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AniMoveMineR: Animal Behavior Exploratory Analysis Using Association Rules Mining

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Abstract—Environmental changes and major natural disasters are most prevalent in the world due to the damage that humanity has caused to nature and these damages directly affect the lives of animals. Thus, the study of animal behavior and their interactions with the environment can provide knowledge that guides researchers and public agencies in preservation and conservation actions. Exploratory analysis of animal movement can determine the patterns of animal behavior and with technological advances the ability of animals to be tracked and, consequently, behavioral studies have been expanded. There is a lot of research on animal movement and behavior, but we note that a proposal that combines resources and allows for exploratory analysis of animal movement and provide statistical measures on individual animal behavior and its interaction with the environment is missing. The contribution of this paper is to present the framework AniMoveMineR, a unified solution that aggregates trajectory analysis and data mining techniques to explore animal movement data and provide a first step in responding questions about the animal individual behavior and their interactions with other animals over time and space. We evaluated the framework through the use of monitored jaguar data in the city of Miranda Pantanal, Brazil, in order to verify if the use of AniMoveMineR allows to identify the interaction level between these jaguars. The results were positive and provided indications about the individual behavior of jaguars and about which jaguars have the highest or lowest correlation.

Keywords—Data mining, data science, trajectory, animal behavior.

I. Introduction

THE predatory human actions are transforming the nature and leading the animals suffer the extinction risk due to threats such as hunting, illegal trade and shrinking and destruction of their habitat. One way to protect species is to monitor these animals without interference human direct with their natural environment. Thus, satellite and GPS tracking technologies are used to facilitate the process of monitoring and studying animal movement.

Animal movement data can be used as a basis to identify animal behavior and understand how these animals relate to the environment, considering that these spatiotemporal data are formed by points distributed in time and space and describe the animal's trajectory. The animal behavior study involves analyzing differents individual animal behavior characteristics and their interactions with environmental factors, such as, rainfall, the others animals presence, burned and temperature, which may or not influence behavior.

In the interaction analyze between animal behavior and the environment, it is considered that animals move over a certain space and time, describing their trajectories, being subject to environmental influences that may generate variations in behavior. Since the animal behavior study behavior covers various techniques, methods and algorithms, a challenge is how to combine these different resources by allowing exploratory analysis of animal movement data to provide animal behavior indicators. Thus, in this work we presents the framework AniMoveMineR which brings together algorithms to spatiotemporal data analysis and association rule mining, providing a first step to answer questions about the individual animal behavior and its interactions with the environment, over time and space, based on animal movement data.

The exploratory analysis of animal movement comprises the classification of behavior into states and the identification of when, where and for how long these behavioral states occurred and association rule mining is applied to identify the correlation levels between animals and environmental factors. The AniMoveMineR aims provide the researchers and public agencies with a means to obtain knowledge on animal behavior supporting the regarding environmental preservation and conservation actions. Therefore, the contribution in this work is to present the proposed AniMoveMineR framework and its application in the biodiversity area through a case study using jaguars data monitored by the Onafari Project in the city of Miranda, Pantanal Brazil.

II. Literature Review

Animal behavior provides information about the interaction between animal and the environment [1] and can be obtained through these animals trajectory analysis [2]. The trajectory is the path taken by the animal that is formed by points that represent the spatial position variation of an object in time. Animal behavior can be classified as: states, which occur over a prolonged period; and events, which are counted over time.

The international project Movebank [3] provide on animal tracking data and the Environmental Data Automated Track Annotation System (Env-DATA) [4] which consists of a set of analysis tools that link, through maps and graphs the movement data and environmental factors, but it does not allow analysis more detail the relationship between movement data and different environmental factors.

The animal movement has characteristics such as speed, residence time, direction, distance traveled, or occurrence

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frequency, that are used by segmentation methods to partition animal trajectories and to determine the points of location and timing of the movement that indicate the behavioral transition [5]. There are several examples of applying segmentation methods, such as [6], that used the characteristics of time, velocity and curvature angle to identify behaviors such as migration, rest and foraging. In [7] the Behavioral Change Point Analysis (BCPA) method [8] is used to segment the trajectories by speed and direction of movement, and the k-means clustering, to classify animal trajectories into states. Already [9], proposed a statistical method to detect the change points in the trajectory based on the residence time characteristic.

