

Fig. 2. Workflow of supervised machine learning algorithm [4]

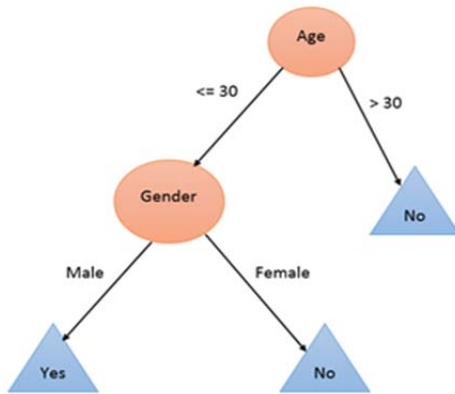


Fig. 3. Decision Tree [5]

2) *Naïve Bayes*: Naïve Bayes mainly targets the text classification industry. It is mainly used for clustering and classification purpose [6]. The underlying architecture of Naïve Bayes depends on the conditional probability. It creates trees based on their probability of happening. These trees are also known as Bayesian Network. An example of the network is given in Fig. 5. The pseudo code is given in Fig. 6.

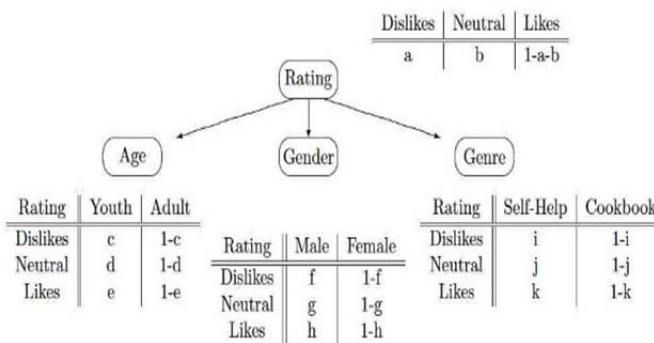


Fig. 5. An Example of Bayesian Network [7]

```

procedure DTInducer( $S, A, y$ )
1:  $T = TreeGrowing(S, A, y)$ 
2: Return TreePruning( $S, T$ )
procedure TreeGrowing( $S, A, y$ )
1: Create a tree  $T$ 
2: if One of the Stopping Criteria is fulfilled then
3:   Mark the root node in  $T$  as a leaf with the most common
   value of  $y$  in  $S$  as the class.
4: else
5:   Find a discrete function  $f(A)$  of the input attributes values
   such that splitting  $S$  according to  $f(A)$ 's outcomes
   ( $v_1, \dots, v_n$ ) gains the best splitting metric.
6:   if best splitting metric  $\geq$  threshold then
7:     Label the root node in  $T$  as  $f(A)$ 
8:     for each outcome  $v_i$  of  $f(A)$  do
9:        $Subtree_i = TreeGrowing(\sigma_{f(A)=v_i} S, A, y)$ .
10:      Connect the root node of  $T$  to  $Subtree_i$  with an
      edge that is labelled as  $v_i$ 
11:    end for
12:  else
13:    Mark the root node in  $T$  as a leaf with the most
    common value of  $y$  in  $S$  as the class.
14:  end if
15: end if
16: Return  $T$ 
procedure TreePruning( $S, T, y$ )
1: repeat
2:   Select a node  $t$  in  $T$  such that pruning it maximally
   improve some evaluation criteria
3:   if  $t \neq \emptyset$  then
4:      $T = pruned(T, t)$ 
5:   end if
6: until  $t = \emptyset$ 
7: Return  $T$ 

