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Machine learning in Neutrosophic Environment: A Survey

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Abstract: Veracity in big data analytics is recognized as a complex issue in data preparation process, involving imperfection, imprecision and inconsistency. Single-valued Neutrosophic numbers (SVNs), have prodded a strong capacity to model such complex information. Many Data mining and big data techniques have been proposed to deal with these kind of dirty data in preprocessing stage. However, only few studies treat the imprecise and inconsistent information inherent in the modeling stage. However, this paper summarizes all works done about mapping machine learning algorithms from crisp number space to Neutrosophic environment. We discuss also contributions and hybridization of machine learning algorithms with Single-valued Neutrosophic numbers (SVNs) in modeling imperfect information, and then their impacts on resolving reel world problems. In addition, we identify new trends for future research, then we introduce, for the first time, a taxonomy of Neutrosophic learning algorithms, clarifying what algorithms are already processed or not, which makes it easier for domain researchers.

Keywords: Neutrosophic; Machine Learning; Single-valued Neutrosophic numbers; Neutrosophic simple linear regression; Neutrosophic-k-NN; Neutrosophic-SVM; Neutrosophic C-means; Neutrosophic Hierarchical Clustering.

1. Introduction

Although Machine learning algorithms have caught extensive attention in last decade, seen their abilities to solve a wide problems remained obscure for years. Most of these techniques work under the some hypotheses that data should be pure, perfect and complete information. As a result, formally if the learning problems are formulated under a set of indeterminate or inconsistent information, the machine learning system becomes unable to work and the data must treated in preparation phase, which is make data science process very long, and impracticable.

However, real learning problems are often involves imperfect information such as uncertainty, inconsistency, inaccuracy and incompleteness. If we can modeling the learning problem as it in real form, exploiting the information's imperfections, we can reduce the data science process which is in many times come back from modeling that is the last step to preparation step that is the first step in the process of data science.

Single-valued neutrosophic set (SVNs) aims to provide a framework to model imperfect information. In contrast to classical machine learning methods, single-valued neutrosophic learning algorithm manipulate information with imperfections to deal with learning problems modeling complex information. To improve the performance of existing learning algorithms and handle the imperfect information in real-world, many machine learning techniques has recently been mapped into Neutrosophic Sets (NSs) environment.

Hence, the main notions and concepts of Neutrosophic are defined, also some achievements and its extensions on the NSs are undertaken. Thus, to manipulate indeterminacy, uncertainty, or inconsistency in information, that often characterizes real situations, Smarandache [1 - 3], introduced Neutrosophic set (NS), which consists of three elements, truth-membership, an indeterminacy membership, and a falsity-membership degrees independently.

Every element of the NS's features has not only a certain degree of truth(T), but also a falsity degree (F) and indeterminacy degree(I). This concept is generated from many others such as crisp set, intuitionistic fuzzy set, fuzzy set, interval-valued fuzzy set, interval-valued intuitionistic fuzzy set, etc.

Nonetheless, the NS as a philosophical concept is hard to apply in real applications. In order to overcome this situation, Smarandache and al. [4] concretize this concept introducing single-valued neutrosophic set (SVNS). SVNS can be applied quite well in real scientific and engineering fields to handle the uncertainty, imprecise, incomplete, and inconsistent information. Broumi and Smarandache [5, 6] studied basic properties of similarity and distances applied in Neutrosophic environment using single valued neutrosophic set (SVN).

Hybridization between Neutrosophic and machine learning algorithms, have also been studied, several papers [7- 11] on Neutrosophic Machine Learning (NML) have been published in the last few years.

However, there is no survey papers summarize those new learning techniques and approaches, removing the barrier for researchers currently working in the area of Neutrosophic Machine Learning. This has the twofold advantage of making such techniques more readily reachable by researchers and, conversely, avoid wasting time for to have idea which Machine learning approaches to be mapped to Neutrosophic.

The rest of this paper is organized as follows. We discuss the origins of the connection between Neutrosophic and machine learning in Section 2. Next, in Section 3, we summarize a wide variety of hybrid Neutrosophic Machine Learning techniques. Research trends and outstanding issues are discussed in Section 4.1. Then, in section 4.2, we introduce, for the first time, a taxonomy of Neutrosophic learning algorithms, clarifying what algorithms are already processed or not, which makes it easier for domain researchers.