Segmentation methods usually focus on the time characteristic of movement, and the lack of treatment of spatial characteristics may limit analyzes of animal behavior. Thus, AniMoveMineR uses the Residence in Space and Time (RST) method [10] which segments trajectories based in the characteristics of time of residence and distance, classifying the animal behavior in foraging, resting, and transit states. This method consider the spacial and time characteristics of the movement, enhancing the analyzes by methods such as BCPA and Lavielle, that segment the trajectories only by time characteristics.

Other important analysis to understand animal behavior is to identify how their use space in their daily activities. Based on animal movement data, the animal home range can be obtained, which is the area covered by the animal in its activities of foraging, mating and parental care [11]. The [12] provides classes and methods for analyzing and identifying home range through AdehabitatHR.

The animal movement occurs in a specific area, there may be influence from surrounding environmental factors, therefore one must analyze the level of relationship between these animals and the environmental factors that can be: co-occurrence, which consists of events that occur together in space and time; correlation [13], which consists of the statistical dependence relationship between two or more variables that occur in the same space and time. In this context have the data mining that encompasses a set of strategies, tools and algorithms that enable data mining and pattern extraction. The mining data is used for forest fire prevention [14], in the discovery of clustered herds [15] and [16], used in the association discovery between products of market basket using the association rules technique. Another way to obtain the association between two variables is using the Cramer coefficient [17] calculated based on the chi-square value [18] and a contingency table.

III. Proposed Framework

The proposed framework AniMoveMiner, Fig. 1, aim support the animal movement exploratory analysis, combining algorithms for spatiotemporal data analysis and association rules mining to obtain indicatives about the animal behavior based on animal movement data. We provide as input data an animal movement dataset, which describing the movement of one or more animals, characterized by location points (latitude/longitude), time (date/time) and animal name.

The AniMoveMiner was built based on data science process [2], considering that it begins with the questions elaboration to be answered; moving to data acquisition, preparation and analysis data. The data analysis stage is the main stage of AniMoveMineR, considering that is the exploratory analysis of animal behavior is performed there. This stage comprises of the phases: (A) Identify individual animal behavior; (B) Identify the environmental factors neighboring the occurrence of animal behavior; (C) Identify the correlation between animals and environmental factors.

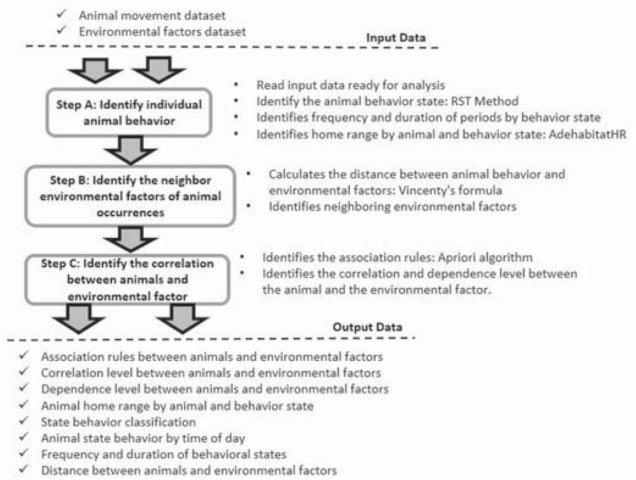

Fig. 1 AniMoveMineR - Data Analysis steps

A. *Identifying Individual Animal Behavior*

The individual animal behavior analysis comprises the identification of the states of the animal's behavior, the occurrence period, the frequency and duration of these states and the animal home range. The animal movement classification into behavior states is realized, in the AniMoveMineR, using R routines [19] to manipulate trajectories and the Residence in Space and Time (RST) method [10] to classify animal behavior into states (rest, traffic and foraging) by segmenting the trajectories according to the amount of space and time occupied by the animal in an area. Around each point on the path, a circle is constructed and calculated: the distance traveled (RD), which is the sum of the path lengths within the circle, and the time residence (RT), which is the sum of residence time between consecutive points within the circle. The residual value (between -1 and 1) is obtained by normalizing and subtracting RD and RT and the states are classified as: Transit (Residue = 0), behavior with short time and distance in the area; Rest (Residue ¡ 0), high time in area, but short distance; forage (Residue ¿ 0), high time and distance traveled within the area In the AniMoveMineR to Identify the frequency, duration and period of the occurrence of the animal behavior states is used a R routine that explore animal movement data and identify the distribution of animal behavior at time intervals (start and end time); the average duration of each behavior state; and the occurrence frequency of states by period (day/night) for each animal over the months and years. The kernelUD function [20] is used to identify the animal home range. This function estimates the Utilization Distribution (UD) that determine the probability density that an animal is found at the minimum area. This analysis provides information on how the jaguars used and shared the space along the time.

