Brief Introduction to AI, DL and KRR

1 Deep Learning versus Knowledge Representation and Reasoning

Many approaches to integrate *Deep Learning* (*DL*) with *Knowledge Representation* and *Reasoning* (*KRR*) are based on the fact that one must give up on having a *fixed symbolic structure* to it. Indeed, they work on a process of *relaxation*, leading to situations where the *KRR* are *induced* by learning algorithms (e.g., deep learning), being therefore mostly opaque to the programmers. This is the key distinction between their approach (in which they assert that the work done is symbolic logic in vector spaces, remaining *discrete* the essential features, and nothing is gained), to the one that will be presented below, where, although it has a symbolic logic in the vector spaces, the elements or attributes of the logical functions thus described go from discrete to continuous, allowing for *unknown*, *incomplete*, *forbidden* and even *self-contradictory information* or *knowledge*.

Undeniably, many approaches to *KRR* have been proposed using the *Logic Programming* (*LP*) epitome, namely in the area of *Model Theory* [2, 3] and *Proof Theory* [4, 5]. In the present work, the *Proof Theoretical* approach in terms of an extension to the *LP* language is followed. An *Extended Logic Program* is, therefore, given by a finite set of clauses, in the form:

$$
\begin{array}{l}
\{ \\
\neg\, p \leftarrow not\ p, not\ exception_p \\
p \leftarrow p_1, \cdots, p_n, not\ q_1, \cdots, not\ q_m \\
?\,(p_1, \cdots, p_n, not\ q_1, \cdots, not\ q_m)\ \ (n, m \geq 0) \\
exception_{p_1},\ \ \cdots\ \ , exception_{p_j}\ \ (0 \leq j \leq k),\quad being\ k\ an\ integer\ number \\
\} :: scoring_{value}
\end{array}
$$

where the first clause stand for predicate's closure, "," denotes "*logical and*", while "*?*" is a domain atom denoting falsity, the p_i, q_j, and p are classical ground literals, i.e., either positive atoms or atoms preceded by the classical negation sign $\neg$ [6]. Indeed, $\neg$ stands for a strong declaration that speaks for itself, and *not* denotes *negation-by-failure*, or in other words, a flop in proving a given statement, once it was not declared explicitly. Under this formalism, every program is associated with a set of *abducibles* [2, 3], given here in the form of exceptions to the extensions of the predicates that make the program, i.e., clauses of the form:

$$exception_{p_1},\ \ \cdots\ \ , exception_{p_j}\ \ (0 \leq j \leq k),\quad being\ k\ an\ integer\ number$$

that stand for data, information or knowledge that cannot be ruled out. On the other hand, clauses of the type:

$$?\,(p_1, \cdots, p_n, not\ q_1, \cdots, not\ q_m)\ \ (n, m \geq 0)$$

also named *invariants*, allows one to set the context under which the universe of discourse has to be understood. The term $scoring_{value}$ stands for the relative weight of the extension of a specific predicate with respect to the extensions of peers ones that make the inclusive or global program.

In order to evaluate the data, information or knowledge's qualities that may be associated to logic program, an assessment of it, given in terms of the metrics *Quality-of-Information* (*QoI*) and *Degree-of-Confidence* (*DoC*), are posted truth-values ranging between 0 and 1 [7, 8].

In terms of a logic program that has as attributes discrete values, $QoI_i = 1$ when the information is *known* (*positive*) or *false* (*negative*), and $QoI_i = 0$ if the information is *unknown*. Finally, for situations where the extension of a given $predicate_i$ is taken from a *abducible* set (i.e., a set of possible terms or clauses that compete with one another to set a possible extension of a given logic function or predicate), $QoI_i \in\ ]0, 1[$, i.e.:

$$QoI_i = {}^{1}\!/_{Card}$$

where *Card* denotes the cardinality of the *abducibles* set for *i*, if the *abducibles* set is disjoint. If the *abducibles* set is not disjoint, the clause's set is given by $C_1^{Card} + \cdots + C_{Card}^{Card}$, under which the *QoI's* evaluation takes the form:

$$QoI_{i_{1 \leq i \leq Card}} = {}^{1}\!/_{C_1^{Card}}, \cdots, {}^{1}\!/_{C_{Card}^{Card}}$$

where C_{Card}^{Card} is a card-combination subset, with *Card* elements (Fig. 1).

