Vol.3 No.3 2019

Universidad de Oviedo

CMR INSTITUTE OF TECHNOLOGY EXPLORE TO INVENT

ISSN: 2581-3242

International Journal of Machine Learning and Networked Collaborative Engineering

Vol.3 No.3 2019

International Journal of Machine Learning and Networked Collaborative Engineering

PREFACE

The International Journal of Machine Learning and Networked Collaborative Engineering (IJMLNCE) with ISSN: 2581-3242 is now indexed in popular databases such as BASE (Bielefeld Academic Search Engine), CNKI Scholar, CrossRef, CiteFactor, Dimensions, DRJI, Google Scholar, Index Copernicus, JournalTOCs, J-Gate, Microsoft Academic, PKP-Index, Portico, ROAD, Scilit, Semantic Scholar, Socolar or WorldCat-OCLC. We are now proud to present the ninth volume of the journal, Volume No-03 Issue No-03, with some high-quality papers written by international authors and covering different aspects related to machine learning and collaborative engineering.

Phan Trong-Thanh and Doan Van Thang published a work entitles “Joint Spatial Geometric and Max-margin Classifier Constraints for Facial Expression Recognition Using Nonnegative Matrix Factorization”. In this paper, they have presented the constrained NMF approach for problem the facial expression recognition. The proposed MNMF_SGR performs well in facial expression recognition task and its effectiveness has been proven in their model. To summarize, with many constraints allows them to build models effectively and specifically on high dimensional, sparse and noisy datasets. For their future work, more sophisticated and efficient way to tune kernel functions will be explored. They also plan to apply the proposed method to problems in other fields, such as bioinformatics and computer vision. Studying the convergence rate for MNMF_SGR and increasing the efficiency, they should be all in consideration.

Praneet Amul Akash Cherukuri published his article “Recommender System for Educational & Corporate Sector In Prediction of Domain Recommendations & Analysis using Machine Learning”. In this manuscript he suggest that his model has a huge impact on the educational institutions and the corporate sector of today's highly competitive world. The model proposes a simple and cross-sector solution to both the corporate and educational sectors that could result in the huge increase of employability solving the problem of wrong decision making of job aspirants as well as mistakes made by the organization whereby suffering losses from those decisions. Hence it could benefit every academician in evaluating his/her students as well as their academic performance in a more sophisticated and a single independent platform that has analysis related to current world trends and scenarios. The model has a vast scope of improvement as well as can provide great accuracy with positive results in the future.

Akshansh Mishra published his article “Understanding Machine Learning for Friction Stir Welding Technology”. In this manuscript, he suggest that there is a loss of time and materials if the optimization of the Friction Stir Welding parameters is done through experimental studies which further leads to increase in the cost of the experiment. Machine Learning approach like Artificial Neural Network and image processing overcome these issues. So, it can be concluded that the mechanical and microstructure properties can be predicted and also the defects formation can also be observed by the implementation of various Machine Learning tools in the Friction Stir Welding process.

Anoop et al. published a work entitled “Study of Energy Efficient Algorithms for Cloud Computing based on Virtual Machine Migration Techniques”. This survey outlined some of the very recent approaches in knowledge graph-based recommendation systems. As knowledge graph is one of the effective representation mechanisms for knowledge that has been unearthed from unstructured text, it got wider acceptance among research communities. A knowledge graph represents entities and relationships as nodes and edges respectively and a large number of meaning-aware applications and algorithms can operate on this graph. One such application is recommendation systems that suggest a user with items based on their previous interactions with the system. Knowledge graph based recommendation systems became very popular recently primarily due to its ability to supply side information for augmenting data and thus enhancing the quality of recommendations. This paper discusses some of the very prominent approaches reported very recently in the recommendation literature. Some interesting research dimensions are also discussed towards the end of this paper. This survey will be useful for the researchers and practitioners who wish to work on entity knowledge graphs based recommendation systems.

Finally Amrit Kaur Saggu and Shivani Agarwal published a work entitled “Performance Evaluation of LAR protocol using real dataset on Highway and City Scenario” In this work they have evaluated the performance of Location Aided Routing protocol (LAR) for Vehicular Ad-hoc Networks (VANETs) in terms of throughput, packet delivery ratio and routing overhead. They have considered two scenarios namely highway and city scenario. For highway they have taken Delhi highway data from OSM map and for city scenario taken real traces of Bologna Ringway dataset. For each of these scenarios the performance is evaluated by considering variation in terms of number of vehicles and simulation time. They observe that with the increase in simulation time the throughput increases for both highway and city scenario. The packet delivery ratio and overhead tend to decrease with increase in simulation time.

REFERENCES

[1] Thanh, Phan Trong, and Thang, Doan Van(2019). Joint Spatial Geometric and Max-margin Classifier Constraints for Facial Expression Recognition Using Nonnegative Matrix Factorization. *International Journal of Machine Learning and Networked Collaborative Engineering*, 3(03) pp 125-134.

https://doi.org/10.30991/IJMLNCE.2019v03i03.001

[2] Cherukuri, Praneet Amul Akash (2019). Recommender System for Educational & Corporate Sector In Prediction of Domain Recommendations & Analysis using Machine Learning. *International Journal of Machine Learning and Networked Collaborative Engineering*, 3(03) pp 135-142.

https://doi.org/10.30991/IJMLNCE.2019v03i03.002.

[3] Mishra. Akshansh(2019). Information Processing in GLIF Neuron Model with Noisy Conductance. *International Journal of Machine Learning and Networked Collaborative Engineering*, 3(03) pp 143-158.

https://doi.org/10.30991/IJMLNCE.2019v03i03.003.

[4] S. Sajisha P., S. Anoop V, A. Ansal K.(2019). Knowledge Graph-based Recommendation Systems: The State-of-the-art and Some Future Directions *International Journal of Machine Learning and Networked Collaborative Engineering*, 3(03) pp 159-167.

https://doi.org/10.30991/IJMLNCE.2019v03i03.004

[5] Saggu, Amrit Kaur, and Agarwal, Shivani(2019). Performance Evaluation of LAR protocol using real dataset on Highway and City Scenario. *International Journal of Machine Learning and Networked Collaborative Engineering*, 3(03) pp 168-181.

https://doi.org/10.30991/IJMLNCE.2019v03i03.005

Editor-in-Chief's

International Journal of Machine Learning and Networked Collaborative

Vijender Kumar Solanki, CMR Institute of Technology, Hdyerabad, TS, Insia
https://orcid.org/0000-0001-5784-1052

Vicente García-Díaz, University of Oviedo, Spain
https://orcid.org/0000-0003-2037-8548

DOI :https://doi.org/10.30991/IJMLNCE.2019v03i02

Vishwanath Bijalwan

- Ph.D, Department of Electronics & Communication
- Institute of Technology, Gopeshwar, Uttarakhand, India
- vishwanath.bijalwan@itgopeshwar.ac.in

INDEX

EDITORIAL OFFICE

CALL FOR PAPER

International Journal of Machine Learning and Networked Collaborative Engineering (IJMLNCE) with ISSN **2581-3242**, is a quarterly published, open access, peer-reviewed, international journal, focuses on publishing authentic and unpublished quality research papers in the emerging field of Machine Learning and Collaborative Engineering.

This is a scientific journal aims to promote highly qualitative and innovative research works, not limited to but focuses on the area of machine learning, collaborative engineering, and allied areas. We publish only original research articles, review articles, and technical notes.

The journal is registered with CrossRef **10.30991/IJMLNCE**. Each accepted manuscript shall be assigned a unique digital object identifier for identification. The abbreviated key title for our journal allocated by ISSN is **Int. j. mach. learn. Networkedcollab.eng**.

The journal appears in popular indexes like BASE (Bielefeld Academic Search Engine), CNKI Scholar, CrossRef, CiteFactor, Dimensions, DRJI, Google Scholar, Index Copernicus, J-Gate, PKP-Index, Portico , ROAD, Scilit, Semantic Scholar, Socolar, WorldCat. Our journals manuscripts can also be found in the directory ofReserachGate& Kudos.

In this present technological era, the areas like machine intelligence, machine learning, and its associated domains are one of the most popular and demanding choices for the researchers as well as the industry personnel.

In last few years, numerous uses of machine learning and its related domain, has drawn ample attention of the people, that has generated a large number of applications in this field, making machine learning and collaborative engineering highly admired one.

Machine intelligence or machine learning is not a new concept. In terms of Artificial Intelligence, we were familiar with several aspects of the field, but nowadays with the introduction of machine learning, the use of this has been highly evolving, especially for improving the lifestyle of the human being.

There are numerous application areas of machine learning or machine intelligence, irrespective of any famous sector, fromHealthcare, Space, Automation, Aviation industries etc. to entertainment industry and even in academia.

With this insight, IJMLNCE invites quality and authentic research works in form of manuscripts, for our forthcoming version. The Journal solicits latest research work carried out bythe researchers, academicians and industry practitioners, in the domain of machine learning and collaborative engineering.