B. Identifying the Neighbors' Environmental Factors of the Animal Occurrences

In the AniMoveMineR as closer the animal behavior occurs of the environmental factor, greater the likelihood of a relationship between them. Thus, to identify the neighbors factors when this factors have informations about space (latitude/longitude) and time, an array is created relating the date according to the date and time of occurrence, and calculating the distance between location points, using the Vincenty formula [21]. For each record of the animal's movement, a circle is created around the point (position and time), with a limit distance radius and the distance between the movement points and the factor is calculated.

C. Identifying the Correlation between Animal Behavior and Neighbors' Environmental Factors

The AnimoveMineR uses the association rules techniques, with the Arules package Apriori algorithm [22] and the Cramer coefficient[23], to obtain indicatives about the correlation between the animals and environmental factors. Elements that imply in the presence of other elements in the same dataset and indicate the co-occurrence frequency of the elements is find using the association rules mining. The Apriori algorithm identify the association rules between the variables based on the frequency which they occur together and pruning the rules that are below the limits of minimum support (minSup) and minimum confidence (minConf). The result obtained are the association rules between the data and the measures that identify the correlation and dependency between the analyzed variables [25]. The measures obtained indicate the: Support A (SupA), occurrence frequency only of the variable A; Support B (SupB), occurrence frequency only of the variable B; Support (Sup), frequency of co-occurrence of two variables (A and B); Confidence (Conf), indicates the probability of B occurring due to the occurrence of variable A.

Other measure is the correlation coefficient (Phi) that indicates the relationship degree between A and B, to determine the correlation level. The Phi classification is: perfect negative correlation (value -1); strong negative correlation (value -1 to -0.68); moderate negative correlation (value -0.67 to -0.36); Weak or no correlation (value -0.35 to 0.35); moderate positive correlation (value 0.36 to 0.67); strong positive correlation (value 0.68 to 1); no correlation (value 0); perfect positive correlation (value 1).

In the correlation analysis is used also the Cramer coefficient, which indicates the association between two categorical variables and is calculated based on the chi-square value [27] obtained in the contingency table analysis. The result varies between 0, totally independent, and 1, totally associated, the higher the association, the higher the coefficient value.

IV. Evaluation

In this section is presented the AniMoveMineR framework application in the exploratory analysis of the jaguars movement of the Pantanal - Brazil, monitored by the Onafari Project [24]. The data analyzed refer to the years 2012 to 2014. How preliminary information about the relationship between the jaguars we knew that: Brutus (15) relates to Teorema (84) and Natureza (69); Natureza (69) relates to Troncha (86) and Esperana (25) relates to Chuva (19), Natureza (69)(her mother) and Brutus (15). Thus, two hypotheses were considered: (A) by means of jaguar movement data, the level of relationship between them can be identified; (B) the foraging behavior of jaguars changes with the seasons.

With the initial analysis of the data we have that for 2012 there are movement data of jaguars Brazuca (14), Chuva (19), Esperana (25) and Vida (87). For the years 2013 and 2014, there are the movements of the Brutus (15), Natureza(69), Teorema (84) and Troncha (86) jaguars.

In the exploratory analysis the three stages of AniMoveMineR were performed: (A) Identify the individual animal behavior; (B) Identify the environmental factors neighboring the occurrence of animal behavior; (C) Identify the correlation between animals and environmental factors.

In step A, the jaguars data were explored obtaining the states behavior classification (rest, traffic and foraging), the states occurrence period (day/night), the state duration (start and end time) and the area occupied by the animal over time. The dataset refers to 2012 year contained the movement of jaguars Brazuca (14), Chuva (19), Esperana (25) and Vida (87) jaguars. However, the data do not correspond to the same month, making it impossible to analyze the relationship between these jaguars over time. However, we performed the space overlap analysis considering just the year, Fig. 2, and identified that there was an overlap indication between the Brazuca (14) and Esperana (25) jaguars; Chuva (19), Esperana (25) and Vida (87); Esperana (25), Brazuca (14), Chuva (19) and Vida (87).