```

Fig. 4. Pseudo code for Decision Tree [5]

```

INPUT: training set  $T$ , hold-out set  $H$ , initial number of components
 $k_0$ , and convergence thresholds  $\delta_{EM}$  and  $\delta_{Add}$ .

Initialize  $M$  with one component.
 $k \leftarrow k_0$ 
repeat
  Add  $k$  new mixture components to  $M$ , initialized using  $k$ 
  random examples from  $T$ .
  Remove the  $k$  initialization examples from  $T$ .
  repeat
    E-step: Fractionally assign examples in  $T$  to mixture components,
    using  $M$ .
    M-step: Compute maximum likelihood parameters for  $M$ ,
    using the filled-in data.
    If  $\log P(H|M)$  is best so far, save  $M$  in  $M_{best}$ .
    Every 5 cycles, prune low-weight components of  $M$ .
  until  $\log P(H|M)$  fails to improve by ratio  $\delta_{EM}$ .
   $M \leftarrow M_{best}$ 
  Prune low weight components of  $M$ .
   $k \leftarrow 2k$ 
until  $\log P(H|M)$  fails to improve by ratio  $\delta_{Add}$ .
Execute E-step and M-step twice more on  $M_{best}$ , using examples
from both  $H$  and  $T$ .
Return  $M_{best}$ .

```

Fig. 6. Pseudo code for Naïve Bayes [6]

3) *Support Vector Machine*: Another most widely used state-of-the-art machine learning technique is Support Vector Machine (SVM). It is mainly used for classification. SVM works on the principle of margin calculation. It basically, draw margins between the classes. The margins are drawn in such a fashion that the distance between the

margin and the classes is maximum and hence, minimizing the classification error. An example of working and pseudo code of SVM is given in Fig. 7 and Fig. 8, respectively.

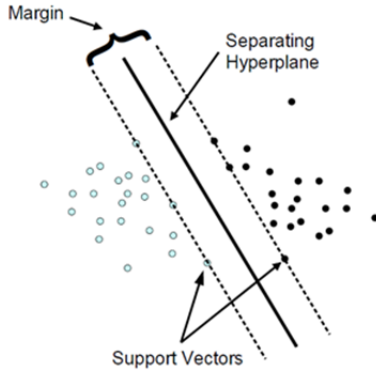


Fig. 7. Working of Support Vector Machine [8]

INPUT:  $S, \lambda, T, k$   
 INITIALIZE: Choose  $w_1$  s.t.  $\|w_1\| \leq 1/\sqrt{\lambda}$   
 FOR  $t = 1, 2, \dots, T$   
     Choose  $A_t \subseteq S$ , where  $|A_t| = k$   
     Set  $A_t^+ = \{(x, y) \in A_t : y \langle w_t, x \rangle < 1\}$   
     Set  $\eta_t = \frac{1}{\lambda t}$   
     Set  $w_{t+\frac{1}{2}} = (1 - \eta_t \lambda)w_t + \frac{\eta_t}{k} \sum_{(x,y) \in A_t^+} y x$   
     Set  $w_{t+1} = \min \left\{ 1, \frac{1/\sqrt{\lambda}}{\|w_{t+\frac{1}{2}}\|} \right\} w_{t+\frac{1}{2}}$   
 OUTPUT:  $w_{T+1}$

Fig. 8. Pseudo code for Support Vector machine [9]

## B. Unsupervised Learning

The unsupervised learning algorithms learn few features from the data. When new data is introduced, it uses the previously learned features to recognize the class of the data. It is mainly used for clustering and feature reduction. An example of workflow of unsupervised learning is given in Fig. 9.

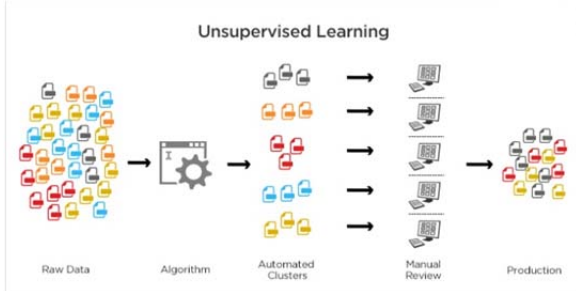


Fig. 9. Example of Unsupervised Learning [10]

The two main algorithms for clustering and dimensionality reduction techniques are discussed below.

