triage, classification, SET, fuzzy logic, decision trees, patients, urgency, hospital emergency, triaje, algorithm

Norberto MONDRAGON[1], Dan ISTRATE[2], Katarzyna WEGRZYN-WOLSKA[3], Juan C. GARCIA[4], Juan C. SANCHEZ[5]

PATIENT CLASSIFICATION ALGORITHM AT URGENCY CARE AREA OF A HOSPITAL BASED ON THE TRIAGE SYSTEM

The time passed in the urgency zone of a hospital is really important, and the quick evaluation and selection of the patients who arrive to this area is essential to avoid waste of time and help the patients in a higher emergency level. The triage, an evaluation and classification structured system, allows to manage the urgency level of the patient; it is based on the vital signs measures and clinical data of the patient. The goal is making the classification in the shortest possible time and with a minimal error percentage. Levels are allocated according to the concept that what is urgent is not always serious and that what is serious is not always urgent. In this work, we present a computational algorithm that evaluates the patients within the fever symptomatic category, we use fuzzy logic and decision trees to collect and analyze simultaneously the vital signs and the clinical data of the patient through a graphical interface; so that the classification can be more intuitive and faster. Fuzzy logic allows us to process data and take a decision based on incomplete information or uncertain values, decision trees are structures or rules sets that classify the data when we have several variables.

1. INTRODUCTION

1.1. TRIAGE SYSTEM

The triage (or triaje) is an evaluation and classification structured system, the term ’triage’ is a neologism from the French word ’trier’, which means choose, split or classify; it was used for the first time in the Napoleon battles and persisted as a concept of classification to the patients in urgency [9]. There are several triage systems, the more used among them are: Manchester Triage System (MTS), Spanish Triage System (SET) which comes from the Andorran Model of Triage (MAT), the Canadian Triage and Acuity Scale (CTAS) and the Emergency Security Index (ESI) [3]. They are similar in many aspects, they set also 4 of 5 urgency levels, and there are some differences in the assistance times. The typical vital signs considered in the triage are Heart Rate, Respiratory Frequency, Oxygen Saturation, Corporal Temperature, and Blood Pressure.

Elaborated in 2003 by the Urgency and Emergency Spanish Society [4],[8],[9], the Spanish Triage System (SET) classifies the patients in the urgency zone of a hospital in 5 levels, each one with an assistance time [9], the first being the most urgent and the fifth the less urgent. It has 32 symptomatic

[1]IPN, MEXICO - nor.monher@gmail.com.
[2]ESIGETEL, FRANCE - dan.istrate@esigetel.fr.
[3]ESIGETEL, FRANCE - katarzyna.wegrzyn@esigetel.fr.
[4]IPN, MEXICO - jcnet21@yahoo.com.
[5]IPN, MEXICO - jcsanchezgarcia@gmail.com.

Table 1. SET's levels and times.

Level	Color	Assistance time
1	Red	Immediately
2	Orange	7 minutes
3	Yellow	15 minutes
4	Green	30 minutes
5	Blue	40 minutes or more

categories and includes more than 500 causes of urgency in each category and defines the urgency level considering the vital signs and the clinical data of the patient.

The clinical data (discriminants) is all the information the patient can give as whether he has pain, hemorrhage, dehydration, etc. and the intensity of these symptoms, the nurse can also introduce information like the visible status of the patient (skin color, reaction capacity, etc.). Once the patient is assigned to a certain category, Triage system sets a protocol of how the patient has to be classified, depending on his vital signs or clinical data, or the combination of both, the result is the highest possible level of urgency of the patient. In this work we take base on SET because it is one of the most used and supported, and we focus in the first symptomatic category: fever, due to the several reasons of consultation this category implies. Some of the discriminants in this category are: typical vital signs, shock state, pain, asthma scale, non-traumatic coma scale, dehydration, hemorrhage, diarrhea, and diabetic patient; each one with its owns variables. The SET propose 5 levels as shown in Table 1. These five levels or colors define the maximum time the patient should wait.

