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Situation Identification using Context Space Theory and Decision Tree

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Abstract

Context Space Theory (CST) is a geometrical approach used to represent contexts and situations in situation-aware computing applications. In this theory, situations are represented in a multidimensional space, where each dimension corresponds to an interesting feature of the context. The primary advantage of CST lies in its capacity to effortlessly integrate multiple factors, creating a meaningful representation of situations that can be observed and manipulated by experts. Moreover, it empowers experts to customize the situation space to align with their knowledge and understanding of the situation. However, when applied to real-world scenarios, modeling complex situation spaces can be time-consuming and labor-intensive. This is due to the manual effort required in defining contribution functions for each context feature, as well as determining weights and thresholds to identify the situation space.

To address this challenge, the paper proposes a hybrid approach that combines decision trees with the CST, thereby expediting the definition of situation spaces. Decision trees are employed to automatically identify an initial definition of the contribution functions and weights, reducing the workload on human experts. To demonstrate the efficacy of this approach, the paper showcases a case study focused on the management of the Covid-19 pandemic situation in Italy.

1 Introduction

In complex and dynamic environments, having good situation awareness (SA) is essential for making rapid and coherent decisions. SA involves being aware of ongoing events in the environment and understanding their implications for current and future objectives, enabling informed decisions and actions [18, 5]. Both human and artificial smart agents should possess adequate levels of situation awareness to exhibit intelligent behavior and adapt to their surroundings. SA has been extensively studied in numerous fast-paced and dynamic settings, such as aviation, healthcare, military operations, industrial processes, command and control rooms, transportation, cybersecurity, and more. Various studies [6] have suggested that the absence of SA is often the underlying factor behind many human errors, emphasizing the significance of SA in ensuring safety and achieving optimal human-machine teaming in such dynamic environments.

However, attaining and sustaining sufficient levels of SA is a challenging and crucial aspect for numerous operational tasks performed by both human and artificial agents.

In order to enable both human and artificial agents to be aware of situations, it is necessary to provide them with:

- Adequate explicit computational models of situations that can be manipulated by artificial agents and easily understood by human agents.

- Techniques and approaches that allow human operators to analyze, reason about, project, and track situations over time, supported by human-computer interaction techniques and decision support systems.

Various models and computational approaches for representing, identifying, and projecting situations have been proposed. Situation identification techniques can be broadly categorized into two groups [18]: learning-based and specification-based techniques. Learning-based techniques, such as Naive Bayes, hidden Markov models, and neural networks, have the ability to identify situations without the need for explicit supervision. However, they might not offer a formal and explicit model of these situations, which can hinder a deeper understanding by human operators. On the other hand, ontological approaches, fuzzy cognitive maps, evidence theory, and other logic-based techniques offer powerful capabilities for formally and explicitly representing situations. Nevertheless, they might lack the flexibility to adapt to users' interactions or to different domains without significant modifications.

An intriguing expert-based model is Context Space Theory (CST) [15, 2], a versatile technique for modeling and identifying contexts and situations in context-aware systems. CST strikes a balance between an easy-to-use approach and a strong foundation in mathematical theory. CST involves representing context in a multidimensional space known as the context space, where context attributes, typically generated by sensors, serve as the dimensions of this space. To illustrate how a multidimensional space can be used to represent context and situations, let's consider the following example related to the comfort level in an office. In this case, the multidimensional space contains two contextual attributes, represented by two axes: one is related to the noise level, and the other is related to the light level. The combination of these two attributes defines the comfort level in the office. Points in the contextual space with coordinates corresponding to a high level of noise and a low level of light define an uncomfortable situation, while low noise and a high level of light define comfortable situations. This approach provides a formal, general-purpose and easy representation of contexts in context-aware systems. However, as in the previous example, this method involves the manual definition of context spaces, which entails defining contribution functions and weights to mathematically express the significance and influence of each environmental aspect on the perceived situation. Creating this context space necessitates domain experts with the necessary knowledge of the environmental dynamics. Therefore, this manual process can be labor-intensive and time-consuming.

