Classification Model for Hotspot Occurrences Using Spatial Decision Tree Algorithm

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ABSTRACT

Developing a predictive model for forest fires occurrence is an important activity in a fire prevention program. The model describes characteristics of areas where fires occur based on past fires data. It is essential as an early warning system for preventing forest fires, thus major damages because of fires can be avoided. This study describes the application of data mining technique namely decision tree on forest fires data. We improved the ID3 decision tree algorithm such that it can be utilized on spatial data in order to develop a classification model for hotspots occurrence. The ID3 algorithm which is originally designed for a non-spatial dataset has been improved to construct a spatial decision tree from a spatial dataset containing discrete features (points, lines and polygons). As the ID3 algorithm that uses information gain in the attribute selection, the proposed algorithm uses spatial information gain to choose the best splitting layer from a set of explanatory layers. The new formula for spatial information gain is proposed using spatial measures for point, line and polygon features. The proposed algorithm has been applied on the forest fire dataset for Rokan Hilir district in Riau Province in Indonesia. The dataset contains physical data, socio-economic, weather data as well as hotspots and non-hotspots occurrence as target objects. The result is a spatial decision tree with 276 leaves with distance from target objects to the nearest river as the first test layer and the accuracy on the training set of 87.69%. Empirical result demonstrates that the proposed algorithm can be used to join two spatial objects in constructing a spatial decision tree from a spatial dataset. The algorithm results a predictive model for hotspots occurrence from the real dataset on forest fires with high accuracy on the training set.

Keywords: Spatial ID3 Algorithm, Spatial Information Gain, Forest Fires, Hotspots Occurrence

1. INTRODUCTION

Forest fires in various parts in Sumatera and Kalimantan, Indonesia occur every year especially in dry season. This phenomenon causes many negative effects in various aspects of life such as natural environment, economic and health. Forest fire is considered as a regional and global disaster because its effects influence not only people in local areas but also those who live in neighbouring countries such as Malaysia and Singapore. Fire prevention has an important role in minimizing the damage due to forest fires. An early warning system as one of the activities in fire prevention needs to be developed in order to assess forest fire risks.

Many studies have been conducted in developing wildfire risk models by integrating Geographical Information Systems (GISs) and remote sensing. Spatial operations in GISs have widely applied to analyze causes

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of fires and their relationships as well as to produce fire risk maps. The GIS-based method of Complete Mapping Analysis (CMA) is applied in (Boonyanuphap *et al.*, 2001) to create the wildfire risk model for the area of Sasamba in East Kalimantan in Indonesia. A model of forest fire hazard in East Kalimantan in Indonesia using the remote sensing technique integrated with the GIS has been constructed in (Darmawan *et al.*, 2001). In other studies, GISs and remote sensing are used to analyze forest fire data to create forest fires risk models for some regions in Indonesia (Hadi, 2006; Danan, 2008). The method Complete Mapping Analysis (CMA) in (Hadi, 2006) and Multi-criteria Analysis (MCA) in (Danan, 2008) are also applied to analyse the fire risk factors and relations between the factors. A-GIS-based peat swamp forest fire hazard model that integrates Analytical Hierarchy Process (AHP) and GIS analysis was developed for the region Pekan in Pahang Malaysia (Setiawan, 2007). The model is based on five parameters: fuel type, road proximity, elevation, slope and aspect, which influence the occurrence and spread of forest fires. A GIS is utilized in fire hazard modeling and mapping of fire hazard rating in peat swamp forest of Penor/Kuantan District of Pahang in Malaysia (Sheriza, 2007). The data used in this work include fuel types, roads and canals.

Studies about forest fire risks may include huge spatial data including physical, climate and socio-economic data. The data are stored in spatial databases in GISs. Spatial databases contain large number of spatial features and their relationships for further manipulation and analysis to help users in decision making process. Criteria evaluation and weighting methods, such as Complete Mapping Analysis (CMA) and Multi-criteria Analysis (MCA), are most applied to evaluate small problems containing few criteria. This situation has lead to the increasing in applying data mining techniques to extract interesting spatial patterns from large spatial data. Data mining tasks including association rules mining, classification and prediction, as well as cluster analysis have been successfully employed to analyse spatial data related to forest fires (Tay *et al.*, 2003; Stojanova *et al.*, 2007; Yu and Bian, 2007; Kalli and Ramakrishna, 2008; Hu *et al.*, 2009).