The first problem to handle is found in the vital signs values, for example: the nurse knows that $38°C$ become in fever, the system has to do that in the same way and fuzzy logic help us, because we know it is fever when $T > 38°C$, but when $T = 37.9°C$ the nurse may say it is almost fever and not febricule, so we needed to set a function to handle this situations and there is where we use fuzzy logic. On the other side, as we have many discriminants involved in the patient classification process, this can be complex for the nurse to select the appropriate one, reading between all the discriminants and variables when trying to do a quick classification. Decision trees allows us to do an appropriate classification analyzing the output of the numerical input data processing, and additionally taking account to the nurse's evaluation.

1.2. FUZZY LOGIC

The theory of fuzzy logic [8],[11],[12] provides a mathematical strength to capture the uncertainties associated with human cognitive processes, such as thinking and reasoning. Fuzzy systems are suitable for uncertain or approximate reasoning, especially for the system with a mathematical model that is difficult to derive and allows decision making with estimated values under incomplete or uncertain information. Fuzzy systems are controlled by fuzzy controllers based on rules in the form IF-THEN-ELSE statements. The image in Figure 1 shows a simple architecture for a fuzzy logic controller.

We use fuzzy logic to process the vital signs values in order to estimate the emergency level, the triage system takes the corporal temperature variable in nominal values such as 'normal', 'hypothermia', 'febricule', 'fever', and 'high fever'; and the value in the input is a numerical one, then we have to convert the corporal temperature input in a suitable value. Also, we used fuzzy logic in some scales

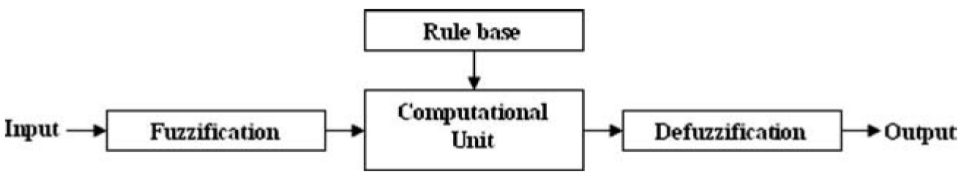

Fig. 1. Fuzzy Controller Architecture.

and discriminants like the Non-Traumatic Coma Scale and Shock. The inputs of the system, vital signs in this case, are converted in the fuzzification module, to be able to enter the computational unit based on rules, after this block is done, the output fuzzy set is defuzzified in the last module to be read by the user.

1.3. DECISION TREES

A decision tree [6],[7],[14] is a classifier which consists of nodes that form a rooted tree. All the nodes have exactly one incoming edge except the 'root'. Each internal node splits the instance space into two or more sub-spaces according to a certain discrete function of the input attributes values. Each leaf is assigned to one class representing the most appropriate target value. Decision trees can incorporate both nominal and numerical values (in numerical cases,the split condition refers a range).

Decision trees are constructed by algorithms called 'decision tree inducers'. These algorithms construct the decision tree from a given data set, typically the goal is to find the optimal decision tree with the smaller number of errors, other goals can be also, minimizing the number of nodes or the average depth. In this work, we have a little number of data to be classified (decision trees can handle hundreds, even thousands of data set), so we implement a very simple decision tree algorithm, a C5 based algorithm, it uses information gain, and gain ratio criteria, and does pruning. The information gain is a criterion that uses the entropy measure (eq. 1 and 2), and the gain ratio normalizes the information gain (eq. 3).

$$InfGain(a_i, S) = Entropy(y, S) - \sum_{v_{i,j} \in dom(a_i)} \frac{\left|\sigma_{a_i} =_{v_{i,j}} S\right|}{|S|} \cdot Entropy(y, \sigma_{a_i} =_{v_{i,j}} S) \tag{1}$$

$$Entropy(y, S) = \sum_{c_j \in dom(y)} -\frac{\left|\sigma_y =_{c_j} S\right|}{|S|} \cdot log_2 \frac{\left|\sigma_y =_{c_j} S\right|}{|S|} \tag{2}$$

$$GainRatio(a_i, S) = \frac{InformationGain(a_i, S)}{Entropy(a_i, S)} \tag{3}$$

where:

- S is the training set,
- a is the input feature set, and
- y is the target feature.
- σ is a subset of instances in S

2. RELATED WORKS AND JUSTIFICATION

In Andorra, it was developed the web_e-PAT V3 [5], which is the original Triage Assistance Program designed to be used in the Andorra main hospital based in the SET. It was used for a long time but validated until 2005. Another system is the Triagem TRIUS [13], a commercial solution developed in Brazil, this product is a full triage system, that has devices to measure the vital signs of the patient to enter automatically to the program and helps the nurse in the medical decision, but it is based on MTS; the price of this system is over 8.500 USD. In USA, is known they have an efficient assistance triage system, but they keep it closed to public.