A CST-like approach, combining formality with simplicity and lightweight attributes, would be highly beneficial for situation-aware systems in effectively represent situations. In pursuit of this objective, this paper introduces a novel technique called Decision Tree-based Context Space Theory (DT-CST). This approach employs decision trees in a data-driven manner to semi-automatically define the context space and contribution functions, hereby reducing the reliance on experts to manually define and fine-tune these functions. We present a real case study focused on monitoring the management of the Covid-19 pandemic in Italy to demonstrate the effectiveness of DT-CST.

2 Context-Space Theory

The Context Space Theory (CST) is a specification-based technique introduced by Padovitz, Boytsov et al. in [15, 2]. It employs a geometric approach to represent context and situation, with the aim of achieving a clear and insightful context representation [7].

In CST, a multidimensional space represents the context space. Each dimension (axis) of this space corresponds to a context attribute, which represents a feature of the context. With respect to the example reported in the introduction, the context attributes are the light level and the noise level. At a specific time instant, the state of the context X is given by the values of the context attributes and is visually represented as a point in the context space. Furthermore, the set of real situations that can occur in the domain of interest is defined as the situation space. The current situation can be identified using the formula:

$$S(X) = \sum_{i=1}^{N} w_i * contr_{Si}(x_i) \tag{1}$$

Where $S(X)$ is the confidence level of situation S in the context state X; the context state X includes the values of relevant context attributes x_i for situation S, weighted by coefficients w_i that indicate their importance for situation S. The contribution function, typically a step function, denoted as $contr(x_i)$, indicates the contribution of the context attribute x_i to the situation $S(X)$. The confidence level, denoted as $S(X)$, is the output of situation reasoning, with its value ranging between 0 and 1. A situation's confidence value is considered a composition of contributions from multiple contextual attributes. Therefore, the interpretation assigned to this value depends on the specific application. In the previous example, it indicates the comfort level (with higher values of $S(X)$ signifying greater comfort in the office). In other cases, it might represent a risk level, as in the case study outlined in Section 4.

Furthermore, it's possible to assign a binary value to the situation $S(X)$ by comparing the confidence value with a predetermined threshold:

$$S(X) = \begin{cases} true, & \sum_{i=1}^{N} w_i * contr_{Si}(x_i) \geq threshold \\ false, & \text{otherwise} \end{cases} \tag{2}$$

In this case, the situation S(X) is said to be true if its confidence value, for the current state X, is greater than the threshold.

3 DT-CST: Decision Tree-based Context Space Theory

Figure 1 depicts the steps of the Decision Tree-based Context Space Theory (DT-CST). The primary aim of DT-CST is to simplify the process of defining the context and situation spaces when employing the Context Space Theory as the situation model for an artificial agent.

The DT-CST approach requires the availability of few situation examples stored in an Information Table (or dataset) **IT**. This information table $\mathbf{IT} = \{\mathbf{A}, D\}$ contains the interesting attributes or features observed in the environment, where $\mathbf{A} = \{a_1, a_2, ..., a_m\}$ is the set of m attributes, and D is the decision attribute which represent the decision, or the risk level, or the confidence level of a situation. The Information Table **IT**, undergoes a transformation to become a Context Space Information Table (**CSIT**) through the calculation of context attributes. A context attribute can be defined as a combination of k attributes using the function $f_{c_i}(a_1, a_2, ..., a_k)$, where $k \leq m$. In this stage, the attributes that will define the context space need to be selected. This selection can be carried out by the user, domain experts, or automated methods that identify the most crucial attributes for situational classification. One such automated approach involves utilizing feature selection techniques like Random Forest to rank attributes based on their significance in the classification task and then choosing the top-k attributes [17].