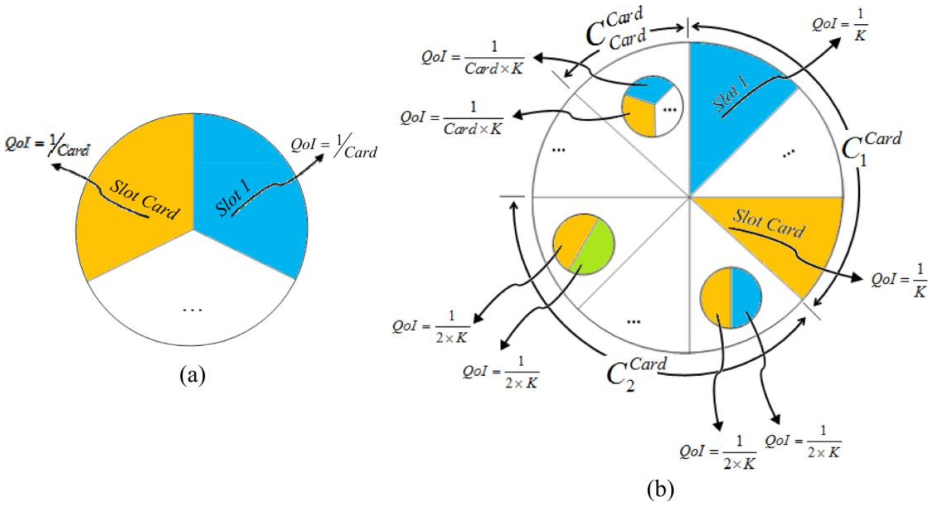

Fig. 1 *QoI's* values for the abducible set for $predicate_i$ with (a) and without (b) constraints on the possible combinations among the *abducible* clauses.

On the other hand, and in general, one has situations such as the one depicted below, where the predicates' attributes may be unknown, discrete or taken from a set or an interval, having into consideration their domains.

$$\begin{array}{l} \{ \\ \neg f_1(X,Y,Z) \leftarrow not\ f_1(X,Y,Z), not\ exception_{f_1(X,Y,Z)} \\ f_1(\underbrace{[5,\ 7],\quad \perp,\qquad 6.5}_{attribute`s\ values}) \\ \quad \underbrace{[0,8]\ [12,36][5,10]}_{attribute`s\ domains} \\ exception_{f_1}(4,\ [30,\ 35],\ \perp),\ \cdots\ ,exception_{f_k}(\perp,\ 10,\ [7,\ 8]) \\ \} :: 1\ \textit{(once the universe of discourse is set in terms of the extension of only one predicate)} \end{array}$$

where $\perp$ denotes a null value of the type *unknown*, stands for a logic program that denotes a particular universe of discourse in its initial form. Then, it is now possible to split the *abducible* or *exception* set into the admissible clauses or terms and evaluate their *QoIs*. A pictorial view of this process, in general terms, is given below as a pie chart (Fig. 2).