2. Origins of connection between Neutrosophic and Machine learning

We cannot understand this connection without understanding how the Neutrosophic community works. In recent years there has been an augmenting passion from this community of neutrosophic in working, in different directions, the use of Neutrosophic to treat imperfections information in many methods and domaines. This has led to the development of a new mathematic domaine called Neutrosophic, then the connections with many others areas, such as machine learning and artificial intelligence. In the early 1999s, the pioneer of the field Florentin Smarandache generalized the intuitionistic fuzzy set (IFS), paraconsistent set, and intuitionistic set to the neutrosophic set (NS), and he underlined the distinctions between NS and IFS by reel examples. With his biggest passion and faith, Florentin Smarandache, in a quiet small town in south U.S. called Gallup, start defend his theory of Neutrality and why the three elements truth-membership (T), indeterminacy (I), and falsehood-nonmembership (F) are over 1, reproducing the history of science by story as many concepts and theory that considered primitives, and then changed by new ones.

In addition to several papers of the Neutrosophic science international association (NSIA) members, gathered in Encyclopedia Neutrosophic Researchers [12], much advances has been done. Today there are several fields of Neutrosophic to tackle a variety of problems, including Neutrosophic Computing and Machine Learning. These efforts are valued by launching a science international journal of Neutrosophic Computing and Machine Learning [13], which issued its 7th volume in 2019. In which, all published papers have wrote by NSIA's researchers.

The international journal of Neutrosophic Computing and Machine Learning with its all volumes can be seen as broad overview of the field of machine learning in Neutrosophic provided by NSIA's researchers.

The main contributions of this paper: (1) summarizes research achievements on Neutrosophic Computing and Machine Learning from the point of view of non NSIA's researchers. In a different way, try to collect the different articles on Neutrosophic machine learning papers published on several journals around the world other than those published in Neutrosophic Computing and Machine Learning journal, among it, each volume is can be considered a state of art. In order to present to researchers, the global state of art of advances research on Neutrosophic Machine Learning approaches. (2) Try to taxonomy, cluster and identify differences Neutrosophic Machines learning approaches.

3. Literature review

There are several Machine learning in Neutrosophic algorithms and approaches surveyed in this article. Then, a natural questions arise: how we can categorize all hybrid methods?

Our view of the general relationship between the fields of machine learning and Neutrosophic is the re-searchers try to map the basic operations from crisp number to Neutrosophic environment, however they rewrite machine learning algorithm instead of using simple mathematical formulas, and they use Neutrosophic formulas. But the main question should the researchers in this hybrid field (Machine learning and Neutrosophic) respond is, does this hybridization make sense to tackle the real world issues or just a theoretical formulation?

Before trying to respond this question, we synthesis all hybrid methods according to commonly used categories, summary all surveyed papers in a table 1. There are four categories of machine learning algorithms, supervised learning with two subcategories classification and prediction, semi-supervised learning, unsupervised learning and reinforcement learning.

3.1. Neutrosophic supervised learning

3.1.1. Neutrosophic Classification

Neutrosophic-k-NN Classifier [14]: K-Nearest Neighbor (K-NN) method isn't a learning method, but based on saving the training examples (all training examples), at prediction time, it find the k training examples $(x_1, y_1), \cdots, (x_k, y_k)$ that are closest to the test example x, and then affect to the most frequent class among those y_i's. This initial version of K-NN suffers from slowness because to classify x, one need to loop over all training examples. Actually, some tricks to speed are introduced such as classes represented by medoid (Representative point), or centroid (central value), etc. The Neutrosophic K-NN method we present here is the mapping of method based on Centroid, in which we consider c_j the center of cluster or class j, a constant m, regularization parameter δ, and (T_{ij}, I_{ij}, F_{ij}), where T_{ij} denote truth, I_{ij} indeterminacy and N_{ij} falsity membership values of point i for class j.