Once the attribute selection and context attribute computation are completed, the resulting CSIT will encompass the set $C = (c_1, ..., c_n)$ consisting of n context attributes. Additionally, the situation S is derived from the decision attribute D. This derivation can involve applying a threshold operation to the values of D or utilizing various types of functions, whether linear or non-linear, for this transformation.

The CSIT is employed to train a binary decision tree (DT). However, in general, other machine learning techniques could be utilized to derive the contribution functions, as long as these techniques facilitate the identification of classification rules. Examples of such techniques include fuzzy neural networks, classification and regression techniques, and more. The essential requirement is that the chosen ML technique can effectively extract classification rules from the CSIT table to classify situations based on the values of the contextual features. In this work, our emphasis will be on the utilization of decision trees

A decision tree is a predictive model used in machine learning for both classification and regression tasks. It is a tree-like structure where each internal node represents a decision based on a specific feature (attribute), and each leaf node represents the predicted outcome or target variable. The process of building a decision tree involves recursively partitioning the data into subsets based on the values of different attributes, aiming to create branches that best separate the data points into distinct classes or predict numerical values.

The decision tree is constructed using a top-down, recursive approach. The goal is to split the data into homogeneous subsets with respect to the target variable. The root of the tree represents the entire dataset, and at each internal node, a splitting rule is applied to partition the data based on a chosen attribute.

In a binary decision tree, the splitting rule typically involves finding the attribute that results in the best separation of classes. Therefore, applying the decision tree to the CSIT allows to obtain a DT whose leaves corresponds to the different values of situation S, and the path from the root to the leaf, traversing the nodes of the three, represents the combination of splits on the context attributes $c_i \in \mathbf{C}$. The values on which each context attribute c_i is split will represent one of the step in the contribution function $contr_i(c_i)$. This enables the automatic definition of a preliminary version of the contribution functions for all the context attributes.

In order to compute the situation confidence level $S(X)$ (Eq. 1), the weighting factor for each contribution function needs to be defined. A good approximation of the weights can be obtained by computing the feature importance of each context attribute using a Random Forest. Random Forest is an ensemble learning method that combines multiple decision trees to create a more robust and accurate model. One of the advantages of using a random forest is its ability to calculate the importance of features used in the model. This is done by measuring how much the model's accuracy decreases when each feature is removed or shuffled. Features that have a larger impact on the model's performance are considered more important.

The importance of each context attributes is utilized as the weight w_i of the context attribute c_i in Eq. 1. The resulting function $S(X)$ represents an initial model of the situations contained in the CSIT. However, manual intervention might be necessary to fine-tune and optimize the function further. Alternatively, other computational approaches, such as reinforcement learning or evolutionary computation, can be employed to automate the fine-tuning process. In either case, this process will demand significantly less effort from the experts, as they will be building upon an already well-established model that accurately captures the nature and relationships present in the data of the Information Table (IT).