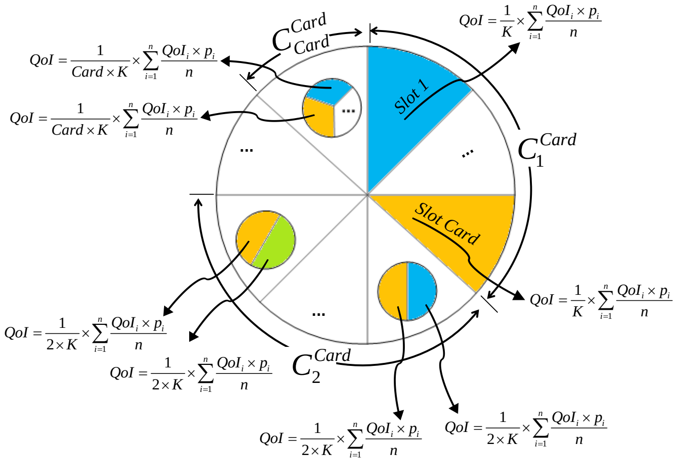

Fig. 2 QoI's values for the *abducible* set of clauses referred to above. The clauses cardinality set, *K*, is given by the expression $C_1^{Card} + C_2^{Card} + \cdots + C_{Card}^{Card}$, where $\sum_{i=1}^{n}(QoI_i \times p_i)/n$ denotes the attributes *QoI's* average of each clause or term. p_i stands for the relative weight of attribute *i* with respect to its peers, being $\sum_{i=1}^{n} p_i = 1$.

Under this setting, a new evaluation factor has to be considered, which will be denoted as *DoC*, that stands for one's confidence that the argument values or attributes of the terms that make the extension of a given predicate, having into consideration their domains, fit into a given interval [9]. The *DoC* is evaluated as shown in Fig. 3 and computed using $DoC = \sqrt{1 - \Delta l^2}$, where Δl stands for the argument interval length, which was set in the interval [0, 1]. Thus, the universe of discourse is engendered according to the information presented in the extensions of such predicates, according to productions of the type:

$$predicate_i - \bigcup_{1 \le j \le m} clause_j\left(\left(\left[A_{x_1}, B_{x_1}\right]\left(QoI_{x_1}, DoC_{x_1}\right)\right), \cdots \right.$$
$$\left. \cdots, \left(\left[A_{x_n}, B_{x_n}\right]\left(QoI_{x_m}, DoC_{x_m}\right)\right)\right) :: QoI_j :: DoC_j$$

where U, *m* and for example $[A_{x_j}, B_{x_j}]$ stand for, respectively, set union, the cardinality of *predicate*$_i$ extension and the extremes of the interval where attribute *attribute*$_j$ may, in principle, be situated.

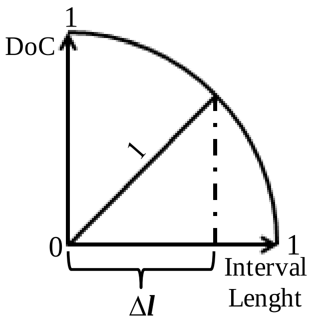

Fig. 3 Evaluation of the attributes' *Degree of Confidence.*

2 Case Based Reasoning

The area of *AI* concerned with *Case Based Reasoning* (*CBR*) denotes an approach to problem solving and learning that puts it in a nutshell, i.e., previously solved problems (cases) are used to suggest solutions for novel but similar ones. This method uses the specific knowledge of past situations of concrete problems as opposed to using the general one of a certain domain [10], i.e., when a problem arises it looks for similar past problems and reuses the solution found for these problems.

In order to represent the CBR process, we will focus on an extended version of the *CBR* cycle (Fig. 4) [13], an extension of the conventional one [1].