$$T_{ij} = \frac{(x_i - c_j)^{-(\frac{2}{m-1})}}{\sum_{j=1}^{C}(x_i - c_j)^{-(\frac{2}{m-1})} + (x_i - c_{imax})^{-(\frac{2}{m-1})} + \delta^{-(\frac{2}{m-1})}}, \quad (1)$$

$$F_{ij} = \frac{\delta^{-(\frac{2}{m-1})}}{\sum_{j=1}^{C}(x_i - c_j)^{-(\frac{2}{m-1})} + (x_i - c_{imax})^{-(\frac{2}{m-1})} + \delta^{-(\frac{2}{m-1})}}, \quad (2)$$

$$I_{ij} = \frac{(x_i - c_{imax})^{-(\frac{2}{m-1}}}{\sum_{j=1}^{C}(x_i - c_j)^{-(\frac{2}{m-1})} + (x_i - c_{imax})^{-(\frac{2}{m-1})} + \delta^{-(\frac{2}{m-1})}}, \tag{3}$$

At the time of prediction, the membership value of unknown point x_u to class j is defined by as follow:

$$x_{uj} = \frac{\sum_{i=1}^{k} d_i(T_{ij} + F_{ij} - I_{ij})}{\sum_{i=1}^{k} d_i}, \tag{4}$$

With $d_i = \frac{1}{(x_u - x_i)^{\frac{2}{q-1}}}$

Then unknown point x_u get the label of class maximizing $max\{x_{uj}; j = 1,2 \cdots, C\}$.

The authors didn't show the usefulness of the proposed method but they proposed an interesting idea to apply it on imbalanced data-set problems.

Neutrosophic SVM (N-SVM) [15] : Let's assume that (x_i, y_i) a set of training data, in which eve

with $i = 1,2 \cdots, N$

$$t_i = 1 - \frac{\|(x_j - C_+)\|}{max_{x_k \in P}\|(x_j - C_+)\|}, \tag{5}$$

ry x_i belonging to class y_i with a triple t_i, f_i, and i_i as its Neutrosophic components.

$$i_i = 1 - \frac{\|(x_j - C_{all})\|}{max_{x_k \in P}\|(x_j - C_{all})\|}, \tag{6}$$

$$f_i = 1 - \frac{\|(x_j - C_-)\|}{max_{x_k \in P}\|(x_j - C_-)\|}, \tag{7}$$

Where P and N represent the positive and negative samples subsets respectively, $y_i = +1$ for all $x_i \in P$ and $y_i = -1$ for $x_i \in N$.

$$t_i = 1 - \frac{\|(x_j - C_-)\|}{max_{x_k \in N}\|(x_j - C_-)\|}, \tag{8}$$

$$i_i = 1 - \frac{\|(x_j - C_{all})\|}{max_{x_k \in N}\|(x_j - C_{all})\|}, \tag{9}$$

$$f_i = 1 - \frac{\|(x_j - C_+)\|}{max_{x_k \in N}\|(x_j - C_+)\|}, \tag{10}$$

with $C_+ = \frac{1}{n_+}\sum_{k=1}^{n_+} x_k$, $C_- = \frac{1}{n_-}\sum_{k=1}^{n_-} x_k$, and $C_{all} = \frac{1}{2}(C_+ + C_-)$

We define g_j as weighting function:

$$g_j = t_i + i_i - f_i, \tag{11}$$

The optimal hyper-plane problem in the reformulated SVM is the solution to:

$$\text{minimize } g_j = \frac{1}{2}\omega \cdot \omega \sum_{j=1}^{k} g_j \zeta_j, \tag{12}$$

Subject to

$$\boldsymbol{y_j(\omega_j + b) > 1 - \zeta_j \quad i = 1, 2 \cdots, n} \tag{13}$$

N-SVM (Neutrosophic-Support Vector Machine) improves performance over standard SVM and reduces the effects of outliers in learning samples.

3.1.2. Neutrosophic Regression

Neutrosophic simple linear Regression: Salama and al. [16] studied and introduced Neutrosophic simple linear regression model with its possible utility to predict value of a dependent variable y according to predictor variable x. Below a pseudo code of Neutrosophic Linear Regression algorithm.

