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# LEARNING TO PREDICT FOREST FIRES WITH DIFFERENT DATA MINING TECHNIQUES

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## ABSTRACT

The motive for this study was to learn to predict forest fires in Slovenia using different data mining techniques. We used predictive models based on the forest structure GIS (geographical information system), the weather prediction model - Aladin and MODIS satellite data. We examined three different datasets: one for the Kras region, one for Primorska region and one for continental Slovenia because of the climate differences. On these datasets we applied logistic regression and decision trees (J48), as well as random forests, bagging and boosting of decision trees, in order to obtain predictive models of fire occurrence. Best results in terms of predictive accuracy were obtained by bagging decision trees.

## 1 INTRODUCTION

Forest fires cause significant material damage in the natural environment followed by violation of the functions in the natural systems and large number of fires is caused by humans, although other factors like drought, wind, topography, plants etc., have important indirect influence on fire appearance and its spreading. Fire threats are increasing by processes of abandonment of farmland and gradual growth of forest (increasing the fire fuel) and growth of recreation in the natural environment.

Fire prevention is a very important way of reducing the damage that can appear if fire occurs. The estimation of fire movement is important for fire prevention, organization of prevention measures and optimal storage of firefighting resources. An important tool for fire movement estimation is modeling the relations between the fire threat and the influence factors, because these areas are more determined by the partial stressed factors. These types of models can be developed in GIS (Geographical Information System). GIS is a computer system capable of capturing, storing, analyzing, and displaying geographically referenced

information; that is, data identified according to location.

There are already two systems operating in Slovenia that evaluate the possibility of fire threat in the natural environment: one operated by the Forest Institute of Slovenia and the other by Slovenian environment agency, but spatial and temporal over-generalization, and in part also outdated input of GIS data are the main problematic issues with these systems. It is possible to improve the models by enhancing the layers of the input data for the influence factors (GIS part), by increasing the thematic and spatial details, as well as including a database of past fires. Improvements of the quality and relevance of the model are possible in technical moderated data that includes statistical modeling as well as machine learning methods for model building beside the domain knowledge.

The intention of this work is to improve the existing models by including GIS, ALADIN (Aire Limitée Adaptation dynamique Développement InterNational), MODIS (Moderate-resolution Imaging Spectroradiometer) data and the models for prediction of the stand height and canopy cover [12] and extending their validity to the whole territory of Slovenia.

The rest of the paper is structured as follows. In section 2 we explain the data used in the research. Section 3 describes the data mining techniques used to build the predictive models of fire outbreaks. In section 4 we explain the experimental setup and in section 5 we present and discuss the results. Section 6 gives the conclusions and future work.

## 2 DESCRIPTION OF THE DATA

In this study we apply data mining techniques and compare their performance (accuracy, precision, recall.) to three datasets that contain data from different regions of Slovenia: Kras region in western

Slovenia, Primorska region and the continental part of Slovenia. The idea is to predict the fire occurrence based on this data.

The descriptive data is divided into 3 groups:

- GIS data (geographic data, part of the land with forest, field, urban part, distance from roads, highways, railways, cities etc.)
- Multitemporal MODIS data with dependence from the day of the year (average temperature for specific quadrant for specific day, average net primary production for specific day)
- Meteorological ALADIN data (temperature, humidity, sun energy, evaporation, speed, direction and course of the wind, transpiration etc.)

The spatial measure used was 1x1 km<sup>2</sup> quadrant, and every spatial and time attribute was adjusted to this resolution.

The GIS data contains time independent attributes for every quadrant. The attributes describe the following GIS properties: ID for every quadrant in Slovenia, median of altitude above sea level, median of the grade of relief in gradients referred to DMR100, modus of exposition of the relief referred to DMR100, distance of roads, distance of cities, distance of railways (if the values are above 15.000 m, 15.000 m is assumed), share of specific land usage in a quadrant (e.g. fields, gardens, forests, buildings and others).

From NASA archives (MODIS satellite) we obtained public data of temperature of the land and net primary production of plants for the period of 5 years (2000 - 2004) with spatial resolution of 1 km and time resolution of 8 days. Multitemporal satellite MODIS data, implicitly give information about the response of the vegetation in periods of drought and the types of fire fuels. The data is time dependent of the day of the year. The MODIS attributes describe the following properties: average temperature in Kelvins for a specific quadrant for the day x of the year (we have 46 values and temperatures for every 8 days. x takes the values of 1, 9, 17, 25, ..., 361), average net primary production for a specific quadrant for the day x of the year.