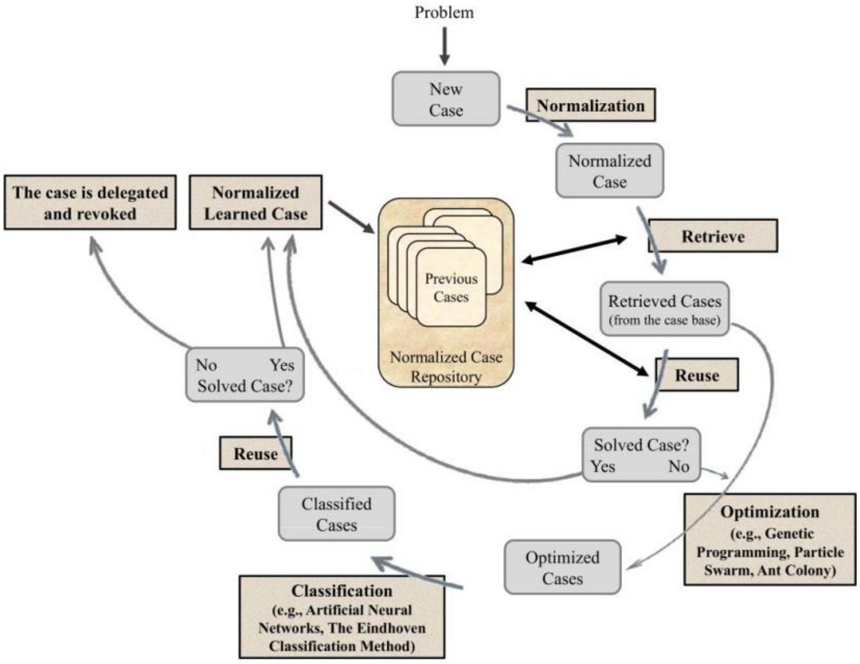

Fig. 4 Extended *CBR* cycle.

The former step comprises an initial description of the problem or new case, where the characteristics and their attributes are identified. Then, in the normalization phase, the feature vector attributes ‘values of the new case are standardized, to values in the range [0,1], given origin to a clause or term in the form:

$$predicate_{new} - \bigcup_{1\leq j\leq m} new_j\left(\left(\left[A_{x_1}, B_{x_1}\right]\left(QoI_{x_1}, DoC_{x_1}\right)\right), \cdots\right.$$
$$\left.\cdots, \left(\left[A_{x_n}, B_{x_n}\right]\left(QoI_{x_m}, DoC_{x_m}\right)\right)\right) :: QoI_j :: DoC_j$$

The retrieved cases from the case base are ranked according to those that present the best overlaps with those of the new case.

After calculating the similarities and dissimilarities between the new case and all the cases recovered, it is possible to find the case or cases recovered that are closer to solving the problem [11].

3 Example of Feature Extraction

At this stage and in terms of the feature set referred to above, it were considered the descriptions:

• *Tumor Volume;* and
• *Tumor Diameter.*

Once having accomplished the segmentation step, the *3D Slicer Ruler* was used to measure the diameter as well as the *LabelStatistics* module that allowed the calculation of the volume. These extracted characteristics will produce a feature vector - VC - that will represent the dataset.

Other characteristics, such as *Age*, *Weight*, or *Risk Factors*, from the patients studied were extracted from a text file, contained in the image repository *The Cancer Imaging Archive* (*TCIA*).

After choosing the sample of patients to be studied and describing the procedures that served as a basis for the pre-processing and extraction of the MRI features, were constructed tables with the numerical values of each attribute studied for the diagnosis of Cervical Squamous Cell Carcinoma. This data constitutes the knowledge base of each patient studied, containing the patient's data, the *Risk Factors* associated with the diagnosis, and the data extracted from the MRI images.

By the observation of Fig. 5, the *Menopause Status* was represented by ranges of values, since prior to the passage of numerical values, this attribute was of the qualitative type. Patient number 1 has Premenopausal stage and has its numerical representation of [0,1]. There are also unknown values (represented by ⊥) that symbolize, in the case of patient number 2 for e.g., the non-knowledge of its *Tumor Grade.*

Patients' Information

#	Age	Weight	Height	Menopause Status	Number Total of Pregnancies	Live Birth Pregnancies	Tumour Grade	Tumour Status	Pathologic Stage	Vital Status
1	26	92	166	[0, 1]	0	0	[0, 1]	[1, 2]	[0, 1]	[1, 2]
2	26	66	160	[1, 2]	5	4	⊥	[0, 1]	[1, 2]	[0, 1]
…	…	…	…	…	…	…	…	…	…	…
19	39	75	160	[1, 2]	5	5	[0, 1]	[0, 1]	[6, 7]	[1, 2]