1) *K-Means Clustering*: Clustering or grouping is a type of unsupervised learning technique that when initiates, creates groups automatically. The items which possess similar characteristics are put in the same cluster. This algorithm is called k-means because it creates k distinct clusters. The mean of the values in a particular cluster is the center of that cluster [9]. A clustered data is represented in Fig. 10. The algorithm for k-means is given in Fig. 11.

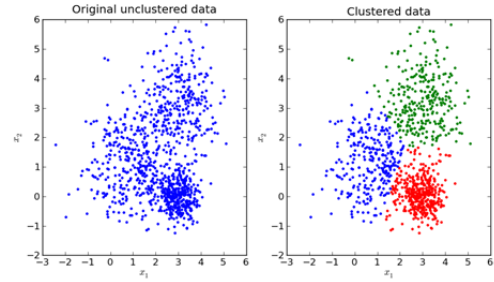


Fig. 10. K-Means Clustering [12]

```
function Direct-k-means()
    Initialize  $k$  prototypes  $(w_1, \dots, w_k)$  such that  $w_j = i_l, j \in \{1, \dots, k\}, l \in \{1, \dots, n\}$ 
    Each cluster  $C_j$  is associated with prototype  $w_j$ 
    Repeat
        for each input vector  $i_l$ , where  $l \in \{1, \dots, n\}$ ,
            do
                Assign  $i_l$  to the cluster  $C_{j^*}$  with nearest prototype  $w_{j^*}$ .
                (i.e.,  $|i_l - w_{j^*}| \leq |i_l - w_j|, j \in \{1, \dots, k\}$ )
        for each cluster  $C_j$ , where  $j \in \{1, \dots, k\}$ , do
            Update the prototype  $w_j$  to be the centroid of all samples currently in  $C_j$ , so that  $w_j = \sum_{i_l \in C_j} i_l / |C_j|$ 
        Compute the error function:
            
$$E = \sum_{j=1}^k \sum_{i_l \in C_j} |i_l - w_j|^2$$

    Until  $E$  does not change significantly or cluster membership no longer changes
```

Fig. 11. Pseudo code for k-means clustering [13]

## 2) Principal Component Analysis

In Principal Component Analysis or PCA, the dimension of the data is reduced to make the computations faster and easier. To understand how PCA works, let's take an example of 2D data. When the data is being plot in a graph, it will take up two axes. PCA is applied on the data, the data then will be 1D. This is explained in Fig. 12. The pseudo code for PCA is discussed in Fig. 13.

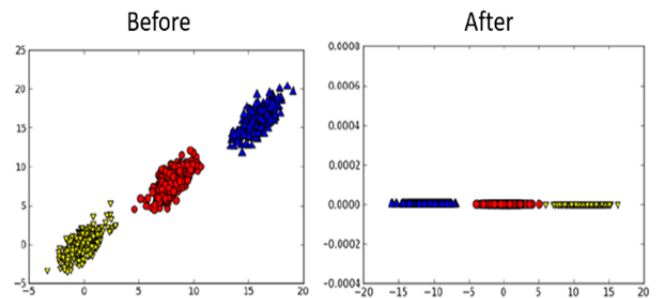


Fig. 12. Visualization of data before and after applying PCA [11]

```

R ← X
for(k = 0, ..., K - 1) do
{
λ = 0
T(k) ← R(k)
for(j = 0, ..., J) do
{
P(k) ← RTT(k)
P(k) ← P(k) ||| P(k) |||-1
T(k) ← RP(k)
λ' ← ||| T(k) |||
if(|λ' - λ| ≤ ε) then break
λ ← λ'
}
R ← R - T(k)(P(k))T
}
return T, P, R

```

Fig. 13. Pseudo code for PCA [14]

### C. Semi - Supervised Learning

Semi - supervised learning algorithms is a technique which combines the power of both supervised and unsupervised learning. It can be fruit-full in those areas of machine learning and data mining where the unlabeled data is already present and getting the labeled data is a tedious process [15]. There are many categories of semi-supervised learning [16]. Some of which are discussed below:

1) *Generative Models*: Generative models are one of the oldest semi-supervised learning method assumes a structure like  $p(x,y) = p(y)p(x/y)$  where  $p(x/y)$  is a mixed distribution e.g. Gaussian mixture models. Within the unlabeled data, the mixed components can be identifiable. One labeled example per component is enough to confirm the mixture distribution.