	14	19	25	87
14	1.034133120	0.000000e+00	8.537878e-03	0.00000000
19	0.000000000	1.296036e+00	4.609574e-05	0.02691267
25	0.008537878	4.609574e-05	1.087283e+00	0.04867276
87	0.000000000	2.691267e-02	4.867276e-02	1.19510245

Fig. 2 Area overlap between jaguars to 2012

Already, when the overlap is analyzed considering the months and year (2012), Fig. 3, there is no area overlap for these jaguars at the same time (month). For example, Chuva (19) and Esperana (25) presented area overlap, but they probably used the same area in different months reinforcing the need to consider time and space in the analyzes. In the distance between animals analysis, no data was found, because each animal has data for a different month. Thus, it was not possible to estimate the distance nor apply the association rules. In the dataset refers to 2013 year, was applied the association rules mining and the results indicated that the Teorema (84) and Brutus (15) jaguars have a strong correlation

Fig. 3 Area overlap map between jaguars to 2012

in all analyzed months (October/November/December), as indicates by the Phi coefficient, Fig. 4.

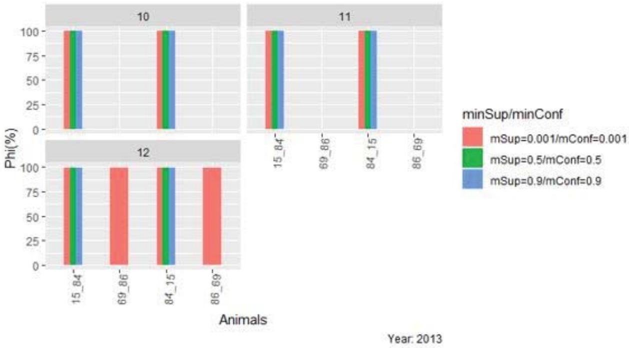

Fig. 4 Level Correlation between jaguars to 2013

We used different values for minimum support and confidence in the tests and even with minSup and minConf equal to 90% the relationship between the Teorema (84) and Brutus (15) jaguars indicated high correlation and confidence, Fig. 5. Confidence is the probability of one jaguar occurs as a function of other jaguar occurrence. The jaguars Natureza (69) and Troncha (86) showed a high correlation only in December/2013 to low minimum support and confidence (1%).

Analyzing the home area overlap between the jaguars in 2013, Fig. 6, we have the pairs jaguars Brutus (15)/Teorema (84) and Troncha (86)/Natureza (69) with moderate overlap and the animals Brutus (15)/Natureza (69) and Teorema (84)/Natureza (69) with low overlap. In Fig. 7, are presented the overlap maps to 2013. In October/2013 (A) the Natureza (69), Teorema (84), Troncha (86) and Brutus (15) jaguars did not have indication of home range overlap. In November/2013 (B), the Brutus (15), Natureza (69) and Teorema (84) jaguars had indication to area overlap. In December/2013 (C), the Troncha (86) and Natureza (69) jaguars and also the Brutus (15) and Teorema (84) jaguars presented area overlap. In the distance analysis between the jaguars we identified between the Natureza (69) and Troncha (86) jaguars an average distance of approximately 60 meters in December 2013. Already in October, November and December 2013 we identified an average distance below 250 meters to Teorema (84) and Brutus (15) jaguars.

The dataset refers to 2014, Fig. 8, contained the jaguars movement to January, February, March, April and May months. However, only in January were identified movement

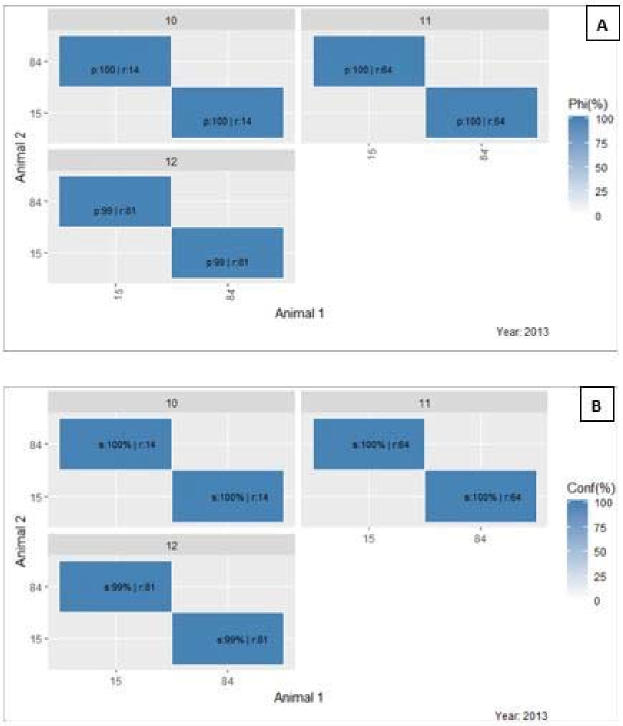

Fig. 5 (A) Correlation level and (B) Confidence level between jaguars to 2013

	15	69	84	86
15	1.35922354	0.03597539	0.3937912194	0.0249268890
69	0.03597539	1.78873495	0.0123756235	0.2474329806
84	0.39379122	0.01237562	1.5631866710	0.0003648923
86	0.02492689	0.24743298	0.0003648923	1.0860950404