Extracting interesting and useful patterns from spatial datasets is more difficult than those from traditional numeric and categorical data because spatial data types are complex (Shekhar *et al.*, 2004). Furthermore, extracting patterns from spatial datasets includes spatial relationships and spatial autocorrelation (Shekhar *et al.*, 2004). Classical data mining methods do not support locations of objects or relationships between objects that implicitly exist in a spatial dataset (Zeitouni,

2000). Therefore the methods cannot be utilized to discover knowledge from spatial datasets. Locations of objects determine relations of the objects to its neighbours. According to Koperski *et al.* (1998), there are three types of relation to relate an object to its neighbor, i.e., topological-relations, metric-relations and direction-relations. In order to handle spatial data and the relations to its neighbors that implicitly exist in the spatial data, new data mining methods need to be developed. One of the spatial data mining algorithms that has been introduced in many studies is spatial classification. Spatial classification methods broaden non-spatial classification methods by involving attributes of neighboring objects and their spatial relations in addition to attributes of the objects to be classified (Koperski *et al.*, 1998; Ester *et al.*, 1997). In a spatial classification task, we want to extract rules that split a spatial dataset consisting of classified objects into a number of classes based on non-spatial and spatial properties, as well as spatial relations of the classified objects to other objects (Koperski *et al.*, 1998; Ester *et al.*, 2000; Zeitouni and Chelghoum, 2001).

In this study, we extend the ID3 decision tree algorithm (Quinlan, 1986) for a non-spatial dataset such that the algorithm can be applied on a spatial dataset containing point, line and polygon features. The proposed algorithm uses information gain for spatial data, namely spatial information gain, to choose a layer as the splitting layer. Instead of using number of tuples in a partition, spatial information gain is calculated using spatial measures. Our study adopts the formula for spatial information gain as described in (Rinzivillo and Turini, 2004). The spatial measure formula is extended for the geometry type of points, lines and polygons rather than only for polygons as in (Rinzivillo and Turini, 2004). The proposed algorithm was applied to the forest fires dataset containing physical, socio-economic and weather data as well as hotspots occurrence for Rokan Hilir district in Riau Province in Indonesia.

2. MATERIALS AND METHODS

2.1. Dataset and Study Area

The dataset for modeling hotspots occurrence contains spread and coordinates of hotspots in 2008, physical, socio-economic, as well as weather data. The study area is Rokan Hilir district in Riau Province in Indonesia (**Fig. 1**). Hotspots and physical data are obtained from Ministry of Environment Indonesia and National Land Agency (BPN) Riau Province respectively.
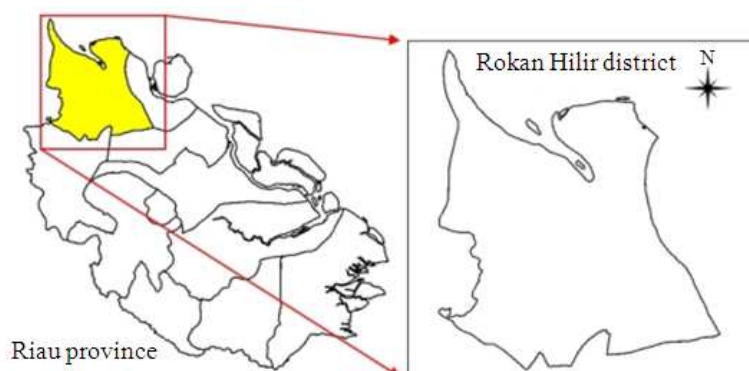
Fig. 1. Area of study