Algorithm 1 Neutrosophic Simple Linear Regression

Require: Training data $(x_i, y_j), i, j = 1,2, \cdots, N$

A model define the relationship between input x and y, y = ax + b, where (a and b) represent estimated Neutrosophic (intercept and slope) coefficients, y estimated Neutrosophic output

Define degree of membership, non-membership, and indeterminacy :
$((\mu_A(x_1), \lambda_A(x_1), \nu_A(x_1)), (\mu_B(x_1), \lambda_B(x_1), \nu_B(x_1)), i, j = 1,2 \cdots, N$
Define cost function $J(a, b) = \sum(ax_i + b - y_i)^2$
Repeat

Calculate the gradients of J

Update the weights a

Repeat until the cost $J(a, b)$ stops reducing, or some other predefined termination criteria is met

3.2. Neutrosophic unsupervised learning

3.2.1. Neutrosophic Clustering

Neutrosophic C-means: In this method, authors [10] have given a meaning to the three basic Neutrosophic components T_{ij} as membership values belonging to the determinate clusters I_i as boundary regions, and N_i noisy data set.

$$\overline{c}_{imax} = \frac{c_{pi} + c_{qi}}{2}, \tag{14}$$

We define p_i and q_i are the cluster numbers with the biggest and second biggest value of T respectively, and m is a constant.

$$p_i = \lambda \cdot argmax_{j=1,2\cdots,C}(T_{ij}), \tag{15}$$

$$q_i = argmax_{j \neq p_i \cap 1,2 \cdots, C}(T_{ij}), \tag{16}$$

Membership Neutrosophic values are defined by follow formulas:

$$T_{ij} = \frac{\varpi_2 \varpi_3 (x_i - c_j)^{-(\frac{2}{m-1})}}{\sum_{j=1}^{C}(x_i - c_j)^{-(\frac{2}{m-1})} + (x_i - c_{imax})^{-(\frac{2}{m-1})} + \delta^{-(\frac{2}{m-1})}}, \tag{17}$$

$$F_{ij} = \frac{\varpi_1 \varpi_3 \delta^{-(\frac{2}{m-1})}}{\sum_{j=1}^{C}(x_i - c_j)^{-(\frac{2}{m-1})} + (x_i - c_{imax})^{-(\frac{2}{m-1})} + \delta^{-(\frac{2}{m-1})}}, \tag{18}$$

$$I_{ij} = \frac{\varpi_1 \varpi_2 (x_i - c_{imax})^{-(\frac{2}{m-1}}}{\sum_{j=1}^{C}(x_i - c_j)^{-(\frac{2}{m-1})} + (x_i - c_{imax})^{-(\frac{2}{m-1})} + \delta^{-(\frac{2}{m-1})}}, \tag{19}$$

with $\boldsymbol{i = 1, 2 \cdots, N}$

$$c_j = \frac{\sum_{i=1}^{N}(\varpi_1 T_{ij})^m x_i}{\sum_{i=1}^{N}(\varpi_1 T_{ij})^m}, \tag{20}$$

$$J_{NCM}(T, F, I, c) = \sum_{i=1}^{N}(\varpi_1 T_{ij})^m (x_i - c_j)^2 + \sum_{i=1}^{N}(\varpi_2 F_i)^m (x_i - \overline{c}_{imax})^2 + \delta^2 \sum_{i=1}^{N}(\varpi_3 I_i)^m, \tag{21}$$

The separation between classes is performed by iteration optimizing objective function, that is based on updating the Neutrosophic membership values (T_{ij},F_i, I_i), the centers c_j , and $\overline{c}_{imax}$ according to the equations defined above. The loop stop when $\parallel T_{ij}^{(k+1)} - T_{ij}^{(k)} \parallel < \epsilon$ with ϵ is condition check and k is step.