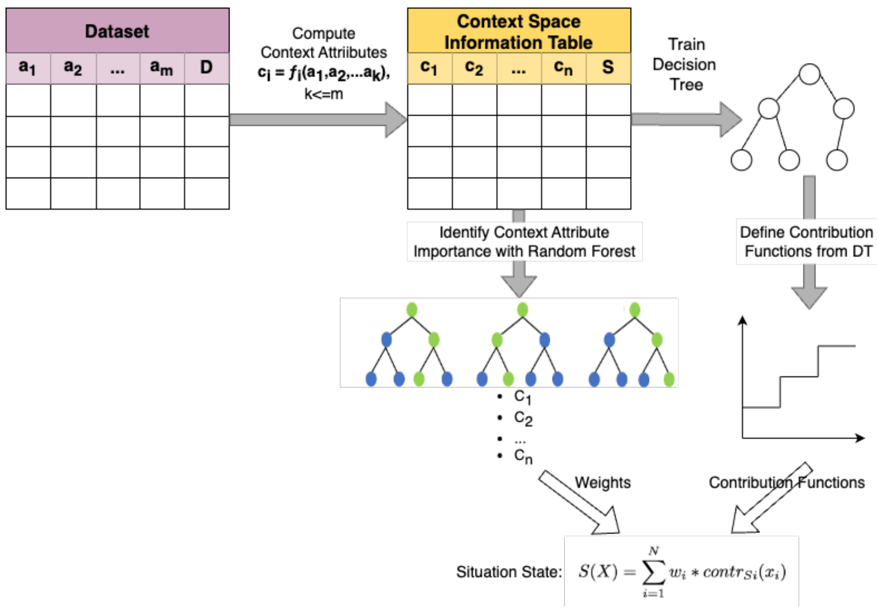

Figure 1: Decision-Tree Context Space Theory

Indeed, one of the advantages of the proposed model compared to traditional learning-based models is that experts retain the ability to comprehend the situation model. The model is represented by a multidimensional space and a set of step functions, allowing experts to visualize and understand how different context attributes contribute to the overall situation representation. Furthermore, the process used to construct the situation model is transparent and visible. The decision tree, being an interpretable model, can be easily visualized and used to make predictions for new, unseen data. This transparency enables experts to inspect and validate the decision-making process, providing them with insights into how the model arrives at its predictions.

Having an interpretable model like the decision tree ensures that experts can comprehend and trust the model's outputs, making it easier to explain the rationale behind its predictions. This transparency is particularly valuable in critical domains where human decision-making plays a significant role in ensuring safety and reliability [12].

4 Case Study: Covid-19 Pandemic in Italy

The COVID-19 pandemic has had a profound and devastating impact on global health, societies, and economies, despite the collective efforts of healthcare professionals, governments, and the general public. This crisis has emphasized the critical need for preparedness in facing future emergencies. It is crucial to equip decision-makers with the appropriate tools to rapidly assess the status of the pandemic situation and analyze potential alternative strategies to mitigate its effects. Swift intervention policies are essential for effectively managing such crises and minimizing their impact on human lives and well-being.

In order to be prepared for eventual novel outbreaks and epidemics, there is a growing demand for methodologies, approaches, and systems to monitor and manage public health emergencies [11]. Within the field of situation awareness research, there have been numerous proposals focusing on what is referred to as Pandemic Situation Management (e.g., as seen in [9, 13]).

In this section, we provide a simple illustrative example in which the DT-CST approach was applied to manage the pandemic situation in Italy.

Italy was the first European country to face severe repercussions from COVID-19, experiencing an acute overload in its healthcare system shortly after encountering the disease for the first time. To respond to the crisis, Italian authorities established an epidemic surveillance system utilizing risk/impact methodologies to promptly categorize risks [8]. This system integrates various factors, including epidemic indicators, risk analysis, healthcare system load and resilience, the effective reproduction index R(t) [14] of the Covid outbreak, and weekly incidence data. By employing these metrics, regions were regularly assigned a color code (ranging from the best situation to the worst: white, yellow, orange, and red zones). Each color code was associated with a specific set of restrictions on activities and movement aimed at containing the outbreak. The criteria for assigning colors to regions, as well as the policies and regulations regarding the imposed restrictions, underwent changes over the course of months to reflect the evolving nature of the pandemic.

The approach used by the Italian government has faced criticism for its excessive complexity, reliance on numerous parameters, over-reliance on qualitative information, and differences among regions [1]. The presence of uncertain elements and significant challenges in the Italian approach emphasizes that both the technological and governance domains lack complete readiness in terms of solutions and procedures to facilitate swift decision-making during the pandemic. This is further exacerbated by the limitations of the implemented healthcare information systems, which fail to ensure a comprehensive understanding of the pandemic situation.

