SPPAM - Statistical PreProcessing Algorithm
An approach for the classification of multiple correlated data

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Abstract
Most machine learning tools work with a single table where each row is an instance and each column is an attribute. Each cell of the table contains an attribute value for an instance. This representation prevents one important form of learning, which is, classification based on groups of correlated records, such as multiple exams of a single patient, internet customer preferences, weather forecast or prediction of sea conditions for a given day. To some extent, relational learning methods, such as inductive logic programming, can capture this correlation through the use of intensional predicates added to the background knowledge. In this work, we propose SPPAM, an algorithm that aggregates past observations in one single record. We show that applying SPPAM to the original correlated data, before the learning task, can produce classifiers that are better than the ones trained using all records.

Keywords: multi-relational data, classification, data preprocessing.

1 Introduction
Machine learning techniques have been successfully applied to various domains. However there is a lack of formal methodology and application of machine learning tools to datasets that are characterized by subgroups of correlated records. Examples are medical records with multiple exams of a single patient, internet customer preferences, weather forecast and prediction of sea conditions, among others. Despite the fact that there are many applications that fall into this category, there is also a lack of available datasets with this characteristic in the main UCI machine learning repository (http://archive.ics.uci.edu/ml).

Machine learning tools usually learn classifiers from a single table where each row is an instance and each column is an attribute. Each cell of the table contains an attribute value for an instance. Most of these tools treat each row of this table as independent from each other, which prevents one important form of learning based on groups of correlated records. Tools based on first order logic (inductive logic programming) can partially overcome this problem because they can do multi-relational learning. But first order rules in the form of intensional predicates need to be added to the background knowledge, in order to code the multi-relational meaning intended by the observer [1].

When dealing with data that have this multi-relational characteristic, one additional problem arises when using cross-validation. Ideally, records that belong to the same observation period need to be manually separated in a way that all records of a certain period falls into just one fold. Machine learning tools like WEKA [2], for example, do not allow training based on pre-defined folds (unless when using the percentage split training option).

In this work, we propose a general method that connects records that are correlated (either through the same location or observation period). To the best of our knowledge, this is the first work that tackles this problem.

We propose SPPAM (Statistical PreProcessing Algorithm), an algorithm that aggregates past observations in one single record. We apply SPPAM to two datasets of surf conditions. Our task is to learn a classifier that predicts well if a certain beach is adequate for surfing in a certain day. We perform our experiments using the WEKA machine learning tool and compare the performance of various WEKA algorithms trained on the original datasets and on the SPPAM-transformed datasets. We show that applying SPPAM to the original correlated data, before the learning task, can produce classifiers that are better than the ones trained using the original datasets with all records.

Some work has been done on characterizing relations from weather observations and forecasts using machine learning techniques. For example, Ingsrisawan et al. used support vector machines, decision trees and neural networks to develop models to predict rainfall occurrences in Thailand [4]. Lai et al. proposed a preprocessing technique for weather data in order to predict temperature and weather conditions [5]. Williams et al. proposed the use of Random Forests to predict and classify storm forecastings [3]. However, we are not only interested in temporal patterns nor pure weather forecast. Our goal is to provide a generic preprocessing technique that increase the classification task’s performance for every suitable dataset.

This paper is organized as follows. In Section 2 we describe the SPPAM algorithm. In Section 3 we discuss the methodology used to run our experiments and present the
datasets. In Section 4, we present and discuss our results. Finally, in Section 5, we draw our conclusions and give perspectives of future work.

2 An approach to classify multiple correlated data

SPPAM is a two-step algorithm that captures the hierarchical aspect of learning from a dataset with multiple records for the same observation period (or location). The first step is to separate and consolidate records that belong to the same time/location interval. The user needs to provide the name of the attribute that will be used to perform this separation and the name of the class attribute. We also assume that each record has a unique identifier. We use a transformation that maps several records into just one record along with a transformation on the original attributes. The algorithm can be seen in Algorithm 1.