2) *Self-Training*: In self-training, a classifier is trained with a portion of labeled data. The classifier is then fed with unlabeled data. The unlabeled points and the predicted labels are added together in the training set. This procedure is then repeated further. Since the classifier is learning itself, hence the name self-training.

3) *Transductive SVM*: Transductive support vector machine or TSVM is an extension of SVM. In TSVM, the labeled and unlabeled data both are considered. It is used to label the unlabeled data in such a way that the margin is maximum between the labeled and unlabeled data. Finding an exact solution by TSVM is a NP-hard problem.

### D. Reinforcement Learning

Reinforcement learning is a type of learning which makes decisions based on which actions to take such that the outcome is more positive. The learner has no knowledge which actions to take until it's been given a situation. The action which is taken by the learner may affect situations

and their actions in the future. Reinforcement learning solely depends on two criteria: trial and error search and delayed outcome [17]. The general model [18] for reinforcement learning is depicted in Fig. 14.

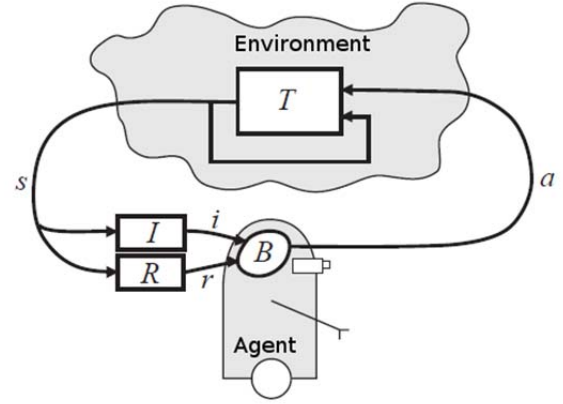


Fig. 14. The Reinforcement Learning Model [18]

In the figure, the agent receives an input  $i$ , current state  $s$ , state transition  $r$  and input function  $I$  from the environment. Based on these inputs, the agent generates a behavior  $B$  and takes an action  $a$  which generates an outcome.

### E. Multitask Learning

Multitask learning has a simple goal of helping other learners to perform better. When multitask learning algorithms are applied on a task, it remembers the procedure how it solved the problem or how it reaches to the particular conclusion. The algorithm then uses these steps to find the solution of other similar problem or task. This helping of one algorithm to another can also be termed as inductive transfer mechanism. If the learners share their experience with each other, the learners can learn concurrently rather than individually and can be much faster [19].

### F. Ensemble Learning

When various individual learners are combined to form only one learner then that particular type of learning is called ensemble learning. The individual learner may be Naïve Bayes, decision tree, neural network, etc. Ensemble learning is a hot topic since 1990s. It has been observed that, a collection of learners is almost always better at doing a particular job rather than individual learners [20]. Two popular Ensemble learning techniques are given below [21]:

1) *Boosting*: Boosting is a technique in ensemble learning which is used to decrease bias and variance. Boosting creates a collection of weak learners and convert them to one strong learner. A weak learner is a classifier which is barely correlated with true classification. On the other hand, a strong learner is a type of classifier which is strongly correlated with true classification [21]. The pseudo code for AdaBoost (which is most popular example of boosting) is give in Fig. 15.

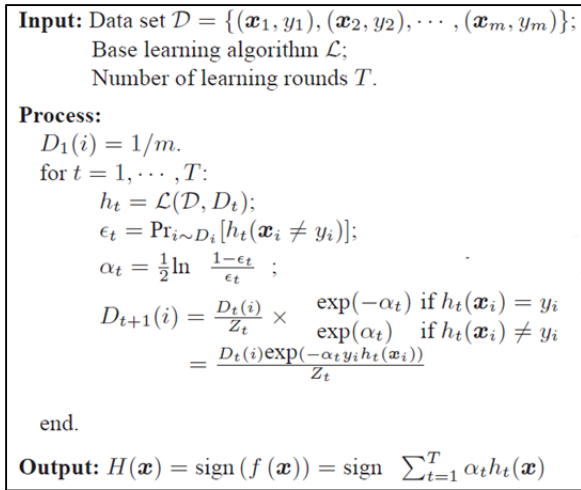


Fig. 15. Pseudo code for AdaBoost [21]

