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Label dependent evolutionary feature weighting for remote sensing data

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- 1. *Introduction***
- 2. *Data description and preprocessing***
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Introduction

- ***Remote sensing is useful for resource management, environmental monitoring, disaster response...***
- ***Land Use and Land Cover maps (LULC) are one of the main products obtained from remote sensing knowledge***
- ***LULC maps provide knowledge about the functional and morphological characteristics of the land. It is therefore, a classification problem***
- ***Several techniques have been used to develop LULC maps satisfactorily (k-NN, Naive Bayes, SVM, etc.)***
- ***Some researches have started to exploit optimization techniques for improve results***



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Introduction

- ***Evolutionary computation is widely used to improve prediction models by weighting***
- ***There are basically three main areas of weighting application in supervised machine learning:***
 - Support vector machines optimization,
 - Artificial neural networks (training and topology),
 - Feature weighting
- ***We apply an evolutionary algorithm to search optimal weights for each feature depending on the label***
- ***The same weights are applied to all features in most existing methods***
- ***This work shows that the importance of each feature can depend on the class to predict***



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- ***The data for this study belongs to the north of Galizia (Spain)***
- ***The data was obtained from fusion of sensors: LIDAR (Light Detection and Ranging) + orthophotograph***
- ***LIDAR is a laser-based sensor technology to determine distance to an object or surface***
- ***Orthophotograph is an aerial photograph geometrically corrected such that the scale is uniform***



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- ***Every instance has 61 basic statistics from:***
 - LIDAR data: height and intensity
 - Image data: red band, green band and blue band
- ***Every instance has 5 classes: road, farming land, middle vegetation, high vegetation and buildings***
- ***Three different filters are executed:***
 1. Each missing value is replaced with the average value of the corresponding feature
 2. Data is standardized
 3. Correlation Feature Selection method (CFS) is applied in order to reduce the search space (18 features are selected)



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Algorithm

- ***The goal of the proposed evolutionary algorithm is to find an optimal set of weights to improve the classification process***
- ***This set of weights depends on each label and it makes a linear space transformation***
- ***After the evolutionary execution the classification process is performed in two steps:***
 - The weights are applied to the training instances according to its label
 - Given a test instance, the label of the transformed nearest neighbour is chosen



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Algorithm

- ***Build the initial population of individuals***
- ***Evaluate the fitness of each individual and save the best individual***
- ***Repeat until termination***
 - Select several individuals for reproduction according to a criterion
 - Create new individuals through crossover and mutation operations
 - Evaluate the fitness of new individuals and save the best individual
 - Replace the population with new individuals

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Algorithm – Initial population

An individual is a matrix which represents the weights per label for every feature

$$\begin{bmatrix} w_{11} & \cdots & w_{1f} \\ \vdots & \ddots & \vdots \\ w_{b1} & \cdots & w_{bf} \end{bmatrix}$$

where there are b rows (number of different labels), and f columns (number of features)

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Algorithm – Crossover and mutation

- **Given two individuals selected by roulette-wheel method, the i^{th} row of one is crossed with the i^{th} row of the other one**
- **Two rows are crossed by two ways:**
 - **Uniform crossover:** selection of a weight from one parent at random
 - **BLX- α crossover :** If w_1 and w_2 are the i^{th} weight from each parent, the new weight is a real number randomly selected in the interval $[W_{\min} - I\alpha, W_{\max} + I\alpha]$, where:

α = positive real number,

$$W_{\max} = \max(w_1, w_2),$$

$$W_{\min} = \min(w_1, w_2),$$

$$I = W_{\max} - W_{\min}$$



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Algorithm – Crossover and mutation

- ***The mutation operator increases or decreases the value of a weight according to a probability p . The increase (or decrease) is a random value Δ that satisfies:***

$$\Delta = \frac{r}{10^z}, \text{ where :}$$

$$r \in \mathbb{R} : [0 \leq r \leq 1] \text{ and}$$
$$z \in \mathbb{Z} : [0 \leq z \leq n]$$

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W is the matrix
$$\begin{bmatrix} w_{11} & \cdots & w_{1f} \\ \vdots & \ddots & \vdots \\ w_{b1} & \cdots & w_{bf} \end{bmatrix}$$

```
1: fitness=0
2: for  $i = 1$  to  $m$  do
3:   We divide  $P$  into  $n$  bags:  $B_1, \dots, B_n$ 
4:   for all bag  $B_k$  do
5:     We apply the  $W$  transformation to every point from the remaining  $n - 1$  bags,
       obtaining the set of points  $P'$ 
6:     for all point  $p_i$  in  $B_k$  do
7:       for all label  $l \in \{1..b\}$  do
8:         We construct the tranformed point  $p_i^l$  so that  $p_{ij}^l = w_{lj} * p_{ij}$ 
9:         We calculate  $d_l =$  minimum distance from  $p_i^l$  to the points of  $P'$ 
10:        We apply the  $W$  transformation to  $p_i$  according to its label, and we add it
           to  $P'$ 
11:      end for
12:      We calculate the minimum from the distances  $d_l$ . Let  $h \in \{1..b\}$ , the label of
         the point of  $P'$  which makes  $d_l$ .
13:      if the label of  $p_i \neq h$  then
14:         $fitness = fitness + 1$ 
15:      end if
16:    end for
17:  end for
18: end for
```

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- **Evolutionary algorithm setup:**
 - Population of 20 individuals
 - 100 generations
 - 20% of mutation probability
- **Testing:**
 - Competitors: Naive Bayes, SMO, Nearest Neighbour, Multilayer Perceptron
 - Stratified 3 x 10-fold cross-validation
 - Friedman test, in which the null hypothesis is that all classifiers have the same performance

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Results

Algorithm	Error
Naive Bayes	0.15
SMO	0.14
Nearest Neighbour	0.13
Neural Network	0.10
Weighted-Nearest Neighbour	0.10

Table 1: Averaged error rate for each studied algorithm

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Results

Class	Features			
Road	MINSNDVI	PEC	IMAX	HCV
Farming Land	IMEAN	IGMEAN	HMAX	HCV
Middle Vegetation	HSTD	IGKURT	MINSNDVI	IGVAR
High Vegetation	IMAX	IRVAR	IGVAR	IGMEAN
Buildings	IGKURT	PCT32	EMP	MINSNDVI

H*: height statistic, I*: Intensity statistic, IG*: Intensity green band stat., IR*: Intensity red band stat., *SNDVI: Simulated Normalized Difference Vegetation Index stat., PEC: Penetration coef., PCT32: Percentage third or later returns over second returns, EMP: Empty pixels that surrounds the current pixel

Table 1: **Most important features according to its weight for the study zone.**



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Conclusions

- ***We have presented a simple method to transform the feature space***
- ***Different weights are assigned to every feature depending on each class***
- ***The results showed an improvement of the 3% on the Nearest Neighbour, and resemble the results of the best competitor***
- ***We provide valuable information about the importance of each feature in order to distinguish among the different classes***
- ***The accuracy improvement and the algorithm definition as an independent preprocessing method, is the aim of future work***

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Thanks for your patience !

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