Fig. 6 Home range overlap between jaguars in 2013

Fig. 7 Home range overlap map between jaguars in 2013

data to Brutus (15), Natureza (69), Teorema (84) and Troncha (86) jaguars. For the other months only data from Natureza (69) jaguar were identified (69).

We obtained indication of high correlation between Teorema (84) and Brutus (15) jaguars, Fig. 9, even with the minimum support and confidence equal to 90%.

Analyzing the area overlap per year, Fig. 10, among the animals we identified a high correlation for Natureza (69) and Teorema (84), Teorema (84) and Brutus (15) and Natureza

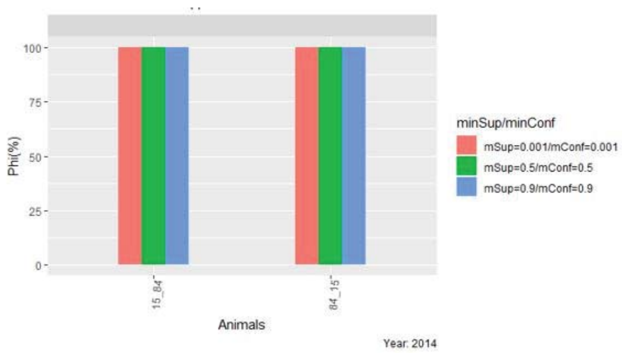

Fig. 8 Level Correlation between jaguars to 2014

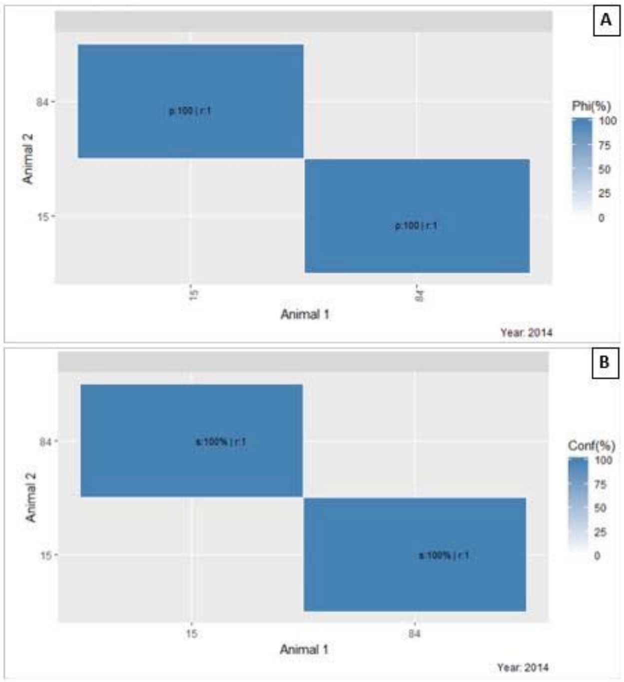

Fig. 9 (A) Correlation level and (B) Confidence level between jaguars to 2014

(69) and Troncha (86) jaguars in the 2014 dataset.

	15	69	84	86
15	1.076534679	0.000000e+00	4.741488e-03	0.0000000
69	0.000000000	1.255586e+00	3.333235e-05	0.1115276
84	0.004741488	3.333235e-05	1.315082e+00	0.0000000
86	0.000000000	1.115276e-01	0.000000e+00	1.1006272

Fig. 10 Area overlap between jaguars to 2014

In the home range overlap analysis per month and year, Fig. 11(A), there is no overlap record between the jaguars. However, when the analysis was performed considering the states of behavior, Fig. 11(B), it is observed that there was area overlap just during foraging. Overlap was observed in January between animals Natureza (69) and Troncha (86) during the foraging state.