2) *Bagging*: Bagging or bootstrap aggregating is applied where the accuracy and stability of a machine learning algorithm needs to be increased. It is applicable in classification and regression. Bagging also decreases variance and helps in handling overfitting [23]. The pseudo code for bagging is given in Fig. 16.

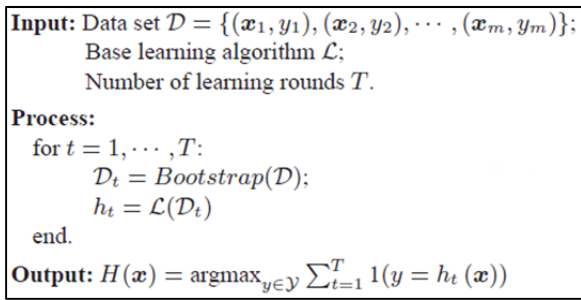


Fig. 16. Pseudo code for Bagging [21]

### G. Neural Network Learning

The neural network (or artificial neural network or ANN) is derived from the biological concept of neurons. A neuron is a cell like structure in a brain. To understand neural network, one must understand how a neuron works. A neuron has mainly four parts (see Fig. 17). They are dendrites, nucleus, soma and axon.

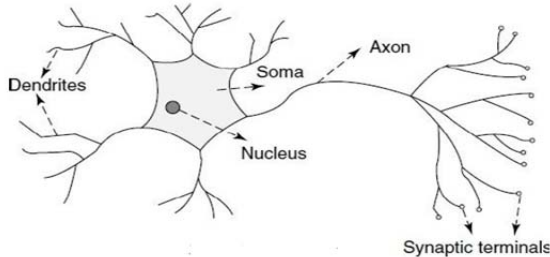


Fig. 17. A Neuron [24]

The dendrites receive electrical signals. Soma processes the electrical signal. The output of the process is carried by the axon to the dendrite terminals where the output is sent to next neuron. The nucleus is the heart of the neuron. The inter-connection of neuron is called neural network where electrical impulses travel around the brain.

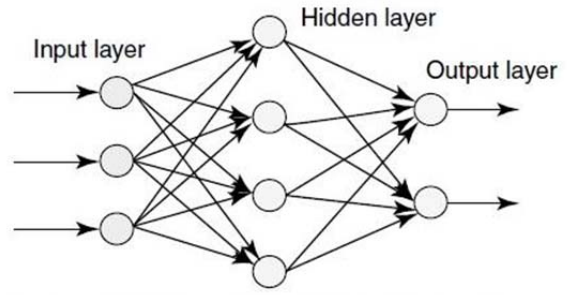


Fig. 18. Structure of an Artificial Neural Network [24]

An artificial neural network behaves the same way. It works on three layers. The input layer takes input (much like dendrites). The hidden layer processes the input (like soma and axon). Finally, the output layer sends the calculated output (like dendrite terminals) [24]. There are basically three types of artificial neural network: supervised, unsupervised and reinforcement [25].

1) *Supervised Neural Network*: In the supervised neural network, the output of the input is already known. The predicted output of the neural network is compared with the actual output. Based on the error, the parameters are changed, and then fed into the neural network again. Fig. 19 will summarize the process. Supervised neural network is used in feed forward neural network.

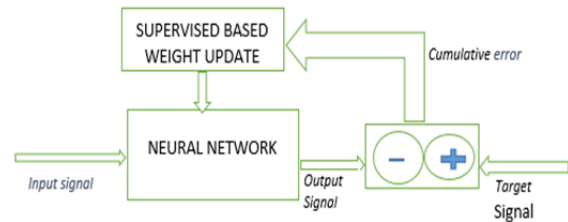


Fig. 19. Supervised Neural Network [25]

2) *Unsupervised Neural Network*: Here, the neural network has no prior clue about the output the input. The main job of the network is to categorize the data according to some similarities. The neural network checks the correlation between various inputs and groups them. The schematic diagram is shown in Fig. 20.