There are also works that manage the triage out of the hospital, while the patient is in the ambulance, monitoring the vital signs of the patients by a private local network, and transfer the values to a data base in wireless technology. An examples is The Advanced Health and Disaster AID-Network [2] and e-Triage system [1]. Many triage platforms work as an assistance program, which means, they help to collect the vital sign values through several sensors and propose an electronic-form where the nurse

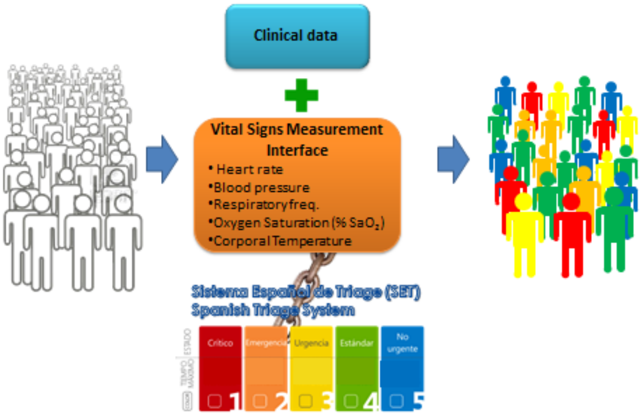

Fig. 2. Diagram of the full triage system in development in Mexico.

will fill the necessary data and make the evaluation, some of these algorithms also help to make the decision.

The algorithm we propose is part of a full triage system (Figure 2) in development in the National Polytechnic Institute (IPN) in Mexico, it will acquire the signals through several sensors and process it to obtain the values, then the data will enter the program to evaluate this signals and the clinical data that the nurse will enter; and, by this algorithm it will propose an emergency level as soon as possible.

To do this, we propose an intelligent algorithm which goes further than collect data and values, this algorithm propose the more appropriate urgency level from a minimum of inputs (signal sensors and discriminants screen). Also, the proposed system help the nurse to choose the level emergency showing the more appropriate discriminants to each variable, according with the entered information in the system or the symptomatic category selected, in some cases, vital signs can determine the level of the patient, or choosing a category, decreases the number of discriminants involved in the selection process; all this leads to a diminution of decision time. The proposed system is a decision support one, and not a decision system. We will evaluate the time saving in the decision but also the sensitivity and specificity so it will help to make the triage more uniform and help the nurse to improve the decision of the correct triage level.

3. METHODOLOGY

3.1. FUZZY LOGIC IN VITAL SIGNS AND GRAVITY SCALES IN TRIAGE

Evaluation of the patient needs a fuzzification of the vital signs numerical values; when a nurse does an evaluation manually, the fuzzification is done intrinsically, according to the SET [1]:

- Hypothermia $T < 35°C$
- Normal $36°C \leq T \leq 37°C$
- Febricule $37°C < T \leq 38°C$
- Fever $T > 38°C$

The Figures 3 and 4 show how we assign nominal values to the possible corporal temperature and heart rate ranges according to the SET limits and values in the literature. We did the same to the rest of typical measures (respiratory frequency, SaO_2, and blood pressure). We assign usually Gaussian functions to assign a gradual degree of membership to the values; this helps to prevent the abrupt changes in memberships as explained before. In the case of heart rate, is known that the stable states vary from one person to another; so it is needed a set of functions that allows us to handle this situation.

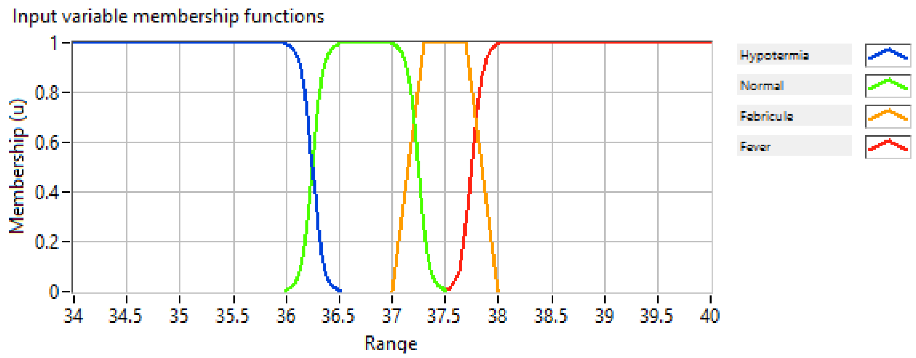

Fig. 3. Fuzzification of corporal temperature values.