To verify hypothesis (B) the foraging behavior of jaguars

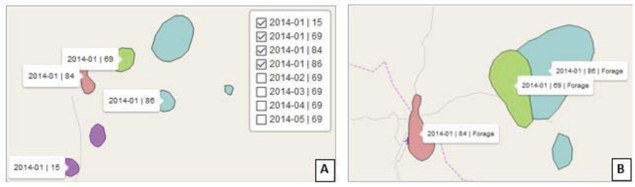

Fig. 11 (A) home range jaguar per year (B) home range jaguar per state behavior to 2014

can change with the seasons. We focus on the analysis of the duration and period (day/night) of behavioral states and association rule mining was applied to identify the correlation level between the seasons (Full, Low, Flood and Dry) and the jaguars behavior states (rest, transit and forage). Analyzing the foraging state duration for jaguars in 2013, as showN in the example of the Brutus (15) and Teorema (84) jaguars, Fig. 12, all jaguars presented a decline in foraging duration in November. In the case of Brutus (15) and Natureza (69) jaguars, the decline continued in the following month. Teorema (84) and Troncha (86) jaguars showed an increase in the foraging duration in December.

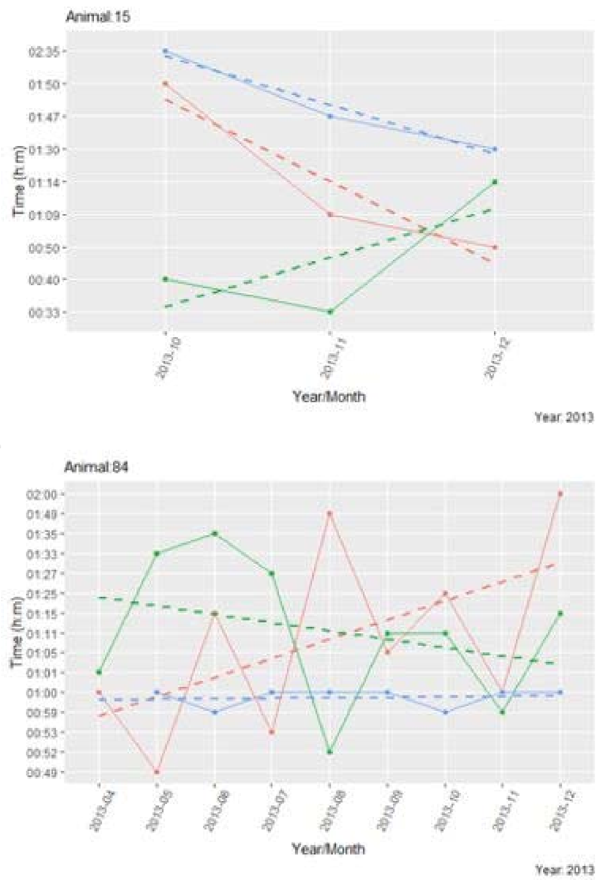

Fig. 12 Forage state behavior duration example to Brutus (15) and Teorema (69) jaguars in 2013

Regarding the occurrence period of the foraging we identified that occured mostly during the day. As an example,

Fig. 13, is shown the Natureza (69) and Brutus (15) jaguars that foraged most during the day over the months of October, November and December with an increase in November.