4.1 Dataset

The data utilized in this study is a fusion of information gathered from two sources: the weekly reports issued by ISS (Istituto Superiore di Sanità - Italian National Institute of Health) [1] and the daily report of the Italian Protezione Civile (Civil Protection), available on GitHub [2]. The study focused on the period between November 2020 and October 2021, with data aggregated on a weekly basis for each region. Consequently, the dataset contains 51 samples with weekly data for each of the 21 Italian regions/PAs, amounting to a total of 1071 samples.

The weekly reports from ISS consist of 21 indicators categorized into three groups: i) monitoring capacity; ii) diagnostic assessment capacity and contact tracing; iii) virus transmission and healthcare system resilience. These 21 indicators are utilized to estimate the probability of the virus spreading and its impact on both hospitals and individuals. By combining probability and impact, a risk level is determined for each region, which then dictates the assigned risk color. A detailed explanation of this procedure can be found in [8]. Out of the 21 indicators, only 16 are mandatory and consistently available in all weekly reports, while the remaining five are optional and may not always be provided. On the other hand, the Italian Protezione Civile (IPC) dataset contains daily data related to Covid incidence, such as the number of new cases, for each province and region. From this dataset, three indicators were calculated: weekly

[1] https://www.iss.it/monitoraggio-settimanale
[2] https://github.com/pcm-dpc/COVID-19

Table 1: Indicators selected from ISS and IPC dataset based on feature importance evaluated using a Random Forest

ID	Description	Feature Importance
a_1	R_t effective reproduction number \cite{JUNG202147}	0.231
a_2	# Weekly incidence = $\frac{\text{weekly positives}}{\text{population}} \times 100,000$	0.226
a_3	Weekly deaths = $\frac{\text{week deaths}-\text{previous week deaths}}{\text{population}} \times 100,000$	0.124
a_4	%non-ICU: occupancy rate of total medical area beds for Covid-19	0.145
a_5	%ICU: occupancy rate of total ICU beds for Covid-19	0.157

incidence, weekly prevalence, and weekly death rate.

4.2 Method

The situation that the DT-CST approach aims to represent and identify is the risk level of each region for each week. The situation S can take on the following values: white, yellow, orange, and red, indicating an increasing level of risk. The Information Table IT consists of a row for each region and each week, encompassing 19 indicators. These indicators include the 16 mandatory indicators from the ISS and three additional ones from the IPC dataset. The decision attribute in the Information Table contains the weekly color assigned to each region, reflecting its risk level.

To obtain the Context Space Information Table (CSIT), only the relevant attributes that are useful for identifying the situation S need to be selected and, if necessary, combined to define the context attributes. For the case study, to simplify the context space, a subset of the 19 indicators was chosen. To identify the most important attributes for the classification of the situation, a Random Forest was employed to select the most significant features. The selected features are presented in Table 1.

Attributes a_1, a_2, and a_3 will be directly used in the CSIT table as they are already the combination of several factors, as described in Table 1. They will be denoted as c_1, c_2, and c_3, respectively. Attributes a_4 and a_5 are combined to form a new context attribute, referred to as c_4 "resilience", which indicates the load on hospitals. The context attribute resilience is calculated as follows:

$$c_4 = \frac{w_{ICU} \times a_4 + a_5}{w_{ICU} + 1} \tag{3}$$

In Eq. 3, the weight w_{ICU} is utilized to assign more importance to ICU occupancy compared to non-ICU beds. To determine the value of this parameter, a Random Forest was employed to assess its significance in classifying the situation S with different values of w_{ICU} in the range of $[1-2]$ [17]. The best performance was observed when setting $w_{ICU} = 1.5$.

Once we have defined the CSIT table with the four context attributes, the decision tree is trained to classify the risk level S. The Gini splitting criterion [16] has been employed for the decision tree, and the maximum depth of the tree has been limited to 4.

Figure 2 displays the resulting decision tree. Each node contains one of the context attributes with a splitting criterion, and the leaves of the tree contain the value of the situation. The numbers in each leaf represent the count of CSIT samples classified with that color. The decision tree was employed to classify the available regions using the configuration mentioned above. It achieved the performances reported in Table 3 for each individual color category. Table 4 reports the overall accuracy and F1-score. Specifically, the decision tree attained an F1-score (macro) of 0.789 and a balanced accuracy of 0.835.