Plagiarism is considered as a serious ethical and professional malpractice in case of IJMLNCE. So similarity check should be taken care at its highest level. The originality of the work will be highly appreciated. Each paper will be peer-reviewed by the expert reviewers and in a multilayer approach. The editorial board of the journal believes in high moral and ethical practices.

The authors are invited to submit their authentic and unpublished manuscripts online only. They will get final decision about the acceptance or rejection of themanuscript within 06-12 weeks from the date of submission of manuscripts. Once the manuscript gets accepted, author will be asked to complete the copyright agreement. An e-mail communication will also be sent to the author’s registered mail ID, after verification of incorporation of all reviewers’ comments, in term of their final camera-ready-paper; it will be published to the upcoming journal’s volumes.

Please note that there is **no article processing cost** for publishing articles in this journal and the journal is open access.

IJMLNCE JOURNAL

International Journal of Machine Learning and Networked Collaborative Engineering

Journal Homepage: http://www.mlnce.net/home/index.html

DOI : https://doi.org/10.30991/IJMLNCE.2019v03i03.001

Joint Spatial Geometric and Max-margin Classifier Constraints for Facial Expression Recognition Using Nonnegative Matrix Factorization

[a]Phan Trong-Thanh, [b]Doan Van Thang

[a]Vietnam Korea University of Information and Communication Technology, The University of Da Nang, Da Nang, Viet Nam

ptthanh@vku.udn.vn

[b]Industrial University Of Ho Chi Minh City

vanthangdn@gmail.com

Abstract

Based on the constrained non-negative matrix factor algorithm, the article presents a new approach to facial recognition recognition. Our proposed method incorporated two tasks in an automatic expression analysis system: facial feature extraction and classification into expressions. To obtain local and geometric structure information in the data as much as possible, we amalgamate max-margin relegation into the constrained NMF optimization, resulting in a multiplicative updating algorithm is additionally proposed for solving optimization quandary. Experimental results on JAFFE dataset demonstrate that the effectiveness of the proposed method with improved performances over the conventional dimension reduction methods.

Keywords

facial expressions;

classification;

nonnegative matrix factorization;

graph regularization;

spatial constraints

1. Introduction

Facial expression recognition (FER) is increased the attention from psychologist's anthropologists, and computer scientists [1, 2, 3]. The computer researchers attempt to create complicated human-computer interfaces which are able to recognize automatically and classify human expressions or emotions. Fasel et al. [1] has defined facial features that will deform over time and the compression of facial muscles will give skin texture. Research has also shown that the general changes of muscle activity occur quickly and usually only a few seconds. The study also provides for the fact that emotions are the only source of facial expressions in addition to other things such as verbal and nonverbal correspondence, or physiological activities.

Usually facial expressions and emotions are different (and the terms are commonly not correctly exchanged), for PC vision group, the expression " facial expression recognition" frequently refers to the characterization of facial components in one of the six alleged essential feelings: sadness, disgust, happiness, surprise, fear and anger, as presented by Ekman in 1971 [2]. The endeavor of an elucidation depends on the suspicion which the appearances of feelings are widespread crosswise over people and also human ethnics and societies.

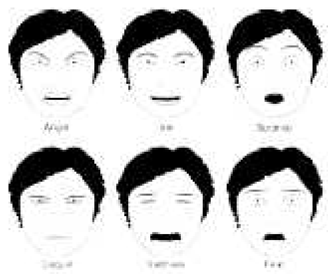


Figure 1. Six universal emotions

An automatic expression analysis system has two tasks that are compulsory [4]: facial feature extraction and relegation into expressions. There are generally two kinds of methods in facial feature extraction: appearance-predicated and geometric feature-predicated methods. After focalizing the face, the exhibited countenance has to be extracted as much information as possible. In visage apperception, most automatic expression analysis systems endeavor to apperceive a diminutive set of prototypic expressions (i.e. fear, anger, joy, surprise, sadness, and disgust).

Table 1. Universal emotion identification

Universal emotion identification		
Emotion	**Definition**	**Motion of facial part**
Anger	Anger shows the emotion which is the most dangerous, it could be very harmful, this emotion should be tried to avoid by human.	Pulling down eyebrows, ocular perceiver opening, teeth shutting and lips tightened, upper and lower lids pulling up.
Fear	Fear is also the emotion of danger. It may lead to physical or psychological harms.	Outer eyebrow going down, inner eyebrow going up, mouth opening and jaw dropping.
Happiness	Happiness is most desired expression by human.	Eyes opening, mouth edging up, mouth opening, lip corner pulling up, cheeks raising up and wrinkles around eyes.
Sadness	Sadness is opposite emotion of Happiness.	External eyebrow going down, internal corner of eyebrows raising up, mouth edge going down, eye shutting, lip corner pulling down.
Surprise	This emotion comes when unexpected things happens.	Eyebrows going up, eye and mouth opening, jaw dropping down.
Disgust	Disgust is a feeling of dislike such as taste, smell, sound or tough.	Lip corner depressor, nose wrinkle, lower lip depressor, Eyebrows pulling down

2. Facial expression recognition

2.1. Feature Extraction Using Nonnegative Matrix Factorization

In this section, we describe the most important step in a facial expression recognition system which is feature extraction step that it can be analyzed in terms of facial action occurrence after the face has been located in the image or video frames. Over the last several decenniums, massive endeavor has been made and exceptional. Immense endeavor has been made over the past several years and consequential results have been successful finished in FER. A main step in FER is to engender or abstract features of verbalization from the pristine facial images. A main step in FER is to build or abstract features of verbalization from the pristine images of the ocular perceivers. Several wide-ranging methods of extraction of features such as the key element analysis (PCA) [5], Eigen-face [6], Singular value decomposition (SVD) [7] Non-negative matrix factorization (NMF) [8].

In NMF algorithm, it was described as follow:a non-negative m×n matrix has been given: $X=(x_0,x_1,\ldots,x_{(m-1)})\in R^{(m\times n)}$ is exactly the facial data will be analyzed, it's the need of finding non-negative matrix factor U (m×k) and matrix factor V=(k×n) such that X≈UV where k is smaller than m and n.

In the original X matrix a column vector can be considered as the sum of the weights of all the vectors in the left matrix U, but the opposite the elements of the corresponding column vector in the right matrix V are weight coefficients. The un-negativity constraints of U and V consistent with the intuitive notion of combining parts to form a whole, which is how NMF learns a part-based representation.

$$\min_{\mathbf{U},\mathbf{V}} f(\mathbf{U},\mathbf{V}) = \frac{1}{2}\|\mathbf{X}-\mathbf{U}\mathbf{V}\|_F^2, s.t.\ \mathbf{U}\geq 0, \mathbf{V}\geq 0 \qquad (1)$$

where $\|.\|_F$ is Frobenius norm of a matrix, and the product $\mathbf{U}\mathbf{V}^T$is the non-negative matrix factorization approximation of $\mathbf{X}$ of rank at most k. The non-negativity constraints on $\mathbf{U}$ and $\mathbf{V}$ enables only additive (non-subtractive) combine of parts to build entire data.

In the utility for consciousness of facial expression, the grey values on each facial picture are non-negative and saved as a type of matrix $X=[X_1,X_2, \ldots ,X_n]$, the place X_j is a column vector of m dimensions, consisting of the non-negative gray facial picture. The X matrix can be divided into the product of a non-negative U matrix representing simple NMF images and a non-negative weight coefficient matrix V, NMF decomposition renders expression pix reconstructed in a nonsubtractive manner and a great deal like the approach of forming harmony from sections.

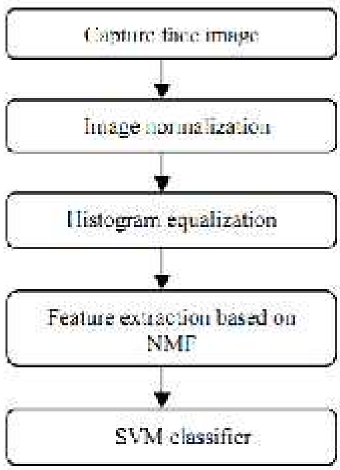


Figure 2. Basic structure of facial expression analysis system [4]

2.2. Classification by SVM Classifier

The last task of the FER system is classification based on machine learning theory. The input to the classification process is a combination of features retrieved from the face area in the earlier stage. The earlier stage which will contain a set of features formed to describe facial expressions. Classification is in need of supervised training, so the training set has to be made up of labeled data.

Support Vector Machines (SVM) are data classification techniques based on optimization theory and statistical theory. In the SVM technique the initial input space will be mapped into the feature space and in this feature space the optimal dividing hyperplane is determined. To divide multiple class, the original SVM technique will divide the data space into two parts and the process is repeated many times. Thus, the multi-class problem using the SVM method can completely perform like the two-class problem. Assuming the problem needs to be classified with k classes (k> 2), the "one-against-one" strategy will proceed to implement k (k-l) / 2 binary classifications using the SVM method. Each class will conduct separation with the remaining k-1 class to determine the k-1 separation function based on the two-class division problem by SVM method.