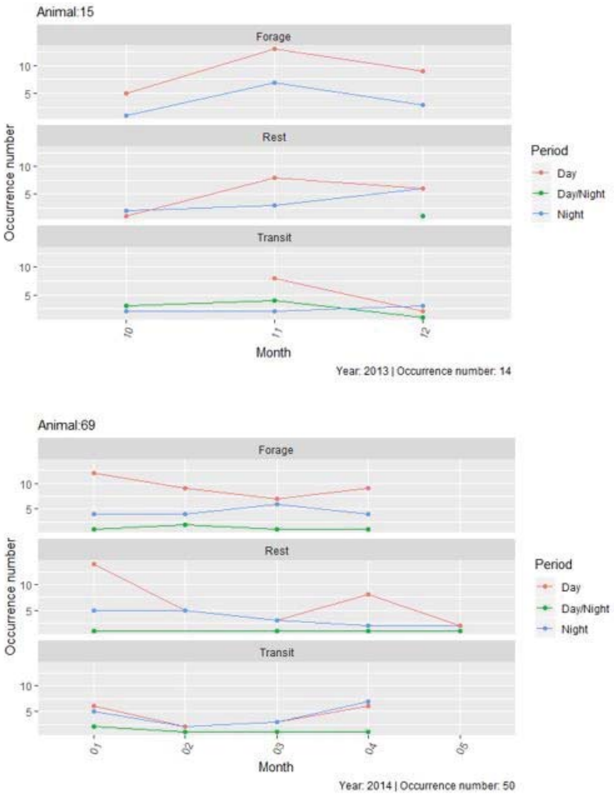

Fig. 13 Example of Occurrence period of forage to Natureza (69) jaguar

The seasons in the Pantanal are divided into: dry, from June to October; low, from March to June; flood from October to December; full, from January to March. Based on association rules mining of the 2013 dataset, as example shown in Fig. 14, we obtained indications that Brutus (15), Natureza (69) and Troncha (86) jaguars foraged more during flood season.

lhs	rhs	support	confidence	lift	phi	count
{fator=Flood}	{estado=Forage}	1	1	1	1	653
{fator=Low}	{estado=Forage}	0.123842592592593	1	1	1	214
{estado=Forage}	{fator=Low}	0.123842592592593	0.123842592592593	1	1	214
{fator=Dry}	{estado=Forage}	0.428240740740741	1	1	1	740
{estado=Forage}	{fator=Dry}	0.428240740740741	0.428240740740741	1	1	740
{fator=Flood}	{estado=Forage}	0.447916666666667	1	1	1	774
{estado=Forage}	{fator=Flood}	0.447916666666667	0.447916666666667	1	1	774

Fig. 14 Association rules mining between jaguars to 2013

As shown in the Brutus (15) jaguar example, Fig. 15, the confidence and correlation level were high for flood season foraging even for minSup and minConf equal to 90% for all jaguars. Thus, it is observed that there is an indication that the number of foraging records is higher in the flood season in 2013. Based on association rule mining of the 2014 dataset, as example in Fig. 16, we obtained indications that Brutus (15), Natureza (69), Teorema (84) and Troncha (86) foraged more during Full season. As shown in the Brutus jaguar example

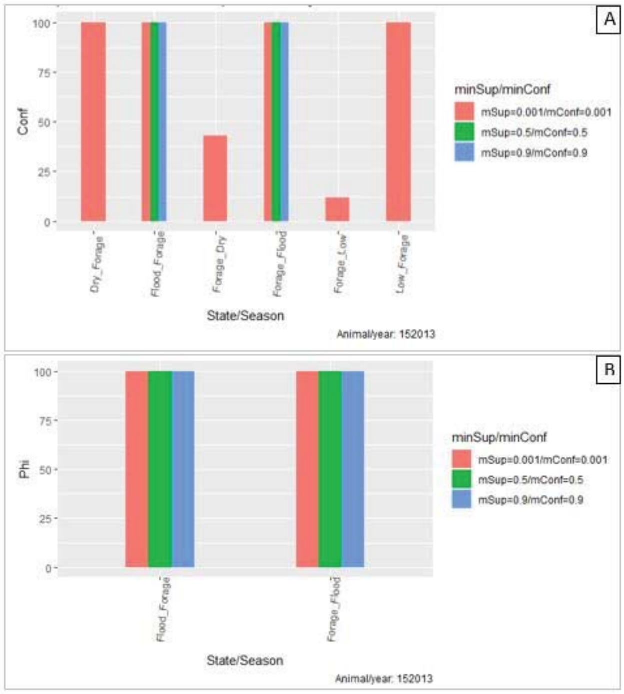

Fig. 15 (A) confidence level (B) correlation level between jaguars state behavior and seasons in 2013

lhs	rhs	support	confidence	lift	phi	count
{estado=Forage}	{fator=Low}	0.325478645066274	0.325478645066274	1	1	221
{fator=Full}	{estado=Forage}	0.674521354933726	1	1	1	458
{estado=Forage}	{fator=Full}	0.674521354933726	0.674521354933726	1	1	458
{estado=Forage}	{fator=Full}	1	1	1	1	119
{fator=Full}	{estado=Forage}	1	1	1	1	119
{estado=Forage}	{fator=Full}	1	1	1	1	50

Fig. 16 Association rules mining between jaguars to 2014

(15), in Fig. 17, the confidence and correlation level were high for Full season foraging even for minSup and minConf equal to 90% for all jaguars. Thus, it is observed that there is an indication that the number of foraging records was higher in the Full season in 2014.