Socio-economic data are collected from Statistics-Indonesia (BPS). Weather data of 2008 including precipitation (mm/day), screen temperature (K), 10m wind speed (m/s) and surface height (m) are gathered from Meteorological Climatologically and Geophysical Agency (BMKG) Indonesia. There are two categories of data: spatial and non-spatial data. Non spatial data are socio-economic data for villages in Rokan Hilir which are represented in the DBF format. The data include population density and inhabitant's income source and number of schools. For mining purpose using the spatial decision tree algorithm, these non spatial data were converted to spatial data in the shp format by involving the shp files for administrative borders of villages and subdistricts in Rokan Hilir. Spatial data include physical (roads, rivers land cover and city centers) and weather data (precipitation, screen temperature, 10m wind speed and surface height). We assign the spatial reference system UTM 47N and datum WGS84 to all data. Preprocessing was conducted for hotspots occurrence to generate target objects, as well as for physical and socio-economic data. Data preprocessing is important to improve the quality of the data, thereby it can improve the accuracy of the resulted model as well as efficiency of data mining process. Moreover, we performed spatial interpolation using Cokriging method for weather data that are originally represented in the Net CDF format.

2.2. Spatial Relationships

Determining spatial relationships between two features is a major function of a Geographical Information System (GIS). Spatial relationships include topological (Egenhofer and Franzosa, 1991) such as overlap, touch and intersect as well as metric such as distance. For example, two different polygon features may be either overlap, touch, or intersect each other. Spatial relationships make spatial data mining algorithms differ from non-spatial data mining algorithms. Spatial relationships are implemented by an extension of the well-known join indices (Valduriez, 1987). The result of join index between two relations is a new relation consisting of indices pairs each referencing a tuple of each relation. The pairs of indices refer to objects that meet the join criterion. The structure Spatial Join Index (SJI) as an extension of the join indices (Valduriez, 1987) in the relational database framework is introduced in (Zeitouni *et al.*, 2000). Join indices can be handled in the same way as other tables and manipulated using the standardized SQL query language (Zeitouni *et al.*, 2000). In addition to two columns of object identifiers, a SJI has a third column that contains spatial relationship between two layers. Our study adopts the concept of SJI as in (Zeitouni *et al.*, 2000) to store relations between two different layers in a spatial database. Instead of spatial relationship that may be either numerical or Boolean value, the quantitative values in the third column of SJI are spatial measures of features resulted from spatial relationships between two layers.

We consider an input for the algorithm a spatial dataset as a set of layers L. Each layer in L is a collection of spatial objects and has only one of the following geometric types: polygons or lines or points. Assume that each object in a layer is uniquely identified. Let L is a set of layers; L_i and L_j are two distinct layers in L. A spatial relationship applied to L_i and L_j is denoted $SpatRel(L_i, L_j)$ that can be topological relation or metric relation. For the case of topological relation, $SpatRel(L_i, L_j)$ is a relation according to the dimension extended method proposed by (Clementini *et al.*, 1993). Meanwhile, for the case of metric relation, $SpatRel(o_i, o_j)$ is a distance relation proposed by (Ester *et al.*, 2001), where o_i is a spatial object in L_i and o_j is a spatial object in L_j.

Relations between two layers in a spatial dataset can result quantitative values such as distance

between two points or an intersection area of two polygons. We denote these values as spatial measures as in (Rinzivillo and Franco, 2004) which is used in calculating spatial information gain in the proposed algorithm. For the case of topological relation, the spatial measure of a feature is defined as follows. Let L_i and L_j in a set of layers L, $L_i \neq L_j$, for each feature r_i in R = SpatRel(L_i, L_j), a spatial measure of r_i denoted by SpatMes(r_i) is defined as:

- Area of r_i, if $< L_i$ in $L_j >$ or $< L_i$ overlap $L_j >$ hold for all features in L_i and L_j represented in polygons
- Count of r_i, if $< L_i$ in $L_j >$ holds for all features in L_i represented in points and all features in L_j represented in polygons

For the case of metric relation, we define a distance function from p to q as dist(p, q), distance from a point (or line) p in L_i to a point (or line) q in L_j.