Data:
Dataset, //original dataset
Result:
Out, //original dataset transformed
Initialize a new empty dataset Out;
Read Dataset;
foreach Attribute a in Dataset do
  if a has type Numeric then
    create Attributes a-Maximum, a-Minimum,
    a-Average and a-Last on Out;
  else if a is Nominal then
    create Attributes a-Frequency for each nominal value and a-Last on Out;
  else
    copy a to Out;
end
Group correlated records according to the user provided field;
foreach Group i do
  read each individual attribute value A;
  if A has type String or is the ID then
    copy A to Out;
  end
  if A has type numeric then
    calculate Maximum, Minimum, Average and Last values among all values of A for group i;
    copy them to Out;
  end
  if A is nominal then
    copy frequency and the last value of A in group i to Out;
end
Take the value of the class variable of last instance of Group i;
Copy it to Out to complete the record
end

Algorithm 1: The SPPAM algorithm

This basic version of the algorithm maps groups of records of each observation to just one record by computing aggregates for the values of the attributes. But what to do with the class variable? In this algorithm, we keep the last class value of the group (i.e., the most recent observation).

Figures 1 and 2 illustrate an example of this transformation.

Figure 1: Original dataset

```
@ATTRIBUTE Date STRING
@ATTRIBUTE Wind_Knots numeric
@ATTRIBUTE Wind_Dir {N, NE, E, SE, S, SW, W, NW}
@ATTRIBUTE Surf {0,1}
@DATA
18-11-2010,15.6,SE,0
18-11-2010,9.7,SE,0
18-11-2010,3.9,SE,0
18-11-2010,5.8,NE,0
19-11-2010,11.7,NE,0
19-11-2010,15.6,NE,0
19-11-2010,13.6,E,1
19-11-2010,15.6,E,1
```

Figure 2: SPPAM-transformed dataset

```
@ATTRIBUTE Date STRING
@ATTRIBUTE Wind_Knots_MAX numeric
@ATTRIBUTE Wind_Knots_MIN numeric
@ATTRIBUTE Wind_Knots_AVG numeric
@ATTRIBUTE Wind_Dir_LAST numeric
@ATTRIBUTE Wind_Dir_NW_PERC NUMERIC
@ATTRIBUTE Wind_Dir_NE_PERC NUMERIC
@ATTRIBUTE Wind_Dir_E_PERC NUMERIC
@ATTRIBUTE Wind_Dir_SE_PERC NUMERIC
@ATTRIBUTE Wind_Dir_S_PERC NUMERIC
@ATTRIBUTE Wind_Dir_SW_PERC NUMERIC
@ATTRIBUTE Wind_Dir_N_PERC NUMERIC
@ATTRIBUTE Wind_Knots_AVG NUMERIC
@ATTRIBUTE Wind_Knots_MIN NUMERIC
@ATTRIBUTE Wind_Knots_MAX NUMERIC
@ATTRIBUTE Date STRING
@DATA
18-11-2010,15.6,3.9,8.75,5.8,0.0,25.0,0.0,75.0,0.0,0.0,0.0,0.0,NE,0
19-11-2010,15.6,11.7,14.3,15.6,0.0,50.0,0.0,0.0,0.0,0.0,0.0,0.0,E,1
```
on the transformed data, because it is nominal and it has eight values plus the last observed value. The first unfolded value corresponds to the frequency of occurrence of the first value on that observation group. The second, to the frequency of occurrence of the second value and so on.

The total number of attributes on the transformed dataset is given by the equation

\[ 1 + s + 4n + \sum_{i=1}^{w} (V(w_i) + 1) \]

where \( s \) is the number of String attributes on the original dataset, \( n \) is the number of numeric attributes on the original dataset, \( w \) is the number of nominal attributes and the function \( V(w) \) is the number of values of the nominal attribute \( w \), for all non-class attributes.

The number of records on the transformed dataset is equal to the number of different unique ids on the original datasets, in our example the id is the date attribute.

After this preprocessing task, the second step is to feed the new table (transformed dataset) to a machine learning algorithm, like any other dataset.

Although we are dealing with meteorological data, the method above described is fully applicable to any kind of relational data where various records are related to the same individual.