2.3. Adaptive Feature Extraction and Classification Method

There are few existed works that use constrains the aim of increasing the the discriminatory ability for extracted features. Several variants of NMF with discriminant constraints imposed were proposed in [9, 10]. Kumar et al [11] introduced an adaptive feature extraction and classification method which propose a method to obtain the baseline matrix by constructing a soft max-margin constraints calculation for the objective function of NMF that maximized the classification margin using the features that are extracted using those bases. Inspired by this, they aim at finding a set of basis vectors that maximizes the margin of an SVM classifier.

Let $\{x_i, y_i\}_{i=1}^{L}$ denote a set of data vectors and their corresponding labels, where $x_i \in R^{m}, y_i \in \{-1,1\}$. To extract features based on criteria max-margin classifier we use base matrix U. To perform this problem, we impose constraints on the features vectors derived from the matrix U. Features extracted from projections of example data x on base vectors are stored in U ($\mathbf{U}^{\mathbf{T}}\mathbf{X}$) and optimizations are calculated as follows:

$$\min_{\mathbf{U},\mathbf{V},w,b,\varepsilon_i} \lambda \|\mathbf{X}-\mathbf{U}\mathbf{V}\|_F^2 + \frac{1}{2} w^T w + C \sum_{i=1}^{L} \varepsilon_i \quad (2)$$

$$s.t.\ y_i(\mathbf{w}^{\mathbf{T}}\mathbf{U}^{\mathbf{T}}\mathbf{x}_i + \mathbf{b}) \geq 1 - \varepsilon_i, \varepsilon_i \geq 0, 1 \leq i \leq \mathbf{L}, \mathbf{V} \geq 0$$

where $\varepsilon=(\varepsilon_1,...,\varepsilon_i...\varepsilon_L)$ is variable vector, λ is a scalar that controls the relative significance for the NMF cost and C a scalar that controls the overall significance of the punishment forced for the preparation models that are either excessively near the isolating hyper-plane or misclassified.

3. Methodology

We propose a unity of objective function for the model which archives the upper objectives by combining the benefit of max-margin classifiers and NMF constraints together, through adding the pixel dispersion penalty and manifold regularization into the objective function. Following, we drive a multiplicative update rules using optimized gradient method and describe how the systems use this algorithm to perform the classification task we expect it to do.

3.1. Max-margin Nonnegative Matrix Factorization via Spatial Constraints and Graph Regularization

The unified objective function is constructed by jointing the data reconstruction objective function:

$$\min_{\mathbf{U},\mathbf{V},w,b,\varepsilon} \|\mathbf{X}-\mathbf{U}\mathbf{V}\|_F^2 + \lambda_1\left(\frac{1}{2}\|w\|_2^2 + C\sum_{i=1}^{n} \varepsilon_i\right) + \lambda_2 Tr(\mathbf{V}\mathbf{L}\mathbf{V}^{\mathbf{T}}) + \lambda_3 Tr(\mathbf{U}\mathbf{E}\mathbf{U}^{\mathbf{T}}) \quad (3)$$

$$s.t.\ \mathbf{U} \geq 0, \mathbf{V} \geq 0, \varepsilon_i \geq 0, y_i(w^T v_i + b) \geq 1 - \varepsilon_i, i = 1..n$$

All variables are divided into three terms: the coefficient matrix (V), the basis matrix (U) and variables about max-margin projection (w, b, ε). Where $\|.\|_F$ is Frobenius norm of a matrix, and the product $\mathbf{UV}$ is the non-negative matrix factorization approximation of $\mathbf{X}$ of rank at most k; $\varepsilon = (\varepsilon_1, \ldots, \varepsilon_i \ldots \varepsilon_L)$ is the lack variable vector, λ_1 and C are scalars; the regularization parameter $\lambda_2 \geq 0$ controls the smoothness of the new representation; $\lambda_3 \geq 0, L \ll d$ and c_0 is a simple positive constant bound parameter; L is called graph Laplacian, E is called the dispersion kernel matrix.

Multiplicative Update Rules.

Update the Projection Vector and Slack Variables.

When the coefficient matrix and the basis matrix are fixed, MMNMF_MR optimization problem changes into the standard binary soft-margin SVM classification.

$$\min_{W,b,\varepsilon} \lambda_1 \left(\frac{1}{2}\|w\|_2^2 + C\sum_{i=1}^{n} \varepsilon_i\right), s.t.\ \varepsilon_i \geq 0, y_i(w^T v_i + b) \geq 1 - \varepsilon_i, i = 1..n \qquad (4)$$

The hyper-plane parameters w, b and slack variable vector ε are received by the use of SVM classifier.

Update the Coefficient Matrix.

When other variables are fixed, optimizing the coefficient matrix is a quadratic program solution:

$$\min_{\mathbf{V}} \|\mathbf{X} - \mathbf{UV}\|_F^2 + \lambda_2 Tr(\mathbf{VLV^T}) \qquad (5)$$

$$s.t.\ \mathbf{V} \geq 0, y_i(w^T v_i + b) \geq 1 - \varepsilon_i, i = 1..n$$

The Lagrangian of above objective function is

$$L(V, \alpha, \beta) = Tr(\mathbf{X} - \mathbf{UV})(\mathbf{X} - \mathbf{UV})^T + \lambda_2 Tr(\mathbf{VLV^T}) - \boldsymbol{\alpha}^T \mathbf{V} - \sum_{i=1}^{n} \beta_i [y_i(w^T v_i + b) - 1 + \varepsilon_i]$$

where α, β are Lagrangian multipliers, specifically α is Lagrangian multipliers vector. Under the Karush-Kuhn-Tucker (KKT) conditions, we get

$$\begin{cases} 2\mathbf{U^T UV} - 2\mathbf{U^T} X + 2\lambda_2 \mathbf{VL^T} - \alpha - \beta y w = 0 \\ 1^T V = 0 \\ y(w^T V - b) - 1 + \varepsilon = 0 \end{cases}$$

Transform the equation into a matrix for

$$\begin{pmatrix} 2\mathbf{U^T U} + 2\lambda_2 \mathbf{L^T} & -1^T & -yw \\ 1^T & 0 & 0 \\ yw^T & 0 & 0 \end{pmatrix} \times \begin{pmatrix} \mathbf{V} \\ \alpha \\ \beta \end{pmatrix} = \begin{pmatrix} 2\mathbf{U^T X} \\ 0 \\ yb + 1 - \varepsilon \end{pmatrix}$$

where **1** is a unit vector whose size is the same as **v, 0** is the zero vector. We can derive **v** by solving this equation.

Update the Basis Matrix.

When other variables are fixed, the model is transformed to a non-negative matrix factorization:

$$O_3 = \min_{U} \|\mathbf{X} - \mathbf{UV}\|_F^2 + \lambda_3 Tr(\mathbf{UEU^T}), s.t. \mathbf{U} \geq 0 \tag{6}$$

Because of the non-negative constraints, we use gradient descent methods to solve this problem. The gradient of equation (6) is

$$\mathrm{V} = 2\mathbf{UVV^T} - 2\mathbf{X^T V^T} + 2\lambda_3 \mathbf{EU}$$

Classification

To obtain the feature vectors during the implementation then input test vectors x_{test} will be projected onto the base matrix U, $f_{test} = \mathbf{U}^T \mathbf{x}_{test}$. The feature vector is used by the max-margin classifier which predicts the class $\mathbf{y}_{test} = sign(\mathbf{U}^T f_{test} + b)$ where w, b, **U** are calculated during training.

Algorithm for MNMF_SGR

```
Input: Matrix X, rank k, maxIter; positive constants λ1,λ2,λ3
Output: U, V, w, b
```

Begin

```
Initial the basis matrix U0 and the coefficient V0, let t=0
Let s=1, U=Us, V=Vs
Repeat
Fix U and Vs to find ws+1, bs+1 via equation (4)
Fix V, ws and bs+1 to find Us+1 via equation (5)
s=s+1
Until reaches the maximal iteration number;
Let t=t+1, Vt=Vs, wt=ws,bt=bs
Learning the new basis matrix Ut via minimizing equation (3.1)
End
```

Figure. 1. Algorithm for Max-margin Nonnegative Matrix Factorization via Spatial Constrainst and Graph Regularization

4. Experiments

In this subsection, proposed MNMF_SGR method would be experimented and compared against several popular subspace learning algorithms, specifically the unsupervised methods (NMF [8], Spatial NMF [9] and Graph NMF [10]). We also compared with the supervised algorithm Semi-NMF [12] and Max-margin NMF [11].