Spatial measure of R is denoted by SpatMer(R) and defined as Equation 1:

$$
\begin{aligned}
SpatMes(R) &= f(SpatMes(r_1) \\
SpatMes(r_2)&,\ldots,SpatMes(r_n))
\end{aligned}
\tag{1}
$$

for r_i in R, i = 1, 2, …, n and n number of features in R. f is an aggregate function that may be either sum, min, max or average.

A spatial relationship applied to L_i and L_j in L results a new layer R. We define a Spatial Join Relation (SJR) for all features p in L_i and q in L_j as follows (Equation 2):

$$
\begin{aligned}
SJR = \{(p, \ &SpatMes(r),q \,|\, r \text{ is a} \\
&\text{feature in R associated to } p \text{ and } q\}
\end{aligned}
\tag{2}
$$

2.3. An Extended ID3 Algorithm for Spatial Data

A spatial dataset is composed of a set of layers in which all features in a layer have the same geometry type. This study considers only discrete features including points, lines and polygons. There are two groups of layers: explanatory layers and one target layer (or reference layer) where spatial relationships are applied to construct a set of tuples. The target layer has some attributes including a target attribute that store target classes. Each explanatory layer has several attributes. One of the attributes is a predictive attribute that classify tuples in the dataset to target classes. In this study the target attribute and predictive attributes are categorical. Features (polygons, lines or points) in the target layer are related to features in explanatory layers to create a set of tuples in which

each value in a tuple corresponds to value of these layers. Two distinct layers are associated to produce a new layer using a spatial relationship. A relation between two layers produces a spatial measure (Equation 1) for the new layer. Spatial measures are used in the formula for spatial information gain.

Building a spatial decision tree follows the basic learning process in the algorithm ID3 (Quinlan, 1986). The ID3 calculates information gain to define the best splitting layer for the dataset. In the spatial decision tree algorithm, we define spatial information gain to select an explanatory layer L that gives best splitting the spatial dataset according to values of predictive attribute in the layer L. For this purpose, as in (Rinzivillo and Turini, 2004), we apply the spatial measure (Equation 1) to the formula.

Let a dataset D be a training set of class-labelled tuples. In the non-spatial decision tree algorithm, we calculate probability that an arbitrary tuple in D belong to class C_i and it is estimated by $|C_{i,D}|/|D|$ where $|D|$ is number of tuples in D and $|C_{i,D}|$ is number of tuples of class C_i in D (Han and Kamber, 2001). In this study, a dataset contains some layers including a target layer which stores class labels. All objects in the target layer are represented in points. Number of tuples in the dataset is the same as number of objects in the target layer because each tuple is created by relating features in the target layer to features in explanatory layers. One feature in the target layer associates with exactly one tuple in the dataset. For simplicity we use number of objects in the target layer instead of using number of tuples in the spatial dataset in the formula of spatial entropy (Equation 3). Furthermore, in a non-spatial dataset, target classes are discrete-valued and unordered (categorical) and explanatory attributes are categorical or numerical. In spatial dataset, features in layers are represented in a particular geometric type (polygons, lines or points) that have quantitative measurements such as area and distance. Therefore we calculate spatial measures of layers (Equation 1) to replace number of tuples in a non-spatial dataset.

2.4. Entropy

Let a target attribute C in a target layer S has l distinct classes (i.e., c_1, c_2, …, c_l), entropy for S represents the expected information needed to determine the class of tuples in the dataset and defined as Equation 3:

$$
H(S) = -\sum_{i=1}^{l} \frac{SpatMes(S_{c_i})}{SpatMes(S)} \log_2 \frac{SpatMes(S_{c_i})}{SpatMes(S)}
\tag{3}
$$

SpatMes(S) represents the spatial measure of layer S as defined in (Equation 1).