The ALADIN data contains meteorological predictions of the weather. They are issued daily from the Environmental Agency of the Republic of Slovenia. The data includes weather prediction for every 3 hours (00.00-21.00 UTC) of 10 weather attributes. The attributes are: atmospheric precipitation, sun radiation energy, velocity and direction and gust of wind, evapotranspiration, transpiration, evaporation, relative humidity and temperature. For the three hours of

weather data we decided to study the time interval from 12.30 to 15.30. This particular time interval was selected because of the great danger of fire at these hours, as shown from the Aladin data, given in UTC time (winter/summer season is not a factor). An average daily prediction is added to help in removing the noisy data. All of the 10 parameters were averaged for 1, 2, 4 and 14 days.

For the Kras region we also used 3D data of vegetation from LIDAR and LANDSAT images. This data contains attributes that describe the height and structure of vegetation of the Kras region. The values of the attributes were calculated from the LANDSAT and were calibrated with LIDAR. All the data are aggregated on km quadrants and have resolution of 25 x 25 m. The LANDSAT based data describe the following forest properties: average tree canopy height, forest canopy cover, maximum height of the vegetation above the ground, height above the ground that reaches some percentage (99%, 95%, 75%, 50%) of forest biomass. For every attribute we obtain 4 statistic measures – minimum, maximum, average and standard deviation on 1km quadrant.

For building predictive models of forest fires we need positive and negative examples of fire occurrence. Positive examples of fires are locations in the past, where we have noticed the fire occurrence along with the date and hour. Negative examples are represented by an equal number of points with random time stamps and randomly located within the areas at least 15 km away from any positive example detected in timestamp  $\pm 3$  days [11]. This algorithm gives precedence to the area that had smaller probability of fire occurrence in a defined period. Locations of the positive and negative examples of fire occurrence were spatially and temporally linked to the descriptive data. The data for locations of fire occurrences (positive examples) were obtained from the Administration for Civil Protection and Disaster Relief of Slovenia and the Forestry Institute.

### 3 DATA ANALYSIS METHODOLOGY

The data were analyzed with several different data mining algorithms for classification implemented in WEKA data mining system [4]. We used: logistic regression, random forests, decision trees (J48), bagging and boosting ensemble methods.

Logistic regression is part of a category of statistical models called generalized linear models [6]. Logistic regression allows prediction of a discrete outcome, such as group membership, from a set of variables that

may be continuous, discrete, dichotomous, or a mix of any of these. Generally, the dependent or response variable is dichotomous, such as presence/absence or success/failure. There are two main uses of logistic regression. The first is the prediction of group membership. Since logistic regression calculates the probability of success over the probability of failure, the results of the analysis are in the form of an odds ratio. Logistic regression also provides knowledge of the relationships and strengths among the variables.

Random forest [10] is an ensemble of unpruned classification or regression trees, induced from bootstrap samples of the training data, using random feature selection in the tree induction process. Prediction is made by aggregating (majority vote for classification or averaging for regression) the predictions of the ensemble. Random forest generally exhibits a substantial performance improvement over the single tree classifier.

J48 algorithm [4] is an implementation of the C4.5 decision tree learner [5]. The algorithm for induction of decision trees uses the greedy search technique to induce decision trees for classification. There are many parameters which can be tuned in order to obtain better models with respect to the accuracy (or other parameters which can be used as measure for the quality of the model). These parameters allow greater control of the user in the process of learning the models.

Often multiple versions of a classifier give better results than the individual base classifier, because of combining the advantages of the individual classifiers in the final (aggregated) classifier. The simplest way to do the “aggregation” in the case of classification is to take a vote (perhaps a weighted vote); in the case of numeric prediction, it is to calculate the average (perhaps a weighted average).

Bagging predictors [7] is a method for generating multiple versions of a predictor (making bootstrap replicates of the learning set and using these as new learning set) and using them to get an aggregated predictor. In bagging all models receive equal weight. Bagging produces very accurate probability estimates from decision trees and other powerful, yet unstable, classifiers. However, a disadvantage is that bagged classifiers are hard to analyze.

