Evaluation of output embeddings for fine-grained image classification. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, 2015.

[2] B. Romera-Paredes and P. Torr. An embarrassingly simple approach to zero-shot learning. In *International Conference on Machine Learning*, pages 2152–2161, 2015.

[3] Y. Xian, C. H. Lampert, B. Schiele, and Z. Akata. Zero-shot learning-a comprehensive evaluation of the good, the bad and the ugly. *IEEE transactions on pattern analysis and machine intelligence*, 2018.