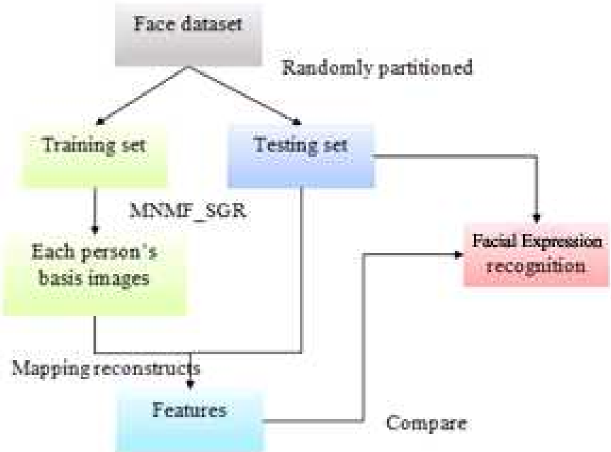


Figure. 2. The flow chart of MNMF_SGR based image reconstruction for facial expression recognition

4.1. Datasets

We using Japanese Female Facial Expression (JAFFE) database [13] to experiments. The dataset have been collected and staging by Michael Lyons, Miyuki Kamachi, and Jiro Gyoba.

4.2. Preprocessing

Due to the background is more immensely colossal than face image; firstly, the Viola-Jones algorithm will be used to find faces. Based on the partitions placed set on already detected frontal faces, we using cascade object detector to detection ocular perceivers, nasal perceiver and mouth. The reality shows that the use of Viola-Jones algorithm as a preprocessing step and want to achieve a good classification then this step needs to be done. Each original image from both databases is cropped and down-sampled in a such way that the final image size is 16 × 16 pixels.

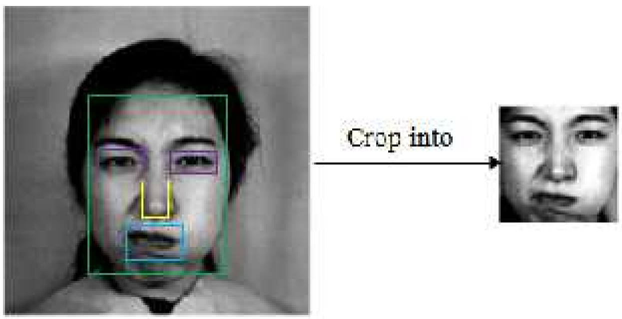


Figure. 3. Face and facial parts detection

All algorithms were initialized with 20 random U and V matrices, each of them was trained for 20 iterations and the one with the minimum objective function value was further trained for 1000 iterations.

4.3. Parameter Settings

For training and testing splits, we repeated the following procedure for ten times. Each time we randomly selected two-thirds of number of image per individual and labeled them. All the other images were unlabeled and used as the testing set.

In MNMF_SGR, λ_1 was tested for the following values {0.01, 1, 10} and λ_2 was tested for {1, 100} and λ_3 was tested for $\{10^{-5}, 10^{-4},..., 10^{2}\}$. Firstly, the dimensionality reduction process with NMF, SpaNMF, GNMF and Semi-NMF algorithms, the trained coefficient matrix is ready to be used for classifying a testing face image. Then we use SVM algorithm for the classifiers in the face recognition.

With MNMF and MNMF_SGR, after training process we compute the feature vector from the input test vector that the basis matrix projected onto. After that, this feature vector is used in predicting class of face recognition. All algorithms were initialized with 20 random U and V matrices, each of them was trained for 20 iterations and the one with the minimum objective function value was further trained for 1000 iterations.

4.4. Classification Results.

The results of facial expression recognition for JAFFE dataset shown in Figure 6. Semi-supervised algorithms outperform all un-supervised ones. MNMF_SGR has highest accuracy, and then followed by MNMF_FA, MNMF, SpaNMF, GNMF, SemiNMF and standard NMF. MNMF_SGR outperforms NMF by 21.87%. The highest classification accuracy of 86.94% is achieved with k=30.

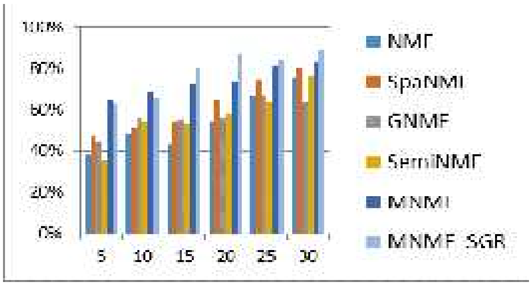


Figure. 4. JAFFE dataset facial expression recognition average accuracies (%) of different algorithms of five iterations

The disarray lattice of outward appearance acknowledgment appeared in Table II utilizing proposed technique with 30 number of highlight vectors (k=30). A portion of the pitiful and satisfaction outward appearance are mistaken for one another. The distinction of satisfaction and dismal fizzled in light of the fact that these articulations had a comparable movement of mouth.

Table 1. The 7-class facial about confusion matrix expression recognition using proposed method MNMF_SGR on JAFFE

An	Di	Fe	Ha	Sa	Su	Ne
0.6268	0.1813	0.7285	0	0.0812	0.0322	0.0333
0.1234	**0.4510**	0.1009	0.0426	0.1268	0	0.0224
0	0.1191	**0.4825**	0.0918	0.0810	0	0.0421
0	0.1289	0.0199	**0.7490**	0.0211	0.0635	0.1289
0.1713	0.1270	0.1197	0.0423	**0.5343**	0.0524	0.1756
0	0	0	0.0203	0.0417	**0.7417**	0.0722
0	0.0000	0.0198	0.0486	0.1222	0.0711	**0.5221**

5. Conclusion

In this paper, we have presented the constrained NMF approach for problem the facial expression recognition. The proposed MNMF_SGR performs well in facial expression recognition task and its effectiveness has been proven in our model. To summarize, With many constraints allows us to build models effectively and specifically on high dimensional, sparse and noisy datasets. For future work more sophisticated and efficient way to tune kernel functions will be explored. We will also apply the proposed method to problems in other fields, such as bioinformatics and computer vision. Studying the convergence rate for MNMF_SGR and increasing the efficiency, they should be all in consideration.

References

[1]. B. Fasel, J. Luettin, "Automatic facial expression analysis: a survey", *Pattern Recognition*, 36 (1) (2003), pp. 259-275.

[2]. Ekman. P, Friesen W.V, "Constants across cultures in the face and emotion", *Journal of Personality and Social Psychology*, 17: 124–129, 1971.

[3]. L. Mai, *"Joint Support Vector Machine with Constrained Nonnegative Matrix Factorization and Its Applications"*, Master Thesis, National Central University, July 2017.

[4]. Ying Zilu, Zhang Guoyi, "Facial Expression Recognition Based on NMF and SVM", *IEEE: International Forum on Information Technology and Applications*, pp. 612-615, 2009.

[5]. H. Moon and P. J. Phillips, "Computational and performance aspects of PCAbased face-recognition algorithms.," *Perception*, vol. 30, no. 3. pp. 303–21, Jan- 2001.

[6]. H. Wechsler, "Enhanced Fisher linear discriminant models for face recognition," *Proceedings. Fourteenth Int. Conf. Pattern Recognit.* (Cat. No.98EX170), vol. 2, pp. 1368–1372.

[7]. L.-F. Chen, H.-Y. M. Liao, M.-T. Ko, J.-C. Lin, and G.-J. Yu, "A new LDA-based face recognition system which can solve the small sample size problem," *Pattern Recognit.*, vol. 33, no. 10, pp. 1713–1726, Oct. 2000.

[8]. D. D. Lee and H. S. Seung, "Algorithms for non-negative matrix factorization", *Advances in Neural Information Processing System*, 2000.

[9]. W. S. Zheng, J. Lai, S. Liao, R. He, "Extracting non-negative basis images using pixel dispersion penalty", *Pattern Recognition*, pp. 2912-2926, 2012.

[10]. D. Cai, X. He, J. Han and T. Huang, "Graph regularized nonnegative matrix factorization for data representation", *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 33(8), pp. 1548–1560, 2011.

[11]. B. G. Kumar, I. Kotsia and I. Patras, "Max-margin nonnegative matrix factorization", *Image Vision Computing*, pp. 279–291, 2012.

[12]. C. Ding, T. Li, and M. Jordan, "Convex and semi-nonnegative matrix factorizations for clustering and low-dimension representation", *Technical Report LBNL-60428*, Lawrence Berkeley National Laboratory, University of California, Berkeley, 2006.

[13]. Matthew N Dailey, Carrie Joyce, Michael J Lyons, Miyuki Kamachi, Hanae Ishi, Jiro Gyoba, & Garrison W Cottrell, "Evidence and a computational explanation of cultural differences in facial expression recognition". *Emotion*, Vol 10(6), Dec 2010, 874-893.

Author's Biography

Phan Trong Thanh holds a Master of Information System and Management in 2016 from Lunghwa University of Sience and Technology – Taiwan He works as a lecturer in Vietnam Korea University of Information and Communication Technology, Danang, Vietnam. His research interests are Information System and Networking.