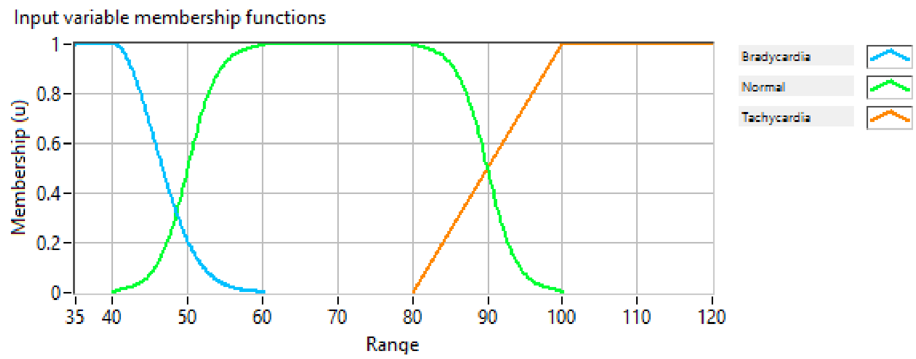

Fig. 4. Fuzzification of heart rate values.

A full fuzzy system is implemented in the Asthma Scale, which based on the heart rate (HR), SaO_2 and respiratory frequency (RF). The asthma scale has 4 levels of gravity at the output: I-Light, II-Moderate, III-Severe, IV- Respiratory pre-stoppage. We design the rules for this system, each level of gravity in this scale has its own rule.

The next is the rule when Asthma scale is level III-severe according to the SET:

$$RF > 30x' \cup HR > 120x' \cup SaO_2 < 92\% \tag{4}$$

- where x' is the number of breaths/beats per minute.

After evaluating the rules we get the area output, this is defuzzified using the center of area method to have only one value, which will be read by the algorithm to analyze with the clinical data together in the discriminants screen. We design another fuzzy system to determine whether the patient can be in shock (or septic shock) taking the needed values from the vital signs input and according to the SET specifications.

3.2. DECISION TREES IN DISCRIMINANTS AND PROPOSED DECISION

Once the vital sign values have been measured and imported to the system, fuzzy based system process these values to determine some discriminant values; also the nurse may choose the more appropriate discriminant that can generate the emergency by asking the patient or visual analysis. In case of fever category, we usually expect that discriminant to be selected, although sometimes, even if the patient has fever, maybe is another symptom or discriminant which induces the emergency situation. We implemented the decision trees to manage this selection and let the program be able to evaluate the patient as soon as it is possible; when the nurse chooses a discriminant value, the program evaluates

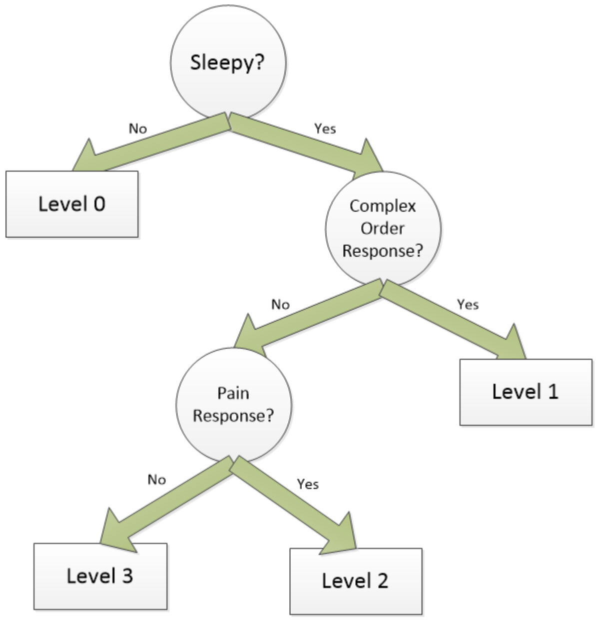

Fig. 5. Decision tree for NIHSS classification.

the patient with this information and depending on the case, the vital signs data; then it proposes the triage level, if the information is not enough, the program ask the nurse to add more information of some other discriminant, to make a more reliable evaluation.