For nonlinear clustering problem an extended Method have been proposed called Kernel NCMA in which we use a function kernel K, $K(x_i, z_j)$ instead of$(x_i - z_j)$, such as $K(x_i, \overline{c}_{imax})$ in place of $x_i - \overline{c}_{imax}$. The NCMA can be summarized as follow :

Algorithm 2 KNCM algorithm

Assign each data into the class with the largest TM
Choose kernel function and its parameters
Initialize $T^{(0)}$, $F^{(0)}$, $I^{(0)}$, C, m, δ, ϵ, ϖ_1, ϖ_2, ϖ_3 parameters
While $\parallel T_{ij}^{(k+1)} - T_{ij}^{(k)} \parallel < \epsilon$ **do**
Calculate the centers vectors $c^{(k)}$ at k ste
Compute the $\overline{c}_{imax}$ using the clusters centers with the largest and second largest value of T_{ij}
Update $T_{ij}(k)$ to $T_{ij}(k+1)$, $F_{ij}(k)$ to $T_{ij}(k+1)$, and $I_{ij}(k)$ to $I_{ij}(k+1)$
End while

NCM and KNCM as mentioned by authors may handle veracity in data such as outliers and noise using their new objective function. And then possibility to deal with raw data in modeling phase instead while data cleaning phase.

3.2.2. Neutrosophic Hierarchical Clustering

Agglomerative Hierarchical Clustering Algorithm [17]: First, every SVNSs A_k with $(k = 1, \cdots, n)$ considered as single cluster. In a loop, until we get a single cluster of size n, the SVNSs A_k the SVNS are then compared to each other and are merged into a single group based on the closest pair of groups (with the smallest distance), based on a weighted distance (Hamming distance or Euclidean distance). At each stage, only two clusters can be merged and they cannot be separated once merged. The center of each cluster is recalculated using the arithmetic mean of the SVNS offered to the cluster. The distance between the centers of each group is considered as the distance between two groups.

Algorithm 3 Agglomerative Hierarchical Clustering algorithm

Let us consider a collection of n SVNSs $A_k(k = 1, \cdots, n)$
Assign each of the n SVNSs $A_k(k = 1, \cdots, n)$ to a single cluster
While All A_k clustered into a single cluster of size n **do**
SVNSs $A_k(k = 1, \cdots, n)$ are then compared among themselves and are merged them into a single
Cluster according to the closest (with smaller distance) pair of clusters, based on a weighted distance
(Hamming distance or Euclidean distance)
End while

Table 1. List of major contributions on machine learning algorithms in Neutrosophic environment.

Authors	Title	Reference	Publisher
Salama, A. A., Eisa, M., ELhafeez, S. A., Lotfy, M. M. (2015)	Review of recommender systems algorithms utilized in social networks based e-Learning systems neutrosophic system	[18]	Neutrosophic Sets and Systems 8 : 32-40
Ansari, A. Q., Biswas, R., Aggarwal, S. (2013)	Neutrosophic classifier: An extension of fuzzy classifer	[19]	Applied Soft Computing, 13(1), 563-573
Zhang, M., Zhang, L., Cheng, H. D. (2010)	A neutrosophic approach to image segmentation based on watershed method	[20]	Signal Processing, 90(5), 1510-1517
Zhang, X., Bo, C., Smarandache, F., Dai, J. (2018)	New inclusion relation of neutrosophic sets with applications and related lattice structure	[21]	International Journal of Machine Learning and Cybernetics, 9, 1753-1763
Mondal, K. A. L. Y. A. N., Pramanik, S. U. R. A. P. A. T. I., Giri, B. C. (2016)	Role of neutrosophic logic in data mining. New Trends in Neutrosophic Theory and Application	[22]	Pons Editions, Brussels, 15-23.
Sengur, A., Guo, Y. (2011)	Color texture image segmentation based on neutrosophic set and wavelet transformation	[23]	Computer Vision and Image Understanding,115(8), 1134-1144
Akbulut, Y., engr, A., Guo, Y., Smarandache, F. (2017)	A novel neutrosophic weighted extreme learning machine for imbalanced data set	[24]	Symmetry, 9(8), 142
Kraipeerapun, P., Fung, C. C., Wong, K. W. (2007 August)	Ensemble neural networks using interval neutrosophic sets and bagging	[25]	In Third International Conference on Natural Computation (ICNC 2007) (Vol. 1, pp. 386-390). IEEE
Kavitha, B., Karthikeyan, S., Maybell, P. S(2012)	An ensemble design of intrusion detection system for handling uncertainty using Neutrosophic Logic Classifier	[26]	Knowledge-Based Systems, 28, 88-96