Doan Van Thang obtained his doctorate in Mathematical Foundation for Computers and Computing Systems in 2014 from the Institute Of Information Technology, Vietnamese Academy Of And Training Science And Technology Viet Nam. He has published over 30 research papers. His main research interests include the fuzzy database, hedge algebras and detection, prevention, avoidance of cloud computing and distributed systems. He serves as a technical committee program member, track chair, session chair and reviewer of many international conferences and journals.

How to Cite

Thanh, Phan Trong, and Thang, Doan Van(2019). Joint Spatial Geometric and Max-margin Classifier Constraints for Facial Expression Recognition Using Nonnegative Matrix Factorization. *International Journal of Machine Learning and Networked Collaborative Engineering*, 3(03) pp 125-134.

doi : https://doi.org/10.30991/IJMLNCE.2019v03i03.001

Vol. 03, No. 3, 135-142, **ISSN:2581-3242**

IJMLNCE JOURNAL

International Journal of Machine Learning and Networked Collaborative Engineering

Journal Homepage: http://www.mlnce.net/home/index.html

DOI : https://doi.org/10.30991/IJMLNCE.2019v03i03.002

Recommender System for Educational & Corporate Sector In Prediction of Domain Recommendations & Analysis using Machine Learning

Praneet Amul Akash Cherukuri

Dept. of Computer Science & Engineering, CMR Institute of Technology, Hyderabad, India

chamul91@gmail.com, https://orcid.org/0000-0003-1408-6784

Abstract

These days Career and Domain options have always been a very big ambiguous decision-making process for many prospective aspirants. Many aspirants make substantial domain changes very late in their career which may result in drastic effects on their career as well as their financial status. Many reports suggested that companies have suffered huge losses because of making wrong choices regarding the domain and employee interest. Hence providing a common platform early in the education sector for both the aspirants as well as companies that would provide appropriate domain suggestions for aspirants as well as right employee choices for companies would be highly beneficial that could help in generating better results when compared to the traditional ways of career choices and employment. In this research, we are proposing a recommender system based model that would bridge the gap and help in formulating their future needs.

Keywords

Machine Learning,

Recommender Systems,

Big Data,

Bayesian Classifiers

1. Introduction

Over the last few years, many technologies have taken over the IT Industry making several changes that are permanently renounced and are still having a huge impact in the present day scenario. In this research paper, we are proposing a model that uses some of these very important and highly applied technologies such as Machine Learning, Recommender Systems, Big Data, Bayesian Classifiers', Regression models and Natural Language processing. Machine Learning is a branch of Artificial intelligence, it is a method of Data analysis in which it builds a model that performs huge amounts' of data analytics and learns from that data by itself, identifies patterns and makes decisions on its own with the minimal human intervention [1]. Recommender Systems is an application of machine learning in which the model learns from the given data and hence proposes a new recommendation. The recommendation system gives the option to comprehend an individual's taste and find the new, appropriate choice for them consequently. However individuals preferences shift, they do-follow patterns. Individuals will in-general like things which are comparable social individual preferences. Most of the times these sorts of examples can be identified with the importance of things[2].

Big Data refers to the advancement in innovation clubbed with an assortment of data, strategies that have now furnished the instrument to manage a wide range of issues that show up during the procedure of data assortment and during working with enormous volume, assortment, and speed of data. The main purpose behind Big Data is the application of information tools to pave the way for data analysis and retrieve appropriate information for better estimation, planning, and judgment in any business process [3]. A thorough machine learning analysis of the student's sentiments does wonders in the student enrolment process. Big Data solutions, therefore, serve as an insight analysis podium [4].

In this paper, we use collaborative filtering because of the main drawbacks that the proposed model consists which are, most users do not provide evaluation and hence user matrix can result in great sparsity. Another such issue is for a given metric there is no previous data then that particular metric could result in not being recommended to any user hence by using collaborative and content-based filtering we can oversee these issues. Bayesian classification will be utilized to arrange items to bring down the components of the user-produced matrix. Likewise, by executing a hereditary calculation on the ordered items the clients can be placed into groups. At that point, by input on significance, it is conceivable to make a profile for new clients, consequently taking care of the first rater issue [5]. Using these technologies and algorithm we build the overall model that can input and output data. On the other hand, a user-interactive platform built using Web Design & Development technologies is very important for the user experience and user interaction that could help in the improvement of data generated daily.

1.1. Prevalent System and Need for Change

In the present day scenario, many educational institutions have their learning management systems that are a majority of temporary or very privately held dealing only concerning a particular educational institution. The disadvantage of these LMS is that they are very inefficient in means of data collection and the scope of doing it. Also, another huge disadvantage is all the data that is being generated concerning that particular institution is not stored well or is made private and hence there is no possibility of doing data analysis in this case that creates a huge impact in the adaption process for the collection and assembling of data. Hence these prevalent systems are mostly data collection systems but not most of them have been in the process of analyzing and proposing a better analysis to the users or the aspirants, rather they have been just made to collect data and provide temporary solutions.

The need for a change of these systems is although all the sectors have been implementing and experiencing a huge change in their activities the education sector has fallen far behind following the same old traditional methodologies. Hence the proposed model could help the education sector in identifying a different perspective of education to help students, users, organizations to benefit their careers in an optimized direction

2. Proposed Model

The proposed model is a machine learning model that generates recommendations' using recommender systems concept of machine learning by analyzing the huge amounts of data assembled using big data technologies. The model would be divided into three major phases of development. The three models clearly define the process of data collection, analysis, classification & recommendation. The model analyses the metrics in a very curated way and could suggest the user or an organization with a recommendation that could be early advice and could help in making better decisions at a given point of time. Also, it would result in making the required changes to achieve the goal even before starting the process so that there are no errors in the early phases of the process.

The model proposed creates a bridge between educational institutions and organizations where data particular to a similar user and their proposed metric are evaluated and established. Since the data is ever recurring hence the probability of using big data to analyze and hold that data is mandatory. The data that was already collected by the present-day learning management systems and other useful softwares both from educational institutions and other companies are evaluated, cleaned and then set the stage for the upcoming platform to generate new data and then combine it. The model starts by accumulating all the data that it has been collecting using various learning management softwares and then are stored using the big data methodologies so that at a later point of time they can be retrieved for analysis. Then the data is divided concerning two databases are User data and the company-specific data which is evaluated and then the states are formulated. Int eh next phase the data which is collected is undergone content and collaborative filtering in which the data is compared to many similar metrics and hence is classified according to its similarities. The data is then prone to the regression models where it is filtered and then is sent to the database with filtered metrics. In the next phase when we retrieve the information that we analyzed in the previous phase and stored in the database is now displayed back according to the need of the user or the company.

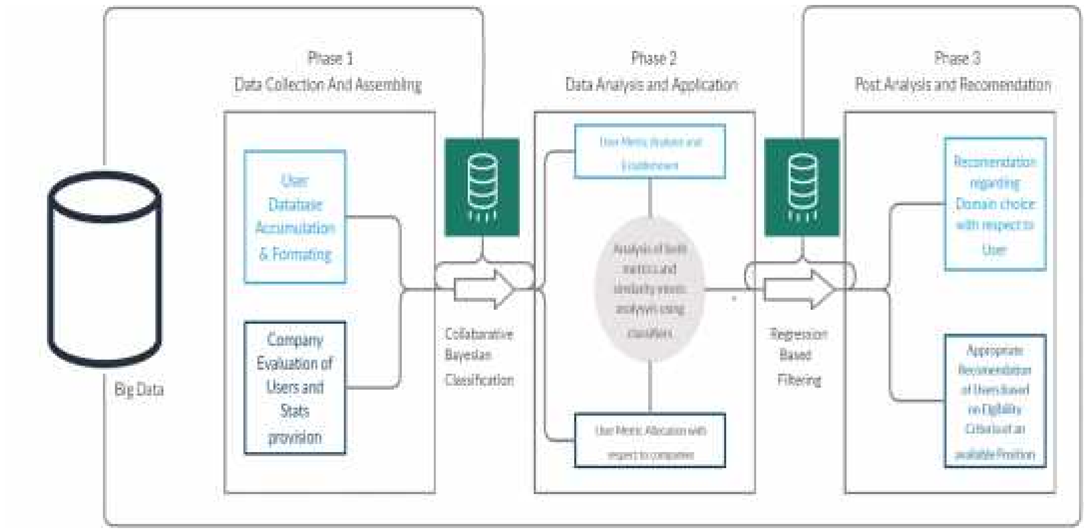


Figure 1. Representation of The Proposed Model

2.1. Phase 1: Data Collection and Assembling

This phase includes the pre-phase of analysis, where the data that is required for the analysis is recorded using the platform which is provided by the model that is being implemented in the everyday scenario of the user/student’s academics from the very beginning of his/her academic year recording all the required metrics which are stated in Figure 2., which can be used to evaluate the overall metrics. The data being generated will be stored using big data technologies such as NoSQL, Hadoop, and Apache Spark. In the phase of data collection, the data collected is usually concerning the preferred metric and it is received from the platform which is then evaluated to yes or no from the data. Outliers for some metrics are removed such for example A user does not have any concerning specific data related to a metric then that data will become an outlier and would not be just removed because that would become a problem in getting that certain metric being analyzed in a similar user profile. Hence even outliers in this are properly specified and cleaned.