However, at the end, this value can be modified if the nurse is not agree with the final level, (maybe because the patient seems to be more severe or maybe the nurse thinks the patient is over-acting to be assisted faster). The program generates a triage report that includes the values of vital signs measured and the triage level, but another local report is generated including whether the nurse modified the triage level. Decision trees are used for some discriminants that have variables we can discriminate in the classification. As example, the SET propose to evaluate the non-traumatic coma, the National Institutes of Health Stroke Scale (NIHSS), based in Edinburgh coma scale; this scale is shown in Table 2. The decision tree of the Non-traumatic coma scale is shown in Figure 5. It combines all the discriminants that could be involved in the classification if necessary. The advantage of this algorithm is that the nurse can start not only by the root, but by choosing a value in another depth level.

Using a C5 algorithm inducer (which is based on ID3 and C4.5 by Quinlan) [6],[7], we got the decision tree that help us to classify the patient without asking all this information. The tree let us know the patient coma level asking between 1 and 3 variables at maximum, instead of asking always 4.

Finally we have a graphical interface that will not only collect the data automatically, it will also work to make faster the classification. We chose LabVIEW due to its ease in making graphical interfaces, extensive toolbox, the parallel process capability and the possibility of make embedded systems. The Figure 6 shows how the LabVIEW screen of fever symptomatic category looks like, the next screen is where we choose the fever discriminant, we configured a normal vital signs input, except the corporal temperature, which is between $38°C$ and $40°C$, this can lead to a yellow or green level, depending on

Table 2. SET's Non-traumatic coma scale

Sleepy	Complex Order Response	Simple Order Response	Pain Response	NIHSS / Level
No	Yes	Yes	Yes	0 - Alert
Yes	Yes	Yes	Yes	1 - Sleepiness
Yes	No	Yes	Yes	2 - Daze
Yes	No	No	Yes	2 - Stupor
Yes	No	No	No	3 - Deep coma

other discriminants that would help to make more accurate the triage. In the last screen there are options to add information about another discriminant, only one more variable is needed to confirm the final triage level. Then we have the final screen, where the nurse can review the patient data, and change the final level, if necessary.

4. CONCLUSION AND PERSPECTIVES

This algorithm helps the nurse to make the classification easier, faster and more homogeneous, the algorithm can propose a triage level when the nurse enter some discriminant, and, even if there are only the vital signs values, the program can determine the urgency level if these values represent some risk to the patient health or stability by using the fuzzy logic systems which can handle this kind of values and some gravity scales where nominal values are used to take a decision.

Fuzzy logic allows us to know whether this values determine an urgency level without asking for more information. Also decision trees helps to choose the discriminants and final level by choosing the best way to determine a final level in the less steps as possible. If a patient is in shock, the nurse can select this discriminant, and it will not be needed to fill in another fields, the program will check if the patient is in shock by analyzing the vital signs, but also the nurse has the option to force the decision, in a few steps without taking account another discriminants. These features make the triage by algorithm an intelligent semi-automatic decision system, where however, the medical part has the final decision.

In the near future, several tests will be run to prove the algorithm performance, by simulating vital signs data of some patients and nurses testing the program. This will make more accurate the fuzzy system by letting us adjusting the membership function values depending on the test results; it will also help to place strategically in the screen the buttons more used in the triage process or, in some cases, to combine the less used, this would lead automatically to a pruning of decision trees, to increase the performance of the algorithm.

ACKNOWLEDGEMENT

We are grateful to M. Michel Baer (Head of SAMU 92) and Dr Anna Ouzgouler (SAMU 92) for their support and useful remarks.

