

A First Approach to Refine Semantic Spaces in Zero-Shot Learning with a Genetic Algorithm

J.J. Herrera , F. Herrera, I. Triguero

Department of Computer Science and Artificial Intelligence, University of Granada, Spain

Andalusian Research Institute in Data Science and Computational Intelligence (DaSCI)

juanjoa@ugr.es



Introduction

Abstract

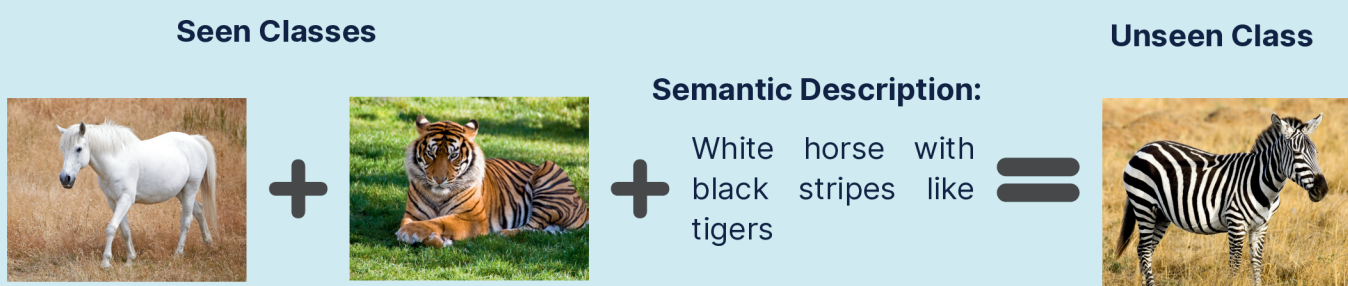
Leveraging the capabilities that **Evolutionary Computation** has recently offered in **GPAIS**, we propose a tailored genetic algorithm (**GAZeLa**) to perform feature selection in the semantic space, removing irrelevant features that negatively affect generalisation capabilities in the **Zero-Shot Learning** paradigm.

Previous Works

No contribution treats the **Semantic Space** to enhance model performance in the literature, except for one work. Nevertheless, it presents many inconveniences as the expert must choose, after applying test data, the correct approximation. In this work, we compare the results obtained using that approach (SVC-T3/T4 & RF-T3/T4) with our proposal.

Zero-Shot Learning

Zero-Shot Learning is a paradigm that allows us to perform a task, in this context, image classification, at the test stage **without being previously trained for it** by **transferring knowledge** from seen classes to unseen classes via the **Semantic Space**.



Semantic Spaces

	Love Bird Colourful: Yes Amphibian: No Bird: Yes Fish: No Wings: Yes Water: No Diet: Herbivorous		Axolotl Colourful: No Amphibian: Yes Mammal: No Bird: No Fish: No Wings: No Water: Yes Diet: Carnivorous		Cockatiel Colourful: No Amphibian: No Mammal: No Bird: Yes Fish: No Wings: Yes Water: No Diet: Herbivorous		Shark Colourful: No Amphibian: No Mammal: No Bird: No Fish: Yes Wings: No Water: Yes Diet: Carnivorous
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- It may be engineered-based or learned-based
- It may contain unnecessary information
- It may contain biases and errors

Experimental Framework

Datasets

- Animals with Attributes 2 (AWA2)
- Scene Understanding (SUN)
- Flowers with Attributes (FLO)
- Caltech-UCSD Birds-200-2011 (CUB)

Fitness Function

- Split the labeled data into pseudo-seen (PS) and pseudo-unseen (PU) subsets (disjoint)
- Semantic Autoencoder (SAE)
- Train the SAE on PS and use its accuracy on PU as the fitness measure, simulating real performance on unseen classes.

Methology



Selection Operator (SO)

p_1 = Select randomly from the Top k individuals of $\mathcal{P}$

$$p_2 = \underset{c \in \mathcal{P}}{\operatorname{argmax}} \left[\alpha \cdot d_{\mathcal{H}}(p_1, c) + (1 - \alpha) \cdot ||f(c)|| \right]$$