One of the areas that volume, variety, and velocity exist together in the information is higher education. A lot of educational information is caught and created regularly from various sources and in various configurations in the advanced education system. The educational information change from those delivered from students' utilization and communication with learning the board frameworks (LMSs) and stages to learning activities and courses information [6].

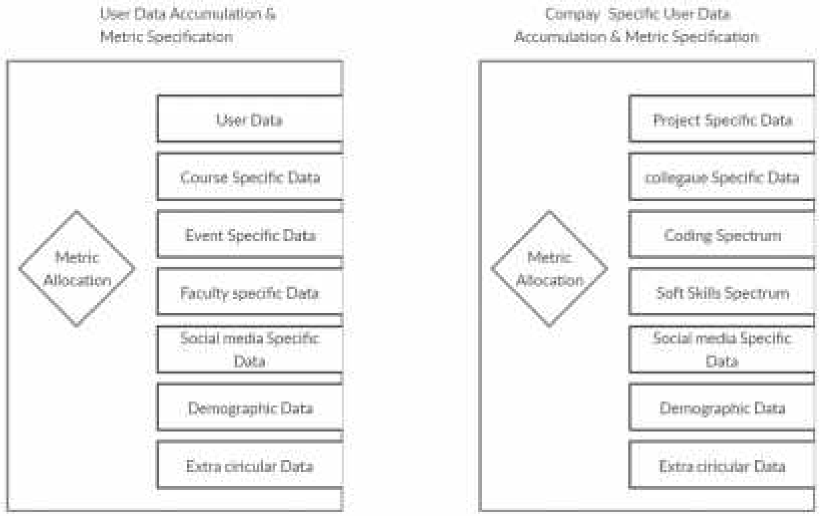


Figure 2. Representation of Phase 1

The constrained exploitation of large educational data and the size and sort of these data inside the setting of advanced education connotes the requirement for unique procedures to be applied to find new advantageous knowledge that at present is hidden up inside data [7]. Since the data generated is huge and recurring data, big data is used to make the process smoother rather than using a traditional SQL database. The data from companies resulting in the evaluation of different user's metrics and evaluation in the particular domain are also generated and records for it to be analyzed in the further phases of the model where the analysis takes place.

2.2. Phase 2: Data Analysis and Application

The second phase of the model deals with the main analysis and the application part. Here the analysis part refers to the metric allocation to all the data that has been generated and then cleaned form the first phase. Metrics then allocated to the data are then sent to the application phase. The application phase is the phase where the different metrics shall be processed into a Collaborative and Content Bayesian classification in which they are classified using the item based classification: that is the probability of similarity taking place and then the features are classified against the 'yes' or 'no' metrics. When we take into account the item based classifier that takes the inputs as 'yes' or 'no' then it will be as follows [8].

The analysis is taken place as follows when a user X with metrics A, C, G, H is given to the database then the data is undergone through the Classification in which the users' metrics are then matched with a yes or no feature under all the various profile in the database and then a compilation of all the similar user profiles is made. Then this compilation is then compared to extract the most similar and redundant career choice metric that has been made between these similar profile sand it analyses them to find a pattern of success rates in them. After finding the most successful career choice using the metrics then the model would run on a database of the company-specific evaluation for that career choice concerning the profile and the user metrics and, hence a proper evaluation that is both concerning the previous user data as well as the feedback from companies for users with such metrics, career success rates have been evaluated for the User X and are stored on to the database. On the other hand, the same evaluation from these users is also evaluated to know the eligibility of the certain user for a job role that has been posted by the company by using the evaluated metrics and can, therefore, understand which user would be highly preferable for a certain job role with concerning metrics.

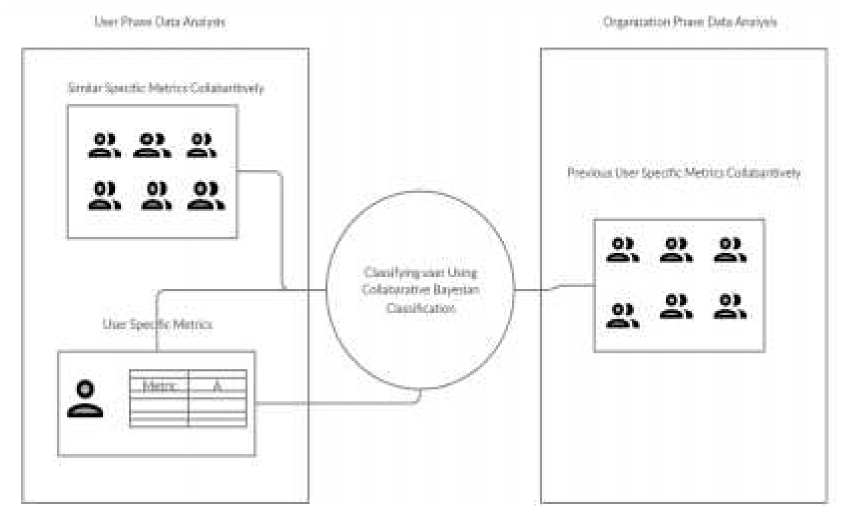


Figure 3. Representation of Phase 2

$$\frac{P_{feature}(yes\ |user\_metric)}{P_{feature}(no\ |user\_metric)}$$

A ‘yes’ metric can be defined as :

$$P_{feature}(yes\ |user\_metric) = \frac{P_{feature}(user\_metric|yes) \times P_{feature}(yes)}{P_{feature}(user\_metric)}$$

A ‘no’ metric can be defined as :

$$P_{feature}(no\ |user\_metric) = \frac{P_{feature}(user\_metric|no) \times P_{feature}(no)}{P_{feature}(user\_metric)}$$

When combined to take the classification:

$$\frac{P_{feature}(yes|user\_metric)}{P_{feature}(no|user\_metric)} = \frac{P_{feature}(user\_metric|yes) \times P_{feature}(yes)}{P_{feature}(user\_metric|no) \times P_{feature}(no)}$$

The classified data is then directed to the regression algorithm where they are filtered and hence the recommendation is made based on which the data and the metrics are defined. To recognize comparative users, we should gauge the closeness between two users. There are two most mainstream strategies: cosine-based closeness and correlation-based similarity[9]. Most recommender systems prefer the correlation similarity since it outperforms the cosine-based similarity in most problems [10]. Then these metrics that have been filtered and reset to the particular user features are again stored in the database for the future use of users as well as organizations. Also, this data can be retrieved when they are being used for the comparison studies of other similar user models.

2.3. Phase 3: Post Analysis & Recommendation

This phase is the last step and the post-analysis phase that deals with the data retrieval from the database in which classification and filtration of the featured metrics are done and displayed onto the portal. This phase displays the appropriate recommendation of a particular domain or career choice listing out all the possibilities of success rates in percentile for that particular field of domain and comparing it with the profile of the user concerning a similar database. The recommendations made by the model are concerning the data that has been already recorded and are real-time examples that are analyzed to find a pattern.

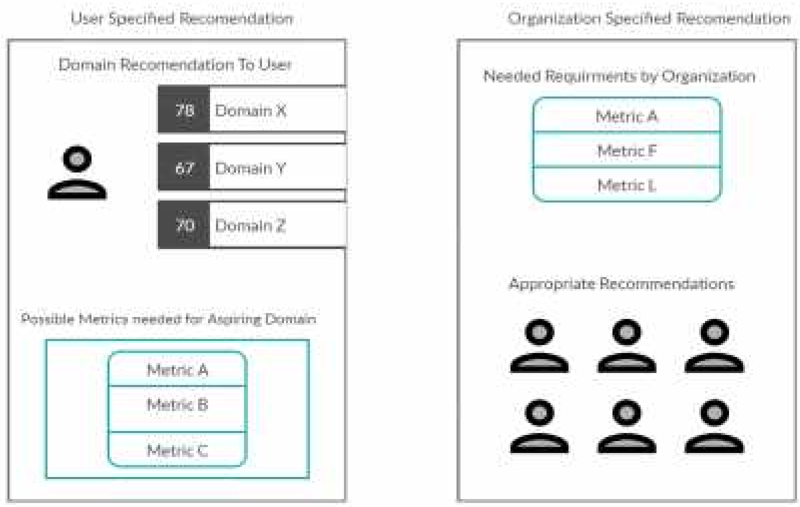


Figure 7. Representation of Phase 3

Also, it intakes the aspired domain choice of the user and provides the outputs and their possibilities of success in that particular domain along with the metrics he/she must improve to be able to sustain in their aspired domain choices. On the other hand, companies get a properly sorted list of the best recommendation for a particular role that had been requested and the proposed success rates of him/her being employed for that particular career choice. Also, the company could list down the particular success rates for a person of their choice. These recommendations are retrieved to the user after undergoing the process of filtration using the regression techniques and hence more accurate results and recommendations are generated to the user that could increase the success rate for him in a particular carer or domain choice. The results generated are accurate and could be improved on the training done to the model that could help the model to generate many accurate recommendations. The next phases of the model are outlined in the future scope of the paper that would help in the improvement of the model from the data generated.