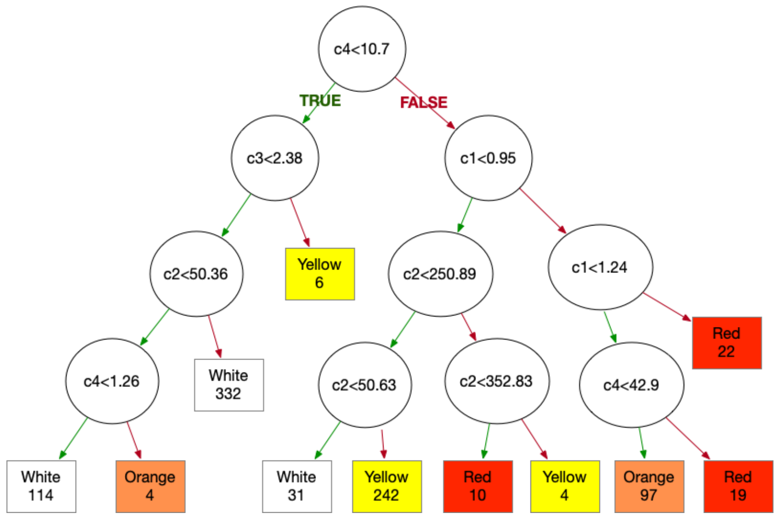

Figure 2: Decision tree for the weekly classification of regions

Starting from the decision tree, we defined the contribution functions reported in Figure 3. The steps in these contribution functions correspond to the thresholds identified by the decision tree during the rule construction process, representing the splits at each node of the decision tree.

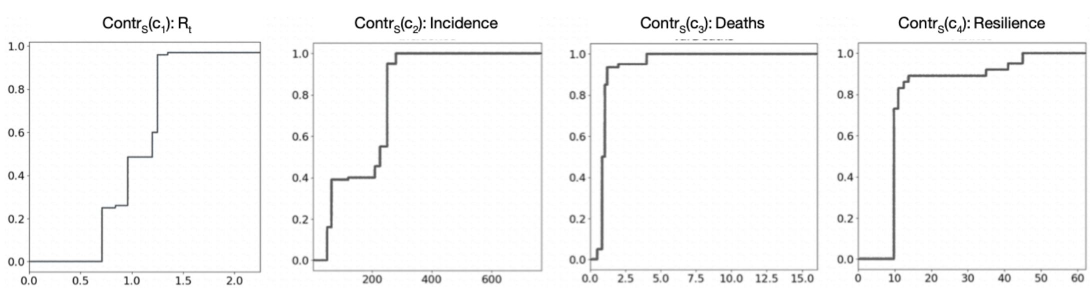

Figure 3: Contribution functions

The next step of the DT-CST approach is the identification of the weights w_i in Eq. 1. This is done by computing the feature importance using a Random Forest (RF) on the CSIT table (with the four context attributes as the features and the situation as the class). The feature importance computed by the RF is used as the weights for each context attribute. The weights are provided in Table 2.

Finally, the situation $S(X)$ is evaluated with equation 4.

$$S(X) = 0.335 * c_1 + 0.225 * c_2 + 0.110 * c_3 + 0.330 * c_4 \tag{4}$$

To transform the numerical situation value $S(X)$ into a categorical value that corresponds to the zone coloring, it is necessary to establish thresholds. The chosed thresholds are as follows:

- white, when $0 \leq S(x) < 0.415$;

Table 2: Weights w_i of each context attribute, identified using a Random Forest

Feature	Importance
w_1: R_t	0.335
w_2: Incidence	0.225
w_3: Deaths	0.110
w_4: Resilience	0.330

- yellow, when $0.415 \leq S(x) < 0.630$;
- orange, when $0.630 \leq S(x) < 0.735$;
- red, when $S(x) \geq 0.735$.