Trade-off Hamming Distance Fitness Function



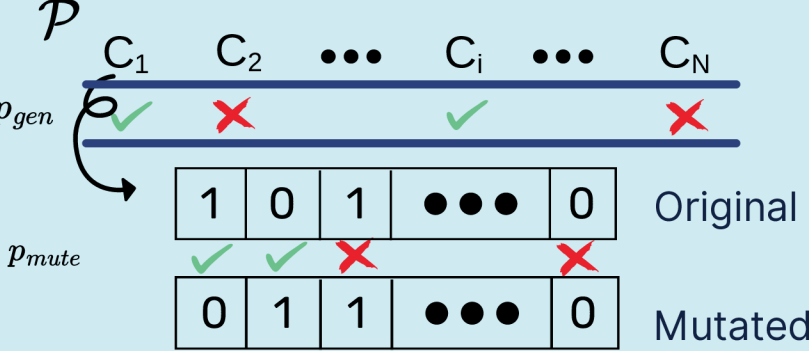
Crossover Operator (CO)

Binary Uniform Crossover Operator

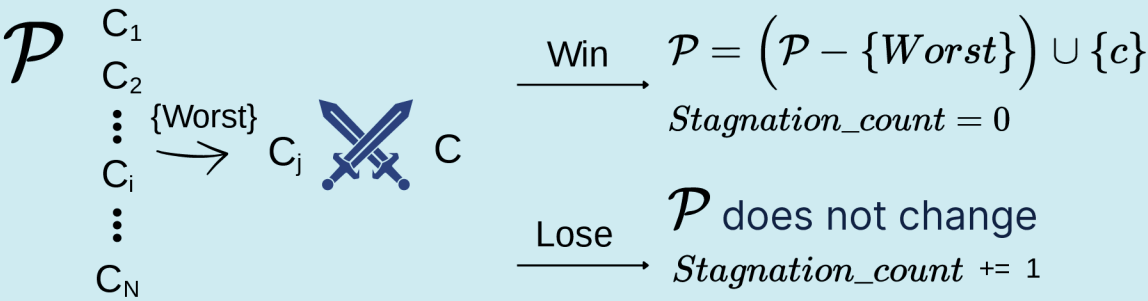
Parents	Offsprings
1 0 1 ... 0	1 0 1 ... 1
0 0 1 ... 1	0 0 1 ... 1



Mutation Operator (MO)



Replacement Operator (RO)



GAZeLa

Input: Population size N , Generations limit G , Mutation probability p_{mute} , Gen mutation probability p_{gen} , catastrophic replacement rate c_{rate} .

- 1: Initialize random seed and population
- 2: **while** generations do not reach G **do**
- 3: Select parents p_1, p_2
- 4: Generate offspring c_1, c_2
- 5: **if** p_{mute} **then**
- 6: Mutate c_1, c_2 via MO according to p_{gen}
- 7: **end if**
- 8: Insert c_1, c_2 into population
- 9: **if** stagnation in replacement detected **then**
- 10: Apply catastrophic mutation according to c_{rate}
- 11: **else if** stagnation in convergence detected **then**
- 12: Apply catastrophic mutation according to c_{rate}
- 13: **end if**
- 14: Update best solution
- 15: **end while**
- 16: **return** best semantic space's configuration



Init Population

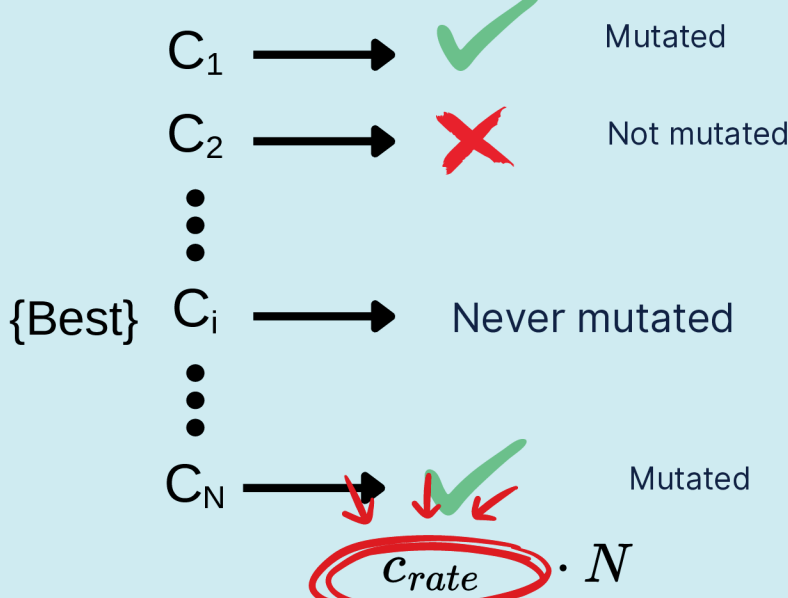
Individuals	Features	0	1	1	...	M-1	M
C_1		1	0	1	...	0	0
C_2		0	1	1	...	1	0
...					...		
C_N		1	1	1	...	1	1