3. Future Scope and Prospective Advantages

The proposed model would aim to help users build a better career by recommending them the best career options that are appropriate to their profile evaluations a well as everyday behavioral data that has been generated by the platform. The model would also help him/her by giving the user an appropriate success rate for the recommended domain and career options by defining their success rates while classifying them using the real-time company profile evaluation data that could help the user in understanding his/her success rates in a defined domain. Another noted advantage would be to organizations where the model could be used to get a recommendation for their recruitment as the proposed model hosts a million bytes of data related to thousands of users along with their evaluated metrics and could help the organization to evaluate the best candidate for a proposed role.

Since this is a real-time model the data is very large and hence causes a lot of disturbances. The future scope of this model has no limits since the collection of data here is only limited to educational institutions of higher level, if the same model is being implemented from the very early stage of the education phases, the data and analysis could become more refined due to the increase in the quality and the quantity of the data and hence the model can become more accurate as far as possible. Also, the model can be used in the overall analysis of job aspirants by linking his social media profiles and then understanding his/her behavioral data could help the model in making more appropriate choices. Also, other classification and regression algorithms could be used that could help in the prostatic increase in the accuracy of recommendations. The metrics that are being observed in the above model are very outlined and can sometimes fail to understand the deep patterns hence the collection of some intuitive metrics that actually defer the user behavior and also his ability to perform a task could also be recorded to provide much more accuracy. Hence adding metrics that are highly particular in detail and analyzing them with an optimal picture would help to unfold various hidden details that could help in the outcome of much more accurate and highly beneficial data. Moreover, results that have generated from the model can be reused for the self-improvement of the model by rolling out the feedback of a particular recommendation that has been previously made by the model. This data could help the model in rectifying wrong recommendations and provide highly accurate decisions in the next recommendations

4. Conclusion

Therefore the approach of this model has a huge impact on the educational institutions and the corporate sector of today's highly competitive world. The model proposes a simple and cross-sector solution to both the corporate and educational sectors that could result in the huge increase of employability solving the problem of wrong decision making of job aspirants as well as mistakes made by the organization whereby suffering losses from those decisions. Hence it could benefit every academician in evaluating his/her students as well as their academic performance in a more sophisticated and a single independent platform that has analysis related to current world trends and scenarios.

The advantage of getting an analysis that is evaluated and compared with data from all over the world could help a user to understand well enough about his/her decision makings and personal evaluation. The only hurdle this model can face is acceptance from educational institutions accepting it to evaluate and generate data from their colleges but if this problem is overseen, then a huge variety of data being generated every day can make and change the model by making it much more accurate system over the days. This way it provides a platform for educational institutions to analyze the students' performance in real-time and his industry level aspects as well. Concluding, the model has a vast scope of improvement as well as can provide great accuracy with positive results in the future.

References

[1]. *Machine Learning* - https://www.sas.com/en_in/insights/analytics/machine-learning.html

[2]. Verma, Jaiprakash & Patel, Bankim & Patel, Atul. (2015). Big Data Analysis: Recommendation System with Hadoop Framework. Proceedings - 2015 *IEEE International Conference on Computational Intelligence and Communication Technology,* CICT 2015. 92-97. 10.1109/CICT.2015.86..

[3]. Michael Yao-Ping Peng, Sheng-Hwa tuan, Feng - Chi Liu “Establishment of Big Data Application for Education Industry”, 2017 *2nd International Conference on Image ,Vision and Computing.*

[4]. Nour Moahammed Almadhoun, P. Dhanapal Durai Dominic and Lai Fung Noon “Social Media as a Promotional Tool in Higher Education in Malaysia”, 978-1-4577-1884-7/11, *IEEE.*

[5]. Ko S., Lee J. (2002) User Preference Mining through Collaborative Filtering and Content based Filtering in Recommender System. In: Bauknecht K., Tjoa A.M., Quirchmayr G. (eds) E-Commerce and Web Technologies. EC-Web 2002. *Lecture Notes in Computer Science,* vol 2455. Springer, Berlin, HeidelbergS.M.R. Islam, D. Kwak, M.D.H. Kabir, M. Hossain, and K. Kwak, "The internet of things for health care: a comprehensive survey," IEEE Access 3, 2015, pp. 678-708.

[6]. Christos Vaitsis, Vasilis Hervatis and Nabil Zary (July 20th 2016). Introduction to Big Data in Education and Its Contribution to the Quality Improvement Processes, Big Data on Real-World Applications, Sebastian Ventura Soto, José M. Luna and Alberto Cano, *IntechOpen*, DOI: 10.5772/63896. Available from: https://www.intechopen.com/books/big-data-on-real-world-applications/introduction-to-big-data-in-education-and-its-contribution-to-the-quality-improvement-processes

[7]. Romero C, Ventura S. Educational data mining: a survey from 1995 to 2005. *Expert Systems with Applications.* 2007;33(1):135–46.

[8]. Introduction to Recommender Systems - https://towardsdatascience.com/introduction-to-recommender-systems-6c66cf15ada

[9]. Yu Chuan, Xu Jieping, and Du Xiaoyong. 2006. Recommendation algorithm combining the user based classified regression and the item-based filtering. *In Proceedings of the 8th international conference on Electronic commerce: The new e-commerce: innovations for conquering current barriers, obstacles and limitations to conducting successful business on the internet (ICEC '06)*. Association for Computing Machinery, New York, NY, USA, 574–578. DOI:https://doi.org/10.1145/1151454.1151463

[10]. Ailin Deng, Yangyong Zhu and Bole Shi, "A Collaborative Filtering Recommendation Algorithm Based on Item Rating F Prediction", 2003 *Journal of Software* , vol.14, No.9.

Author's Biography

Praneet Amul Akash Cherukuri is currently pursuing his Bachelor's in Technology – Computer Sciences & Engineering from CMR Institute of Technology, Hyderabad. He is the CEO of Kirg Technologies an IT startup. He was an International Delegate for the Harvard University's HPAIR Conference 2020, in Boston, USA. His research interests are Data Science, Natural Language Processing, Recommender Systems, Neural Networks, and Prediction Analysis.

How to Cite

Cherukuri, Praneet Amul Akash (2019). Recommender System for Educational & Corporate Sector In Prediction of Domain Recommendations & Analysis using Machine Learning. *International Journal of Machine Learning and Networked Collaborative Engineering,* 3(03) pp 135-142.

doi : https://doi.org/10.30991/IJMLNCE.2019v03i03.002.

Vol. 03, No. 3,(2019),143–158, **ISSN:2581-3242**

IJMLNCE JOURNAL

International Journal of Machine Learning and Networked Collaborative Engineering

Journal Homepage: http://www.mlnce.net/home/index.html

DOI : https://doi.org/10.30991/IJMLNCE.2019v03i03.003

Understanding Machine Learning for Friction Stir Welding Technology

Akshansh Mishra*

Center for Artificial Intelligence and Friction Stir Welding , Stir Research Technologies, UP, India

akshansh.frictionwelding@gmail.com (https://orcid.org/0000-0003-4939-359X)

Abstract

Machine learning process drastically decreases the time it takes to develop stronger, lighter materials. This is important to the aerospace, automotive and manufacturing sectors. Machine Learning techniques like Artificial Neural Networks and Image processing are used in a solid state joining process such as Friction Stir Welding process (FSW) for optimization of mechanical properties like Ultimate Tensile Strength (UTS), Fracture Strength , Elongation percentage and microstructure properties like grain size and understanding defects formation. In the recent paper, application of Machine Learning technique in Friction Stir Welding technology will be discussed.

Keywords

Machine Learning,
Friction Stir Welding,
Neural Network,
Tensorflow,
Artificial Intelligence,
Google Colaboratory

1. Understanding Human Nervous System

The human nervous system can be classified as a three stage system which is shown in the block diagram of Figure 1. The brain is in central position to the nervous system which is represented by the neural net. The function of the neural net is to receive the information continuously, perceive it and then to make appropriate decision.

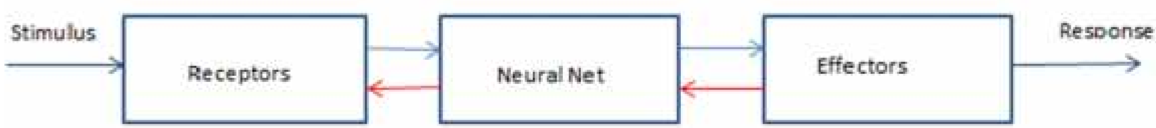


Figure 1. Representation of Nervous System by block diagram

* Corresponding author

Akshansh Mishra

Email: akshansh.frictionwelding@gmail.com

The green arrows which are pointing from left to right represent the forward transmission of information carrying signals through the nervous system. The red arrows in the diagram show the presence of feedback in the nervous system. Stimuli from the external environment or the human body are converted to electrical impulses by receptors which further convey the information to the brain (neural net). Electrical impulses which are generated by the receptors are further converted to a distinguishable response as a nervous system outputs by the effectors [1]. Figure 2 represents the schematic diagram of the human nerve cell.