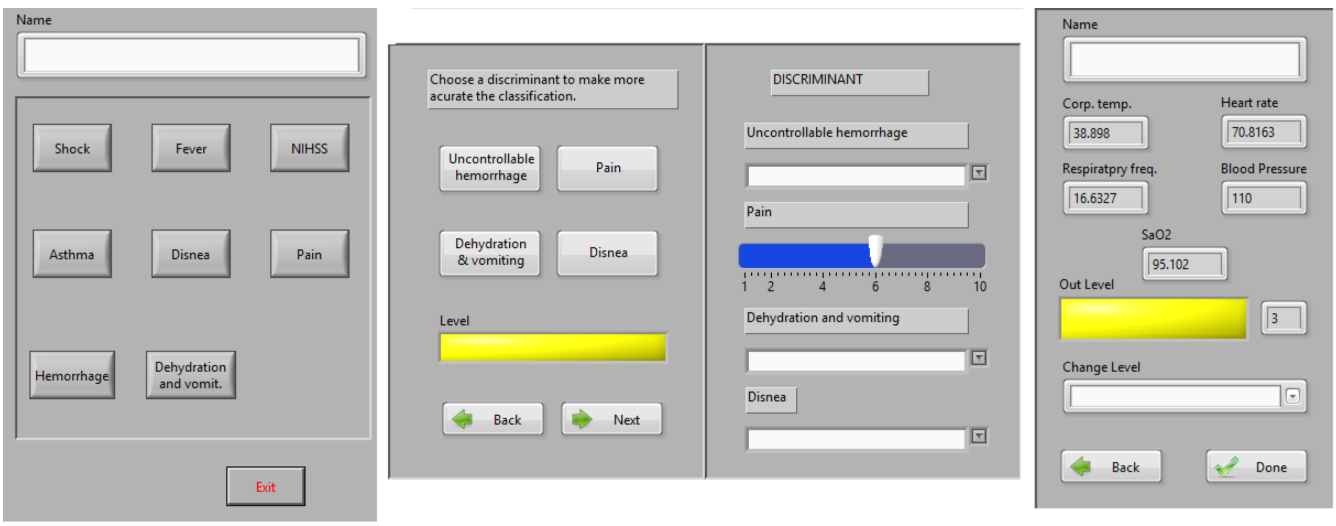

Fig. 6. Fever category screens.

BIBLIOGRAPHY

[1] ADLER C. et al., IT-Supported Management of Mass Casualty Incidents: The e-Triage Project, Proceedings of the 8th International ISCRAM Conference Lisbon, Portugal, May 2011.

[2] GAO T. et al., The Advanced Health and Disaster Aid Network: A Light-Weight Wireless Medical System for Triage. IEEE Transactions on biomedical circuits and systems, September 2007, Vol. 1, No. 3.

[3] GILBOY N. et al., Emergency Severity Index, a triage tool for emergency department care. Implementation Handbook. AHRQ Publications, 2012.

[4] GOMEZ J. et al., Sistema de triaje espaol (SET). Sociedad Espaola de Medicina de Urgencias (SEMES), Andorra, 2003.

[5] GOMEZ J. et al., Clinical validation of the new version of the Triage Assistance Program (web_e-PAT v3) of the Andorran Triage Model (MAT) and Spanish Triage System (SET). Reliability, usefulness and validity in the pediatric and adult population. Servei d'Urgncies, Hospital Nostra Senyora de Meritxell, 2005.

[6] ROKACK L., MAIMON O., Data mining and knowledge discovery handbook, second edition, Springer Science+Business Media, 2010, pp. 149-166.

[7] ROKACK L., MAIMON O., Data mining with Decision trees: Theory and Applications, Series in Machine Perception and Artificial Intelligence, 2008, Vol. 69.

[8] ROSS T., Fuzzy Logic with Engineering Applications, John Wiley and Sons, Ltd. 2004.

[9] SOLER W., Gomez M., Triaje: a key tool in emergency care. An. Sist. Sanit. Navar, 2010, No. 33 Supl. 1, pp. 55-68.

[10] SANCHEZ R. et al., El triaje en urgencias en los hospitales espaoles. U. de urgencias, Hospital Nuestra Seora del Prado, Toledo Espaa, 2012.

[11] SAJFERT Z. et al., Application of fuzzy logic into process of decision making regarding selection of managers. African Journal of Business Management, March, 2012, Vol. 6 (9), pp. 3221-3233.

[12] SUMATHI S. SUREKA P., Computational Intelligence Paradigms: theory & applications using MATLAB, Taylor & Francis group, 2010, pp. 9-11, 203-207.

[13] TOLIFE, TRIUS Triage Station and Emerges Platform. www.tolife.com.br.

[14] WILLIAMS G., Data Mining with Rattle and R, Springer, 2011, pp. 205-244.