Initialization uniformly across the number of features according to

$$g(i) = \lceil p_{min} * M \rceil + \left\lceil \frac{(1 - p_{min})M}{(N - 1)} i \right\rceil$$



Catastrophic Mutation Operator (CMO)

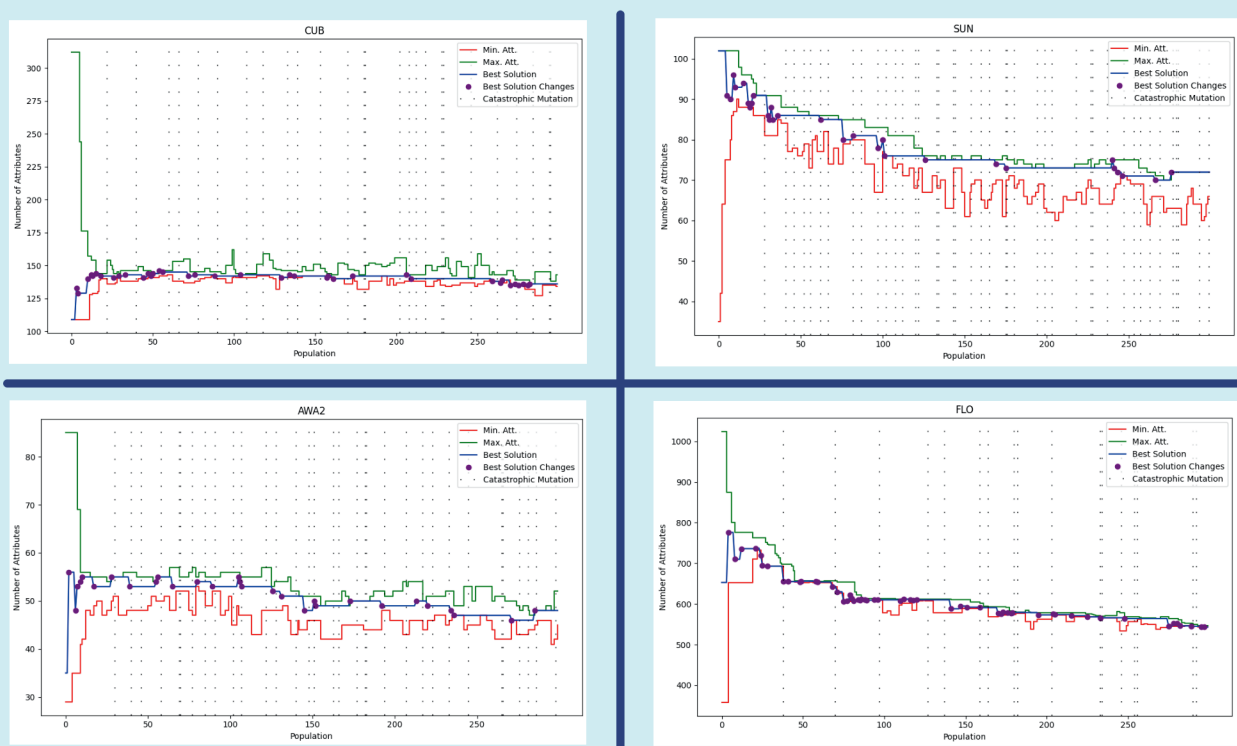


Results

Dataset	Baseline	RF-T3	RF-T4	SVC-T3	SVC-T4	GAZeLa
AWA2	40.364	42.525	42.639	42.260	42.158	44.168
SUN	38.819	38.681	38.681	39.681	39.236	42.500
CUB	33.468	34.446	35.356	34.580	34.783	40.007
FLO	34.892	34.026	32.814	36.450	35.152	36.797

Dataset	Atts	RF-T3	RF-T4	SVC-T3	SVC-T4	GAZeLa
AWA2	85	-11.76%	-24.71%	-5.88%	-8.24%	-16.47%
SUN	102	-0.98%	-3.92%	-1.96%	-1.96%	-30.39%
CUB	312	-17.95%	-37.82%	-9.29%	-16.35%	-56.41%
FLO	1024	-7.42%	-33.40%	-53.61%	-74.02%	-46.88%

Convergence



Conclusion

- GAZeLa significantly surpasses the other approach
- A considerable reduction of the semantic space is achieved
- Premature convergence

Future Works

- Refine GAZeLa by promoting a better exploration
- Integrate GAZeLa in the GZSL paradigm