V. Conclusion

The AniMoveMineR framework is a means to exploring animal movement data and obtaining indicators about the animal's individual behavior pattern is and how it is related to the environmental factors neighbors. In the case study two hypotheses were verified: (A) by means of jaguar movement data, the level of relationship between them can be identified; (B) the foraging behavior of jaguars changes with the seasons. To verify these hypotheses, AniMoveMineR was applied in the analysis of the jaguar movement data from Project Onafari, from 2012 to 2014. In the hypothesis (A) analysis we considered the measurements obtained with the association rules mining, the distance between the jaguars and the home range overlap. As preliminary information we knew some jaguars were related, such as: Brutus (15), Teorema (84) and Natureza (69); Natureza (69) and Troncha (86); Esperana (25),

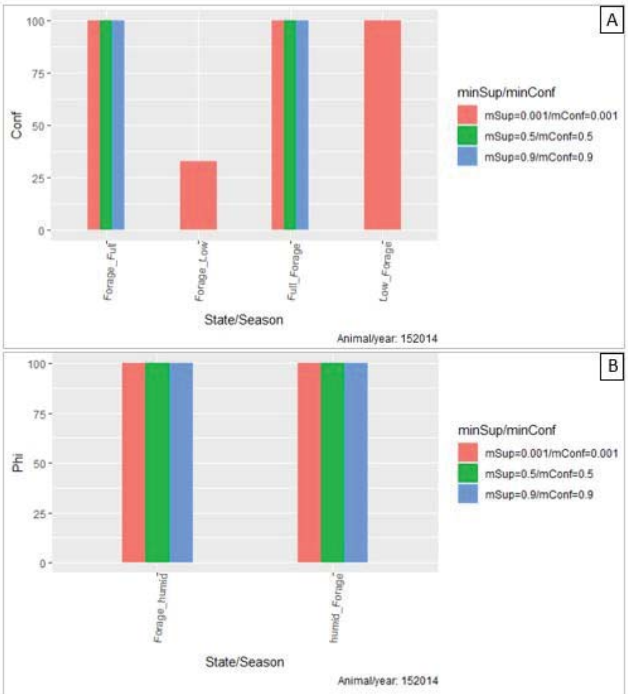

Fig. 17 (A) confidence level (B) correlation level between jaguars state behavior and seasons in 2014

Chuva (19), Natureza (69) (her mother) and Brutus (15). As a result of the exploration of the jaguar movement data, we identified that in 2013, the Teorema (84) and Brutus (15) jaguars showed an indication of high correlation based on association rules measures. In the overlap analysis, in October, there was no area overlap. In November, the area overlap was recorded between Brutus (15), Natureza (69) and Teorema (84). In December, home range overlapping between Natureza (69) and Troncha (86); Brutus (15) and Teorema (84).

The average distance, in December 2013, between Natureza (69) and Teorema (86) was 60 meters, indicating close proximity. In October and November, the average distance between Teorema (84) and Brutus (15) was indicated as below 250 meters. In the exploratory analysis of the 2014 dataset, the Teorema (84) and Brutus (15) jaguars showed a strong correlation. Home range overlap was identified only for the Natureza (69) and Troncha (86) jaguars. Given the results obtained with the case study, we can confirm the hypothesis (A) that by means of jaguar movement data, the level of relationship between them can be identified. The relations between Brutus and Teorema and between Natureza and Troncha were identified by means of measures obtained with the association rules that indicated a strong correlation between these jaguars, which were confirmed by the analysis of distance and home range overlap.

In the hypothesis (B) analysis we observed the duration and period of occurrence of the jaguar behavior states to identify the behavior patterns and the possible variations of behavior. The association rules mining was used to identify the relationship between the behavior states and the seasons. Based on the results we observed that the duration of the foraging state showed a sharp decrease in October and November, which coincides with the beginning of the flood season. However, measures obtained from the association rules indicated that there is a higher occurrence of foraging in flood season in 2013 and full season in 2014. This information may indicate that jaguars forage more but with shorter duration over the flood period and full seasons. However, the framework aim is to provide clues about the individual behavior of the animal and its interaction with the environment. Analyzes and conclusions about the results obtained should be carried out by biodiversity experts. In resume, the exploratory analysis of the jaguar movement using AniMoveMineR allows us to:

- classify jaguar behavior into states;
- identify the proximity between the jaguars;
- identify the relationship level between the jaguars;
- identify jaguar home range and space sharing among jaguars;
- identify of missing data about the jaguar movement over time

The algorithms, graphs, and figures obtained from the study are available from the GitHub repository: https://github.com/suelanegarcia/AniMoveMineR.

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