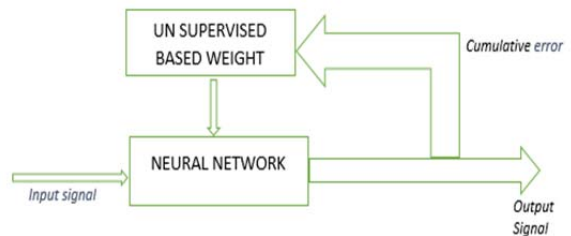


Fig. 20. Unsupervised Neural Network [25]

3) *Reinforced Neural Network*: In reinforced neural network, the network behaves as if a human communicates with the environment. From the environment, a feedback has been provided to the network acknowledging the fact that whether the decision taken by the network is right or



wrong. If the decision is right, the connections which points to that particular output is strengthened. The connections are weakened otherwise. The network has no previous information about the output. Reinforced neural network is represented in Fig. 21.

4)

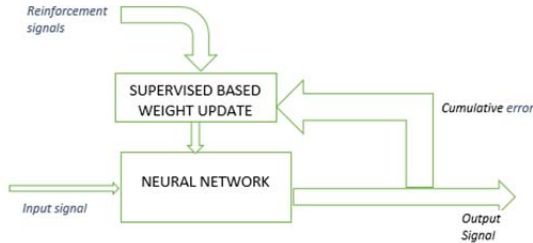


Fig. 21. Reinforced Neural Network [25]

### H. Instance-Based Learning

In instance-based learning, the learner learns a particular type of pattern. It tries to apply the same pattern to the newly fed data. Hence the name instance-based. It is a type of lazy learner which waits for the test data to arrive and then act on it together with training data. The complexity of the learning algorithm increases with the size of the data. Given below is a well-known example of instance-based learning which is k-nearest neighbor [26].

1) *K-Nearest Neighbor*: In k-nearest neighbor (or KNN), the training data (which is well-labeled) is fed into the learner. When the test data is introduced to the learner, it compares both the data.  $k$  most correlated data is taken from training set. The majority of  $k$  is taken which serves as the new class for the test data [27]. The pseudo code for KNN is given in Fig. 22.

```

Let  $W = \{x_1, x_2, \dots, x_n\}$  be a set of  $n$  labeled samples. The algorithm is as follows:
BEGIN
  Input  $y$ , of unknown classification.
  Set  $K, 1 \leq K \leq n$ .
  Initialize  $i = 1$ .
  DO UNTIL ( $K$ -nearest neighbors found)
    Compute distance from  $y$  to  $x_i$ .
    IF ( $i \leq K$ ) THEN
      Include  $x_i$  in the set of  $K$ -nearest neighbors
    ELSE IF ( $x_i$  is closer to  $y$  than any previous nearest neighbor) THEN
      Delete farthest in the set of  $K$ -nearest neighbors
      Include  $x_i$  in the set of  $K$ -nearest neighbors.
    END IF
    Increment  $i$ .
  END DO UNTIL
  Determine the majority class represented in the set of  $K$ -nearest neighbors.
  IF (a tie exists) THEN
    Compute sum of distances of neighbors in each class which tied.
    IF (no tie occurs) THEN
      Classify  $y$  in the class of minimum sum
    ELSE
      Classify  $y$  in the class of last minimum found.
    END IF
  ELSE
    Classify  $y$  in the majority class.
  END IF
END

```

Fig. 22. Pseudo code for K-Nearest Neighbor [28]

### III. CONCLUSION

This paper surveys various machine learning algorithms. Today each and every person is using machine learning knowingly or unknowingly. From getting a recommended product in online shopping to updating photos in social networking sites. This paper gives an introduction to most of the popular machine learning algorithms.

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