Ye, J. (2014).	Single-valued neutrosophic minimum spanning tree and its clustering method	[27]	Journal of intelligent Systems, 23(3), 311-324
Thanh, N. D., Ali, M. (2017, July)	Neutrosophic recommender system for medical diagnosis based on algebraic similarity measure and clustering	[28]	In 2017 IEEE International Conference on Fuzzy Systems (FUZZ-IEEE) (pp. 1-6). IEEE
Akbulut, Y., engr, A., Guo, Y., Polat, K. (2017)	KNCM: Kernel neutrosophic c-means clustering	[10]	Applied Soft Computing, 52, 714-724
Kraipeerapun, P., Fung, C. C., Wong, K. W. (2006)	Multiclass classification using neural networks and interval neutrosophic sets	[29]	World Scientific and Engineering Academy and Society (WSEAS)
Ali, M., Khan, M., Tung, N. T. (2018)	Segmentation of dental X-ray images in medical imaging using neutrosophic orthogonal matrices	[30]	Expert Systems with Applications, 91, 434-441
Long, H. V., Ali, M., Khan, M., Tu, D. N. (2019)	A novel approach for fuzzy clustering based on neutrosophic association matrix	[31]	Computers and Industrial Engineering, 127, 687-697
Kraipeerapun, P., Fung, C. C. (2008, February)	Comparing performance of interval neutrosophic sets and neural networks with support vector machines for binary classification problems	[32]	In 2008 2nd IEEE International Conference on Digital Ecosystems and Technologies (pp. 34-37). IEEE
Thanh, N. D., Ali, M. (2017)	A novel clustering algorithm in a neutrosophic recommender system for medical diagnosis	[33]	Cognitive Computation, 9(4), 526-544
Gaber, T., Ismail, G., Anter, A., Soliman, M., Ali, M., Semary, N., Snasel, V. (2015, August)	Thermogram breast cancer prediction approach based on Neutrosophic sets and fuzzy c-means algorithm	[34]	In 2015 37th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC) (pp. 4254-4257). IEEE
Ye, J. (2017)	Single-valued neutrosophic clustering algorithms based on similarity measures	[35]	Journal of Classification, 34(1), 148-162
Tuan, T. M., Chuan, P. M., Ali, M., Ngan, T. T., Mittal, M. (2018)	Fuzzy and neutrosophic modeling for link prediction in social networks	[36]	Evolving Systems, 1-6
Ju, W., Cheng, H. D. (2008, December)	Discrimination of outer membrane proteins using reformulated support vector machine based on neutrosophic set	[37]	In 11th Joint International Conference on Information Sciences. Atlantis Press
Shan, J., Cheng, H. D., Wang, Y. (2012)	A novel segmentation method for breast ultrasound images based on neutrosophic lmeans clustering	[38]	Medical physics, 39(9), 5669-5682
Basha, S. H., Abdalla, A. S., Hassanien, A. E. (2016, December)	GNRCS: hybrid classification system based on neutrosophic logic and genetic algorithm	[39]	In 2016 12th International Computer Engineering Conference (ICENCO) (pp. 53-58). IEEE
Kraipeerapun, P., Fung, C. C., Wong, K. W. (2007)	Uncertainty assessment using neural networks and interval neutrosophic sets for multiclass classification problems	[40]	WSEAS Transactions on Computers, 6(3)
Dhingra, G., Kumar, V., Joshi, H. D. (2019)	A novel computer vision based neutrosophic approach for leaf disease identification and classification	[41]	Measurement, 135, 782-794
Rashno, E., Akbari, A., Nasersharif, B. (2019)	A Convolutional Neural Network model based on Neutrosophy for Noisy Speech Recognition	[42]	arXiv preprint arXiv:1901.10629