Boosting is based on the observation that finding many rough rules of thumb can be a lot easier than finding a single, highly accurate prediction rule [8]. The boosting algorithm calls this “weak” or “base” learning algorithm repeatedly, each time feeding it a different subset of the training examples (or, to be more precise,

a different distribution or weighting over the training examples). Each time it is called, the base learning algorithm generates a new weak prediction rule, and after many rounds, the boosting algorithm must combine these weak rules into a single prediction rule that, hopefully, will be much more accurate than any one of the weak rules. When using boosting there are two fundamental questions: how should choose each distribution on each round and how the weak rules should be combined into a single rule. There is also the question of what to use for the base learning algorithm.

Widely used method for boosting is AdaBoost [9]. AdaBoost calls a given weak or base learning algorithm repeatedly in a series of rounds. One of the main ideas of the algorithm is to maintain a distribution or set of weights over the training set. Initially, all weights are set equally, but on each round, the weights of incorrectly classified examples are increased so that the base learner is forced to focus on the hard examples in the training set.

## 4 EXPERIMENTAL SETUP

As it was described in Section 2 the purpose of this study is to learn predictive models of forest fires outbreaks. The experiments are performed on three datasets for different regions of Slovenia: Kras, Primorska and continental Slovenia. The Kras dataset contains 159 attributes and has 1439 examples. The Primorska dataset has 129 attributes and 2442 examples. The third dataset for continental Slovenia has 129 attributes and 8476 examples. For all datasets the target attribute is nominal and predicts the possibility of fire occurrence (0-no, 1- yes). For conducting the experiments we used WEKA [4] data mining system. Several algorithms were used in the experiments: logistic regression, random forests, J48 (WEKA’s implementation of decision trees), bagging and boosting of trees.

All of the methods were used with the default parameters. Ensemble methods were run in 10 iterations. The validation of the models was done using 10 fold cross – validation.

## 5 RESULTS AND DISCUSSION

In this section, we present the results we obtained from the experiments. In Tables 1-3 we present the performances of the experiments in terms of precision, recall, accuracy and kappa statistics for each of the datasets respectively. Precision and recall in this case

are calculated for the class 1 (fire occurrence=yes). Kappa statistics is used to evaluate the agreement between predicted and observed nominal values in one dataset, while correcting for agreement that occurs by chance.

Algorithm	Precision	Recall	Accuracy	Kappa
Logistic reg.	0.696	0.563	0.772	0.461
Random F.	0.751	0.585	0.797	0.517
J48	0.639	0.652	0.761	0.465
Bagging	<b>0.754</b>	0.652	<b>0.812</b>	<b>0.560</b>
Boosting	0.725	<b>0.658</b>	0.790	0.520

**Table 1 Performances of DM algorithms on Kras data**

Algorithm	Precision	Recall	Accuracy	Kappa
Logistic reg.	0.826	0.849	0.834	0.668
Random F.	0.820	<b>0.903</b>	0.852	0.703
J48	0.810	0.810	0.809	0.618
Bagging	<b>0.850</b>	0.878	<b>0.860</b>	<b>0.721</b>
Boosting	0.839	0.867	0.856	0.712

**Table 2 Performances of DM algorithms on Primorska data**

Algorithm	Precision	Recall	Accuracy	Kappa
Logistic reg.	0.831	0.855	0.840	0.679
Random F.	0.823	<b>0.877</b>	0.843	0.703
J48	0.809	0.819	0.812	0.624
Bagging	<b>0.846</b>	0.856	<b>0.849</b>	<b>0.698</b>
Boosting	0.842	0.855	0.844	0.688

**Table 3 Performances of DM algorithms on continental Slovenia data**

From the results we can conclude that Bagging of decision trees shows the best results in terms of predictive accuracy, precision and kappa statistics compared to the other algorithms.

## 6 CONCLUSION AND FUTURE WORK

In this work we built predictive models of forest fires. The models were based on GIS, MODIS and Aladin data. The experimental results showed that bagging of decision trees gives the best results in terms of accuracy for all three datasets. In further work we

would like to use some feature selection algorithms and try to extract the relevant features and try to further improve the accuracy of the models.

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