Using these thresholds, we compared the color assigned by DT-CST method with the original one available in the Information Table and assigned by the Italian Government according to the ISS reports.

4.3 Results

The performances of DT-CST approach for the classification of regional risk level for each week and each risk level, compared with those of the decision tree, are shown in Table 3, while Table 4 reports the overall average values.

Table 3: Comparison between DT-CST technique and Decision Tree for the classification of Italian Regions during Covid-19, based on each risk color. F1: F1 score (macro); P: Precision; R: Recall.

	WHITE			**YELLOW**			**ORANGE**			**RED**		
	F1	P	R	F1	P	R	F1	P	R	F1	P	R
Decision Tree	0.951	0.928	0.976	0.827	0.880	0.818	0.529	0.457	0.627	0.850	0.752	0.917
DT-CST	0.968	0.960	0.977	0.881	0.905	0.859	0.703	0.725	0.682	0.860	0.780	0.958

Table 4: Comparison of the overall performance achieved by the DT-CST technique with that of the decision tree.

Metric	Decision Tree	DT-CST
F1 score (macro)	0.789	0.853
Accuracy	0.892	0.910
Balanced Accuracy	0.835	0.869

The results demonstrate a high level of accuracy (0.910), along with good values for the F1 score (0.853) and balanced accuracy (0.869), and all the metrics are slightly better than the decision tree. The white zone exhibits the best performance in terms of F1 score, precision, and recall, which is reasonable as it is influenced by the most significant factors, characterized by low incidence, variations in deaths, and a mix of resilience. On the other hand, the orange zone shows the poorest performance, with F1 score, precision, and recall values of 0.703, 0.725, and 0.682, respectively (but with an improvement with respect to the decision tree). This can be attributed to the fact that the yellow and orange coloration does not always have a clear separation, leading to some overlaps in their classification. Additionally, differences in region coloring have been observed, even when the values of the indicators from the ISS reports are the same [1]. Furthermore, the approach used by the government to color the regions changed significantly over the course of the pandemic to reflect its severity. This introduces some variations in region coloring, even if they have similar values for the considered indicators.

Despite these challenges, the obtained performance shows that the DT-CST approach serves as a solid starting point for defining an initial Situation Space based on available experimental data, thus easing the workload on human experts. With this preliminary definition of situations, experts can engage in reasoning and discussions to refine the desired situation model, incorporating their experience into the representation of the situation space.

5 Conclusion

The paper introduces a novel approach to defining the situation space when using Context Space Theory, based on a data-driven approach. Decision trees are employed to identify the contribution functions that map context attributes to the situation space. Random forests are then utilized to estimate the weights used in the linear combination to calculate the situation state.

A case study using real data regarding the management of the COVID-19 pandemic has been proposed. The approach achieved good accuracy in approximating the decisions of the Italian government in assigning risk levels to different regions. The errors are mainly attributed to different policies adopted by the government during the year, as well as some political decisions that resulted in more or less restrictive measures depending on the case.

To address this issue, future work will explore the utilization of dynamically changing weighting factors and thresholds that can adapt to different conditions over time, thus aligning with the evolving nature of situations.

Another limitation of the proposed approach is the requirement for manual revision by human experts of the generated contribution functions to achieve optimal performance. Although the approach significantly reduces the burden on experts, their input remains essential. Therefore, in future work, we will investigate the possibility of employing reinforcement learning and/or evolutionary computation to automatically fine-tune the contribution functions. This aligns with our overarching goal of establishing a comprehensive and automated context space definition approach. Additionally, we will incorporate the presence of uncertainty in context attribute values through the use of fuzzy contribution functions. Lastly, the approach will be experimented in other domains, including activity recognition [4], autonomous vehicles [10], and e-learning [3].

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