Algorithm: **Generate_SDT (Spatial Decision Tree)**
Input:
    a.   Spatial dataset D, which is a set of training tuples and their associated class labels. These tuples are constructed from a set of layers, **P**, using spatial relations.
    b.   A target layer S ∈ **P** with a target attribute C.
    c.   A non empty set of explanatory layers **L** ⊆ **P** and L ∈ **L** has a predictive attribute V. **P = S ∪ L**.
    d.   Spatial Join Relation (SJR) on the set of layers **P**, SJR(**P**), as defined in (2).
Output: A Spatial Decision Tree
Method:
  1   Create a node N;
  2   **If** only one explanatory layer in **L** then
  3   return N as a leaf node labeled with the majority class in D;   // majority voting
  4   **endif**
  5   **If** objects in D are all of the same class c then
  6   return N as a leaf node labeled with the class c;
  7   **endif**
  8   Apply **layer_selection_method**(D, **L**, SJR(**P**)) to find the "best" splitting layer, L*;
  9   Label node N with L*;
 10   Split D according to the best splitting layer L* in {D(v₁), …, D(vₘ)}. D(vᵢ) is outcome i of splitting layer L* and vᵢ, …,vₘ are possible values of predictive attribute V in L*;
 11   **L = L − {L*}**;
 12   **for each** D(vᵢ), i = 1, 2, …, m, do
 13   let Nᵢ = **Generate_SDT**(D(vᵢ), **L**, SJR(**P**));
 14   Attach node Nᵢ to N and label the edge with a selected value of predictive attribute V in L*.
endfor.

Fig. 2. Extended ID3 decision tree algorithm (Sitanggang *et al.*, 2011)

Let an explanatory attribute V in an explanatory (non-target) layer L has q distinct values (i.e., v_1, v_2, …, v_q). We partition the objects in target layer S according to the layer L then we have a set of layers $L(v_i, S)$ for each possible value v_i in L. In our study, we assume that the layer L covers all areas in the layer S. The expected entropy value for splitting is given by Equation 4:

$$H(S \mid L) = \sum_{j=1}^{q} \frac{SpatMes(L(v_j,S))}{SpatMes(S)} H(L(v_j,S)) \qquad (4)$$

H(S|L) represents the amount of information needed (after the partitioning) in order to arrive at an exact classification.

2.5. Spatial Information Gain

The spatial information gain for the layer L is given by Equation 5:

$$Gain(L) = H(S) - H(S \mid L) \qquad (5)$$

Gain(L) denotes how much information that would be gained by branching on the layer L. The layer L with the highest information gain, (Gain(L)), is chosen as the splitting layer at a node N. Objects in the dataset are partitioned according to the layer L to result the "best classification" such that H(S|L) minimum.

2.6. Spatial Decision tree Algorithm

Figure 2 shows our proposed algorithm to generate a Spatial Decision Tree (SDT) as discussed in our previous work (Sitanggang *et al.*, 2011). Inputs of the algorithm are divided into two groups: (1) a set of layers containing some explanatory layers and one target layer that hold class labels for tuples in the dataset and (2) Spatial Join Relations (SJRs) storing spatial measures for features resulted from spatial relations between two layers. The algorithm generates a tree by selecting the best layer to separate the dataset into smaller partitions as pure as possible meaning that all tuples in partitions belong to the same class.

3. RESULTS

The proposed algorithm has been applied to the real active fires dataset for the Rokan Hilir District in Riau Province Indonesia with the total area of 8,881.59 km². The dataset contains ten explanatory layers and one target layer. The target layer consists of active fires (hotspots) as true alarm data and non-hotspots as false alarm data.

Table 1. Number of features and distinct values in the dataset

Layer	Number of features	Number of distinct values
Physical		
Distance to nearest river (dist_river)	744 points	3 (low, medium, high)
Distance to nearest road (dist_road)	744 points	3 (low, medium, high)
Distance to nearest city center (dist_city)	744 points	3 (low, medium, high)
Land cover (land_cover)	3107 polygons	12 (Dryland_forest, plantation, Water_body and so on)
Social-economy		
Income source (income_source)	117 polygons	7 (Forestry, Agriculture, Trading_restaurant and so on)
Population density (population)	117 polygons	3 (low, medium, high)
Number of school (school)	117 polygons	3 (low, medium, high)
Weather		
Precipitation in mm/day (precipitation)	7 polygons	2, 3
Screen temperature in K (screen_temp)	7 polygons	297, 298, 299
10 m wind speed in m/s (wind_speed)	7 polygons	0, 1, 2
Target		
Target	744 points	

False alarm data were randomly generated and they are located within an area at least 1 km away from any true alarm data. Explanatory layers are grouped into three groups i.e., physical, socio-economy and weather.