Cervical Squamous Cell Carcinoma Diagnosis

	#	Age	Weight	Height	Menopause Status	Number Total of Pregnancies	Live Birth Pregnancies	Tumour Grade	Tumour Status	Pathologic Stage	Vital Status	Tumour Diameter	Tumour Volume	Tobacco Smoking History	Smoking Years	Oral Contraceptives
Attributes of the Feature Vector:	#	Age	Weight	Height	Menopause Status	Number Total of Pregnancies	Live Birth Pregnancies	Tumour Grade	Tumour Status	Pathologic Stage	Vital Status	Tumour Diameter	Tumour Volume	Tobacco Smoking History	Smoking Years	Oral Contraceptives
Feature Vector Attributes' Values:	1	26	92	166	[0, 1]	0	0	[0, 1]	[1, 2]	[0, 1]	[1, 2]	31.2	9921.7	0	⊥	[1, 2]
	2	26	66	160	[1, 2]	5	4	⊥	[0, 1]	[1, 2]	[0, 1]	47.5	37576.7	0	⊥	[1, 2]
	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…
	19	39	75	160	[1, 2]	5	5	[0, 1]	[0, 1]	[6, 7]	[1, 2]	60.1	71754.9	0	⊥	[0, 1]
Feature Vector Domains:		[26, 79]	[44, 113]	[134, 167]	[0, 3]	[0, 14]	[0, 11]	[0, 2]	[0, 2]	[0, 7]	[0, 2]	[25.2, 107]	[9921.7, 711093]	[0, 3]	[0, 39]	[0, 2]

Data Extracted from Uterine Resonance Magnetic Images

#	Tumour Diameter	Tumour Volume
1	31.2	9921.7
2	47.5	37576.7
…	…	…
19	60.1	71754.9

Risk Factors

#	Tobacco Smoking History	Smoking Years	Oral Contraceptives
1	1	⊥	[1, 2]
2	1	⊥	[1, 2]
…	…	…	…
19	1	⊥	[0, 1]

Fig. 5 Knowledge Base for the Diagnosis of Cervical Squamous Cell Carcinoma with Qualitative Representation of Case 1/Patient number 1.

The algorithm of Extension of the Program in Logic, presented in [11] is the objective function of the problem under analysis: the diagnosis of Cervical Squamous Cell Carcinoma in the study patients, $diag_{CSCC}$, presented in the form below:

$$diag_{CSCC}: Age, W_{eight}, H_{eight}, Men_{opause}\ St_{atus}, N_{umber}\ T_{otal} P_{regnancies}, L_{ive} B_{irth} P_{regnancies}, T_{umor}\ G_{rade}, T_{umor}\ S_{tatus}, P_{athologic}\ S_{tage}, V_{ital}\ S_{tatus}, T_{umor}\ D_{iameter}, T_{umor}\ V_{olume}, T_{obacco}\ S_{moking}\ H_{istory}, S_{moking}\ Y_{ears}, O_{ral}\ C_{ontraceptives} \rightarrow \{0,1\}$$

where 0 (zero) and 1 (one) denote, respectively, the truth values *false* and *true*.

By the methodology presented in [11] the following steps have been completed. Firstly, the terms or clauses that are part of the Logical Program Extension (EPL) for the present study were established. In the following step, the intervals of the attributes and values presented in Figure 4 were normalized between [0,1].

The following expression allowed the normalization of attribute values, where Y represents the value of the attribute per line, Y_{min} is the smallest value of the attribute, and Y_{max} is the largest value of the attribute to be calculated.

$$\frac{Y - Y_{min}}{Y_{\max} - Y_{min}}$$

After the normalization of the data, it was evaluated the *Degree-of-Confidence* (*DoC*). To evaluate the *DoC*, it was used an example of the term Patient with the following feature vector data: *Age = 35; Weight = 78; Height = 150; Menopause Status = [1,2]; Number Total Pregnancies = 3; Live Birth Pregnancies = 3; Tumor Grade = [0,1]; Tumor Status = [0,1]; Pathologic Stage = [2,3]; Vital Status = [1,2]; Tumor Diameter = 0.4548; Tumor Volume = 0.0828; Tobacco Smoking History = 2; Smoking Years = 2; Oral Contraceptives = [0,1].*