### 3 Methodology and Applications

We applied our algorithm to two datasets. The first one is the Surf - Praia Grande dataset which has 10 attributes, 5 of them numeric, 4 nominal and 1 string. This dataset contains four daily observations of wind and sea conditions taken from the Praia Grande beach, Portugal, between November 18th 2010 and January 6th 2011, in the total of 192 instances. The 10 attributes are: date, hour, total sea height, wave height, wave direction, wind wave height, wind speed, wind direction, water temperature and wave set quality to practice surf. This last attribute is our class which can have 2 different values: 0 and 1, where 0 means that the weather and sea conditions are not good for surf practice, and 1 means that there are good conditions to surf.

The second dataset is the Surf - Aljezur and it has the same structure (data were collected at the same period of time as Praia Grande). The attributes and number of instances are the same as the Surf - Praia Grande.

Table 1 shows the detailed structure of the original datasets to be transformed by the SPPAM algorithm. A summary of the transformations on both datasets is shown in Table 2.

For both datasets, the number of attributes generated by SPPAM is 44 (which follows from equation 1) and the number of instances is 48 (the number of different observation days).

After applying our algorithm to the datasets, we performed learning experiments using the WEKA tool, developed at Waikato University, New Zealand. The experiments were performed in WEKA using the Experimenter module, where we set several parameters, including the statistical significance test and confidence interval, and the algorithms we wanted to use (we used OneR as reference, ZeroR, PART, J48, SimpleCart, DecisionStump, Random Forests, SMO, Naive Bayes, Bayes with TAN, NBTree and DTNB). The WEKA experimenter produces a table with the performance metrics of all algorithms with an indication of statistical differences, using one of the algorithms as a reference. The significance tests were performed using standard corrected t-test with a significance level of 0.01. The parameters used for the learning algorithms are the WEKA defaults. For all experiments we used 10-fold stratified cross-validation and report results for the test sets.

### 4 Results

We compared the results obtained in WEKA using our preprocessing method SPPAM with the results obtained with the original datasets. In tables 3 and 4 we present the performance obtained by the WEKA algorithms for both the original dataset and the SPPAM transformed dataset for Surf - Praia Grande and Surf - Aljezur. We show the results obtained for Percentage of Correctly Classified Instances (CCI), Kappa Statistic (Kappa), Precision (Precis.), Recall and F-Measure (F-Meas.). We show the performance for each class and the averaged performance for both classes. Our best results with SPPAM are highlighted on both tables. We also present charts showing the average performance gain between the correctly classified instances average for the SPPAM datasets and for the original datasets on all classification algorithms.

#### 4.1 Praia Grande dataset results

For this particular dataset, our best results were obtained using Bayesian Networks (using the TAN and K2 search algorithms), Naive Bayes and DTNB, as shown in Table 4. Naive Bayes is the algorithm that yields the best performance when training with the SPPAM-transformed datasets, for every metric.

In Figure 3 we show graphically the differences between the correctly classified instances percentage average for the original dataset and the SPPAM-preprocessed dataset for the Praia Grande data for all the machine learning algorithms we tested. The values are in percentage.

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**Table 1: Original Surf - Praia Grande and Original Surf - Aljezur attributes**

| Attribute       | Type         | Values                        |
|-----------------|--------------|-------------------------------|
| Date            | String       |                                |
| Hour            | Nominal      | 0, 6, 12, 18                  |
| Wave Total      | Numeric      |                                |
| Wave            | Numeric      |                                |
| Wave Direction  | Nominal      | N, NE, E, SE, S, SW, W, NW    |
| Vega            | Numeric      |                                |
| Wind Speed      | Numeric      |                                |
| Wind Direction  | Nominal      | N, NE, E, SE, S, SW, W, NW    |
| Water temperature| Numeric      |                                |
| Sets            | Nominal (Class) | 0, 1                           |