4. Discussions

4.1. Research trends and open issues

Hybridization between Neutrosophic and machine learning algorithms, have also been studied. In supervision learning, Akbulut and al. [14] introduced intuitive supervised learning method called Neutrosophic-k-NN Classifier K-Nearest Neighbor (K-NN). Due to its results as a powerful machine learning methods, several tries to map SVM in Neutrosophic, Ju and al. [15] proposed Neutrosophic-support vector machines (N-SVM). In [32], authors Compared performance of interval neutrosophic sets and neural networks with support vector machines for binary classification problems. Ju and al [37] reformulated SVM, based on neutrosophic set, to discriminate outer membrane proteins using reformulated support vector machine based on neutrosophic set. In recent years, Artificial neural networks (ANN) has recognized huge advances, which explain many attempts of hybridization between ANN and Neutrosophic, Kraipeerapun and al. [40] demonstrated how to assess uncertainty using neural networks and interval neutrosophic sets for multi-class classification problems, then its application on multi-class classification problems [29], afterward, for more robustness ensemble neural networks using interval neutrosophic sets and bagging [25].

Likewise, in unsupervised learning, Alsmadi and al. [7] introduced a hybrid Fuzzy C-Means and Neutrosophic for jaw lesions segmentation. Inspired from fuzzy c-means and the neutrosophic set framework, Guo and al. [9] proposed a new clustering algorithm, neutrosophic c-means (NCM), for uncertain data cluster-ing. Akbulu and al. [10] developed KNCM: Kernel Neutrosophic c-Means Clustering, neutrosophic c-means (NCM), in order to alleviate the limitations of the popular fuzzy c-means (FCM) clustering algorithm by introducing a new objective function which contains two types of rejection. To deal with indeterminacy, Qureshi and al. [11] improved the Method for Image Segmentation Using K-Means Clustering with Neutrosophic Logic. Ye and al. [35] proposed Single-valued neutrosophic clustering algorithms based on similarity measures. Akhtar and al. [8] applied K-mean algorithm in Neutrosophics environment for Image Segmentation, Gaber and al. [34] to predict thermogram breast cancer, and Shan and al. [38] use neutrosophic l-means clustering to breast ultrasound images based.

Conversely, in reinforcement learning, we haven't find any resources about mixture between the both approaches, because this type of algorithms of reinforcement is under development, to be subject of hybridization.

4.2. Taxonomy of Neutrosophic Machine learning

The trends also involve the question of where machine learning areas to apply Neutrosophic, whether to it is more appropriate to employ instead of crisp number the SVN numbers. Hence, we have classified different Neutrosophic machine learning algorithms. Below a summarizing of all Neutrosophic Learning Methods and algorithms, according to standard taxonomy of machine learning.

- Supervised (inductive) learning (training data includes desired outputs)
    - Prediction : (Regression) to predict continuous values
        - Neutrosophic simple linear regression
    - Classification (discrete labels) : predict categorical values
        - Neutrosophic-k-NN [14]
        - Neutrosophic-Support Vector Machines (N-SVM)[15], [32],[37]
        - Neutrosophy-Artificial neural networks (N-ANN)[40], [29]
        - Neutrosophy-Ensemble neural networks, Bagging [25]
- Unsupervised learning (training data does not include desired outputs)
    - Clustering
        - Neutrosophic C-Means (NCM) [7], [9], [11], [35], [8], [38], [34]
        - Kernel Neutrosophic c-Means(KNCM) [10]
    - Neutrosophic Hierarchical Clustering
        - Neutrosophic Agglomerative Hierarchical Clustering [17]
        - Neutrosophic Divisive Hierarchical Clustering
    - Finding association (in features)
    - Dimension reduction
- Neutrosophic semi-supervised learning : Neutrosophic Semi-supervised learning (training data includes a few desired outputs
- Neutrosophic Reinforcement learning : Learning from sequential data
    - Q-Learning
    - State-Action-Reward-State-Action (SARSA)
    - Deep Q Network (DQN)
    - Deep Deterministic Policy Gradient (DDPG)

5. Conclusions

In this paper, we have explored how Neutrosophic contributes to enhance machine learning algorithms generally and how to modeling and exploit information's imperfection such as uncertainty as a source of information, not a kind of noises. We tried to cover hybrid approaches. However, it is still several machine learning algorithms to map to Neutrosophic environment, demonstrate the utility of Neutrosophic with machine learning to tackle real world challenges.

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