{

$$\neg\, diag_{cscc}\Big(\big((X_{Age}, Y_{Age})(QoI_{Age}, DoC_{Age})\big), \Big(\big(X_{W_{eight}}, Y_{W_{eight}}\big)\big(QoI_{W_{eight}}, DoC_{W_{eight}}\big)\Big), \ldots, \Big((X_{O_{ral}C_{ontraceptives}}, Y_{O_{ral}C_{ontraceptives}})(QoI_{O_{ral}C_{ontraceptives}}, DoC_{O_{ral}C_{ontraceptives}})\big)\Big)$$

$$\leftarrow not\ diag_{cscc}\Big(\big((X_{Age}, Y_{Age})(QoI_{Age}, DoC_{Age})\big), \Big(\big(X_{W_{eight}}, Y_{W_{eight}}\big)\big(QoI_{W_{eight}}, DoC_{W_{eight}}\big)\Big), \ldots, \Big((X_{O_{ral}C_{ontraceptives}}, Y_{O_{ral}C_{ontraceptives}})(QoI_{O_{ral}C_{ontraceptives}}, DoC_{O_{ral}C_{ontraceptives}})\big)\Big)$$

$$diag_{cscc}\Big(\big((35,35)(1_{[35,35]}, DoC_{[35,35]})\big), \big((78,78)(1_{[78,78]}, DoC_{[78,78]})\big), \ldots, \big((0,1)(1_{[0,1]}, DoC_{[0,1]})\big)\Big) :: 1 :: DoC$$

$$\underbrace{[26,79] \qquad [44,113] \qquad \cdots \qquad [0,2]}_{\text{attribute's domains}}$$

} :: 1

Using the expression $(Y - Y_{min})/(Y_{max} - Y_{min})$, the boundaries of each attribute are normalized and defined in the interval [0,1]:

{

$$\neg\, diag_{cscc}\Big(\big((X_{Age}, Y_{Age})(QoI_{Age}, DoC_{Age})\big), \Big(\big(X_{W_{eight}}, Y_{W_{eight}}\big)\big(QoI_{W_{eight}}, DoC_{W_{eight}}\big)\Big), \ldots, \Big((X_{O_{ral}C_{ontraceptives}}, Y_{O_{ral}C_{ontraceptives}})(QoI_{O_{ral}C_{ontraceptives}}, DoC_{O_{ral}C_{ontraceptives}})\big)\Big)$$

$$\leftarrow not\ diag_{cscc}\Big(\big((X_{Age}, Y_{Age})(QoI_{Age}, DoC_{Age})\big), \Big(\big(X_{W_{eight}}, Y_{W_{eight}}\big)\big(QoI_{W_{eight}}, DoC_{W_{eight}}\big)\Big), \ldots, \Big((X_{O_{ral}C_{ontraceptives}}, Y_{O_{ral}C_{ontraceptives}})(QoI_{O_{ral}C_{ontraceptives}}, DoC_{O_{ral}C_{ontraceptives}})\big)\Big)$$

$$diag_{cscc}\Big(\big((0.17,0.17)(1_{[0.17,0.17]}, DoC_{[0.17,0.17]})\big), \big((0.49,0.49)(1_{[0.49,0.49]}, DoC_{[0.49,0.49]})\big), \ldots, \big((0,0.5)(1_{[0,0.5]}, DoC_{[0,0.5]})\big)\Big) :: 1 :: DoC$$

$$\underbrace{[0,1] \qquad [0,1] \qquad \cdots \qquad [0,1]}_{\text{attribute's domains once normalized}}$$

} :: 1

DoC's values are evaluated for the given vector:

{

$$\neg\, diag_{CSCC}\left(\left((X_{Age}, Y_{Age})(QoI_{Age}, DoC_{Age})\right), \left((X_{W_{eight}}, Y_{W_{eight}})\left(QoI_{W_{eight}}, DoC_{W_{eight}}\right)\right), \dots, \left((X_{O_{ral}C_{ontraceptives}}, Y_{O_{ral}C_{ontraceptives}})(QoI_{O_{ral}C_{ontraceptives}}, DoC_{O_{ral}C_{ontraceptives}})\right)\right)$$

$$\leftarrow not\ diag_{CSCC}\left(\left((X_{Age}, Y_{Age})(QoI_{Age}, DoC_{Age})\right), \left((X_{W_{eight}}, Y_{W_{eight}})\left(QoI_{W_{eight}}, DoC_{W_{eight}}\right)\right), \dots, \left((X_{O_{ral}C_{ontraceptives}}, Y_{O_{ral}C_{ontraceptives}})(QoI_{O_{ral}C_{ontraceptives}}, DoC_{O_{ral}C_{ontraceptives}})\right)\right)$$

$$diag_{CSCC}\underbrace{\left(((0.17,0.17)(1,1)), ((0.49,0.49)(1,1)), \dots, ((0,0.5)(1,0.87))\right)}_{\text{attribute's domains once normalized with QoI and DoC values}} :: 1 :: 0.89$$

$$\underbrace{[0,1] \qquad | \; [0,1] \qquad \cdots \qquad [0,1]}_{\text{attribute's domains once normalized}}$$

} :: 1

4 Application of CaseBased Reasoning for New Cases

The use of the Case Based Reasoning concept for the present work will serve to construct a predictive model, that predicts future occurrences of the Cervical Squa-mous Cell Carcinoma. For this, it is necessary to evaluate a new case among the others already studied and obtained in the previous section.

It is again applied the algorithm presented in Fernando et al. [12], using as the new case feature vector values, the following: *Age = 52; Weight = 66; Height = 156; Menopause Status = [0,1], Number Total Pregnancies = 2, Live Birth Pregnancies = 1, Tumor Grade = ⊥, Tumor Status = [1,2], Pathologic Stage = [6,7], Vital Status = [0, 1]; Tumor Diameter = 0.4670; Tumor Volume = 0.0650; Tobacco Smoking History = 1; Smoking Years = ⊥; Oral Con-traceptives = [0,1].*

$$diag_{CSCC_{NEW\ CASE}}\left(((0.49,0.49)(1,1)), ((0.32,0.32)(1,1)), \dots, ((0,0.5)(1,0.87))\right) :: 1 :: 0.84$$

The new case obtained is compared with each case retrieved from the clusters and using the similarity function, which represents the mean of the module of the arithmetic difference between the arguments of each selected case and the arguments of the new case.

Here are some cases recovered from the clusters, already normalized:

$$retrieved\ case_1\left(((0.58,0.58)(1,1)), ((0,0)(1,1)), \dots, ((0,0.5)(1,0.87))\right) :: 1 :: 0.96$$

$$retrieved\ case_2\left(((0.74,0.74)(1,1)), ((0.07,0.07)(1,1)), \dots, ((0,1)(1,0))\right) :: 1 :: 0.64$$

$$retrieved\ case_n\left(((0.47,0.47)(1,1)), ((0.67,0.67)(1,1)), \dots, ((0,1)(1,0))\right) :: 1 :: 0.84$$

Assuming that each attribute has equal weight, the dissimilarity, for *DoC* between the new case and the first retrieved case ($retrieved\ case_1$) is as follows:

$$dis^{DoC}_{NEW\ CASE \to 1} = \frac{||1-1||+||0.94-1||+\dots+||0.87-1||}{15} = 0.022$$

The similarity is also calculated for this new case and given by:

$$sim^{DoC}_{NEW\ CASE \to 1} = 1 - 0.022 = 0.978$$

The same procedure is applied to calculate the similarity of QoI, being returned with the following result:

$$sim_{NEW\ CASE \to 1}^{QoI,DoC} = 1 \times 0.978 = 0.978$$

The dissimilarity and similarity calculations should also be applied to the remaining cases of the recovered clusters, to find the ones closest to solve the problem. This is a method able to define the most appropriate limit of similarity, giving the possibility to reduce the number of selected cases with the increase of similarity [13].

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