**Table 2: Original and SPPAM-transformed datasets summary**

| Dataset         | # Instances | Class = 0 | Class = 1 |
|-----------------|-------------|-----------|-----------|
| Sintra          | 192         | 77 (39%)  | 117 (61%) |
| Sintra SPPAM    | 48          | 18 (38%)  | 30 (62%)  |
| Aljezur         | 192         | 88 (25%)  | 144 (75%) |
| Aljezur SPPAM   | 48          | 9 (19%)   | 39 (81%)  |

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Table 3: Transformed Surf - Praia Grande results

| Algorithm          | Original Dataset | SPPAM transformed dataset |
|-------------------|-----------------|---------------------------|
|                  | CCI% Kappa Prec. Recall F-Meas. | CCI% Kappa Prec. Recall F-Meas. |
| Bayes Net(K2)     | 51.00 0.34 0.67 0.76 0.70 | 76.15 0.50 0.66 0.74 0.66 |
| Bayes Net(TAN)    | 50.24 0.34 0.67 0.76 0.70 | 75.93 0.49 0.65 0.73 0.65 |
| Naive Bayes       | 50.43 0.34 0.67 0.76 0.70 | 76.15 0.49 0.65 0.73 0.65 |
| SMO               | 50.43 0.34 0.67 0.76 0.70 | 76.15 0.49 0.65 0.73 0.65 |
| Decision Stump    | 50.43 0.34 0.67 0.76 0.70 | 76.15 0.49 0.65 0.73 0.65 |
| J48               | 50.43 0.34 0.67 0.76 0.70 | 76.15 0.49 0.65 0.73 0.65 |
| NB Tree           | 50.43 0.34 0.67 0.76 0.70 | 76.15 0.49 0.65 0.73 0.65 |
| Random Forest     | 50.43 0.34 0.67 0.76 0.70 | 76.15 0.49 0.65 0.73 0.65 |
| Simple CART       | 50.43 0.34 0.67 0.76 0.70 | 76.15 0.49 0.65 0.73 0.65 |
| DTNB              | 50.43 0.34 0.67 0.76 0.70 | 76.15 0.49 0.65 0.73 0.65 |
| PART              | 50.43 0.34 0.67 0.76 0.70 | 76.15 0.49 0.65 0.73 0.65 |
| ZeroR             | 50.43 0.34 0.67 0.76 0.70 | 76.15 0.49 0.65 0.73 0.65 |
| OneR              | 50.43 0.34 0.67 0.76 0.70 | 76.15 0.49 0.65 0.73 0.65 |

4.2 Aljezur dataset results

With this dataset we achieved even better results. The use of SPPAM before the training task improved the classification performance on almost all analyzed metrics. In some cases, we get 10% gain on the correctly classified instances percentage. These results were statistical significant for BayesNet using K2 and TAN, SimpleCart, ZeroR, SMO and DTNB. For the metrics where the results were not improved (Naive Bayes and DTNB), the difference is not significant.

In Figure 4 we show the difference between the averages of correctly classified instances percentage for the original dataset and the SPPAM-preprocessed dataset for the Aljezur dataset. Here we can see graphically how better in average, the classification algorithms can correctly classify new instances using our method. The values are also in percentage.

5 Conclusions and Future Work

In this work, we proposed a simple, general solution to the problem of learning classifiers for multiple correlated data such as multiple exams of a single patient, internet customer preferences, weather forecast, sea prediction, among others. SPPAM, a Statistical PreProcessing Algorithm, takes the original dataset containing related data, and produces a new dataset with all correlated data aggregated using metrics such as maximum, minimum, average, etc. We tested SPPAM on two datasets that contain records associated according to a date. We used WEKA to train on the original datasets and on

Figure 3: Delta between average CCI% Praia Grande and Praia Grande SPPAM

Figure 4: Delta between average CCI% Aljezur and Aljezur SPPAM
the SPPAM-transformed dataset. Our results indicate that the SPPAM transformation can produce better classifiers than the ones trained on the original dataset.

In its present form, SPPAM has already shown its potential, but we have been working on modifications to the basic algorithm in order to improve performance even further. We also have been working on applying SPPAM to medical datasets that contain multiple records for a single patient.

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