Table 1 summaries the number of features in the dataset for each layer. Spatial relationship *In* is applied to the target layer and explanatory layers represented in polygon (land_cover, income_source, population, school, precipitation, screen_temp and wind_speed) to result spatial measure *Count*. Additionally, the spatial relationship *Distance* is calculated to relate the target layer to the river, road and city centre layer. We use the aggregate function *Min* to determine distance from target objects to nearest river, road and city centre. The aggregate function *Sum* is applied to extract all objects in the target layer which are located inside polygon features.

The decision tree generated from the proposed spatial decision tree algorithm contains 276 leaves with the accuracy of 87.69%. The first test attribute of the tree is distance from target objects to nearest river. Below are some rules generated from the tree:

- IF dist_river (km) > 3 AND $0 \leq$ wind_speed (m/s) < 1 AND income_source = Forestry AND dist_road (km) $\leq$ 2.5 AND dist_city (km) > 14 THEN hotspot occurrence = T

- IF dist_river (km) > 3 AND $0 \leq$ wind_speed (m/s) < 1 AND income_source = Plantation AND land_cover = Shrubs AND dist_city (km) $\leq$ 7 THEN hotspot occurrence = F

- IF dist_river (km) > 3 AND $1 \leq$ wind_speed (m/s) < 2 AND 50 < population_density $\leq$ 100 AND land_cover = Shrubs AND income_source = Other_agriculture THEN hotspot occurrence = F

- IF 1.5 < dist_river (km) $\leq$ 3 AND income_source = Forestry AND dist_city (km) > 14 THEN hotspot occurrence = T

- IF dist_river (km) $\leq$ 1.5 AND land_cover = Bare_land AND dist_city (km) > 14 AND dist_road (km) $\leq$ 2.5 THEN hotspot occurrence = T

4. DISCUSSION

The proposed algorithm performs well on the spatial dataset containing polygon, line and point features to classify 744 target objects (hotspots and non-hotspots) with the accuracy of 87.69%. Based on the experiment on the real forest fires data, the proposed algorithm can be used to join two spatial objects in constructing a spatial decision tree from a spatial dataset. From the tree we can generate 276 rules in which the first test condition for each rule is distance from a target object to nearest river.

The spatial dataset may contain noises and outliers that may result the problem of over fitting. We will implement the tree pruning method for the resulted tree to overcome the problem such that the tree becomes simpler and has higher accuracy. Due to non-availability a real testing dataset, the accuracy was calculated based on the training dataset. Therefore, in the future we will apply the tree to another area as a testing spatial dataset to study the performance of the proposed algorithm on a new area.

5. CONCLUSION

This study presents an extended ID3 algorithm to create a classifier namely spatial decision tree from spatial data. For mining purpose, a spatial dataset is

organized in a set of layers in which the layers are grouped into two categories i.e., explanatory layers and a target layer. All layers are represented in discrete features (polygons, lines and points). The algorithm calculates spatial information gain as the extension of information gain in the non-spatial ID3 algorithm. Spatial measure resulted from the spatial relationships that may be either topological or metric (distance) is used in the formula of spatial information gain instead of number of tuples in the non-spatial information gain. The algorithm selects an explanatory layer which has the highest spatial information gain as the best splitting layer. This layer separates the dataset into smaller partitions as pure as possible such that all tuples in partitions belong to the same class. The extended ID3 algorithm has been applied on the real spatial dataset on forest fires consisting of ten explanatory layers and a target layer. Empirical result shows that the algorithm can be used to join two spatial objects in constructing spatial decision trees. The result is a spatial decision tree consisting of the root (distance from target objects to the nearest river) and 276 leaves. The accuracy of the tree on the training set is 87.69%.

6. ACKNOWLEDGMENT

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