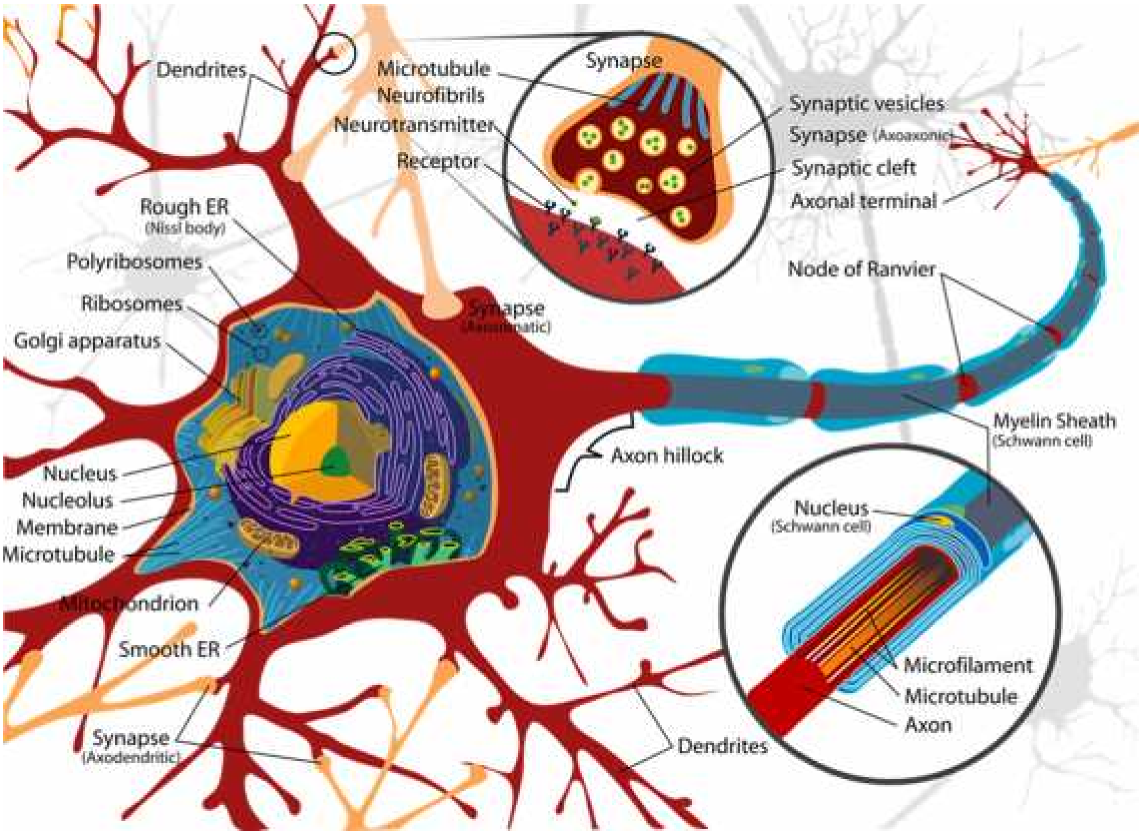


Figure 2. Representation of human nerve cell

Neuron is the fundamental unit of the neural network architecture. Dendrites, soma and axon constitute the neuron structure. Signals from surrounding neurons are received by a tree like structure called Dendrites. Each of the line is connected to one neuron. The signal from one neuron to others is transmitted by a thin cylindrical structure is called an Axon. Synapse is responsible for making contact between at the end of axon and dendrites. At the synapse, the inter neuronal signal is propagated through chemical diffusion or by electrical impulses. Only if certain condition is met, the neuron fires an electrical impulse [2]. If the total weight of the synapses which receive impulses in the period of latent summation become more than the threshold then it causes neuron fire [3].

2. Modelling the architecture of Artificial Neural Network

The information processing unit of the basic neural network architecture is a neuron. Non-linear model of a neuron is depicted in the Figure 3.

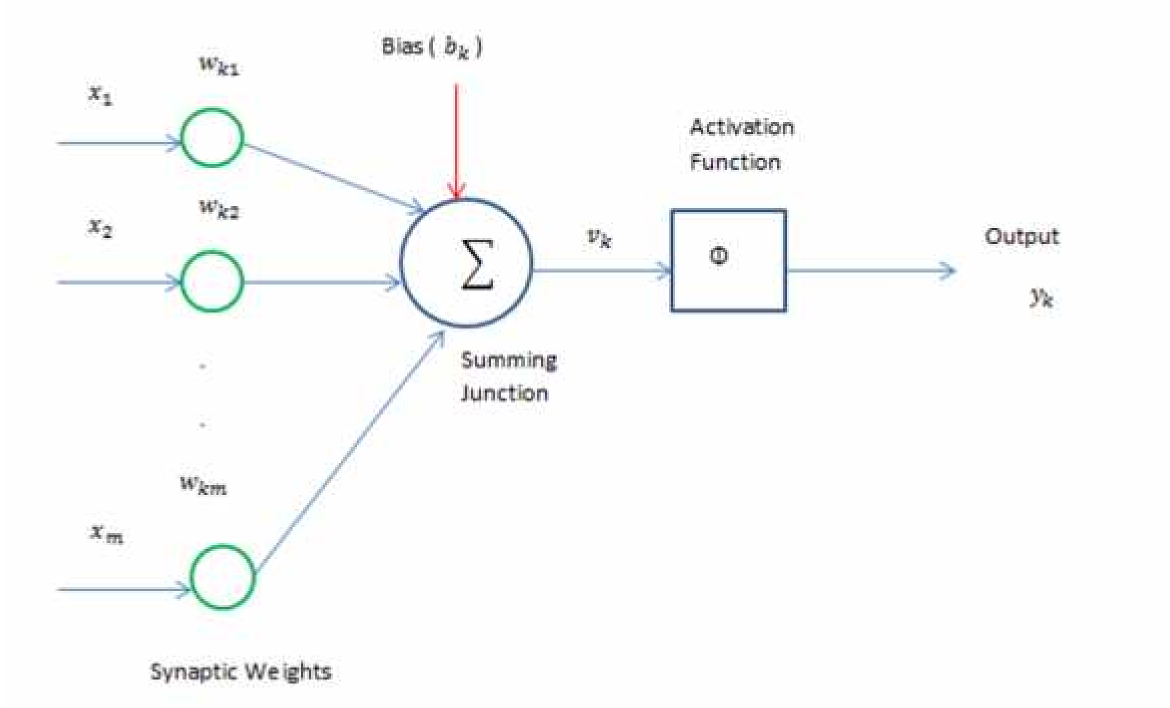


Figure 3. Representation of non-linearity of a neuron

The given neural model has three basic elements i.e. an adder, set of synapses and an activation function. The characterization of the connecting links or set of synapses are done by its own weight or strength. Signal x_j at the input of synapse j which is connected to the neuron k is further multiplied by the synaptic weight w_{kj}. The synaptic weight of the artificial neuron lies between the both positive and negative values. An adder performs the operation of the linear combination. It sums up the input signals which are weighted by the synaptic strengths. The main application of the activation function is to limit the amplitude of the output of neuron. The bias which is shown in the Figure 3 is applied externally and its main function is to decrease or increase the net input of the activation function.

In the form of mathematical expression, we can define the neuron k shown in the Figure 3 with the help of the pair of equations:

$$u_k = \sum_{j=1}^{m} w_{kj} x_j \tag{1}$$

and, $$y_k = \varphi\,(u_k + b_k) \tag{2}$$

3. Machine Learning and its classifications

Machine learning technique give priorities to the development and execution of the computer programs that can process data and use that particular data to learn for themselves. It's just like before solving calculus exercise numerical problems, you go through the various examples given in that particular chapter i.e. you are training your mind and when you solve new question it is called testing your mind and the result you get for that particular question measures the accuracy of your performance. So we can define Machine learning as a subset of artificial intelligence (AI) which provides the given systems or state the ability to learn by itself and further modify from the experience without being explicitly programmed [4-8]. Machine learning classified into three main types i.e. reinforcement learning, supervised learning and unsupervised learning which will be discussed one by one in the following sub sections.

3.1 Supervised Learning

Supervised learning can be referred to as the situation of learning a concept with a teacher. The working of supervised machine learning is shown in the Figure 4. We may assume that the teacher possess the knowledge of the given environment which is unknown to the neural network architecture. The representation of the knowledge is done by a set of input-output examples.

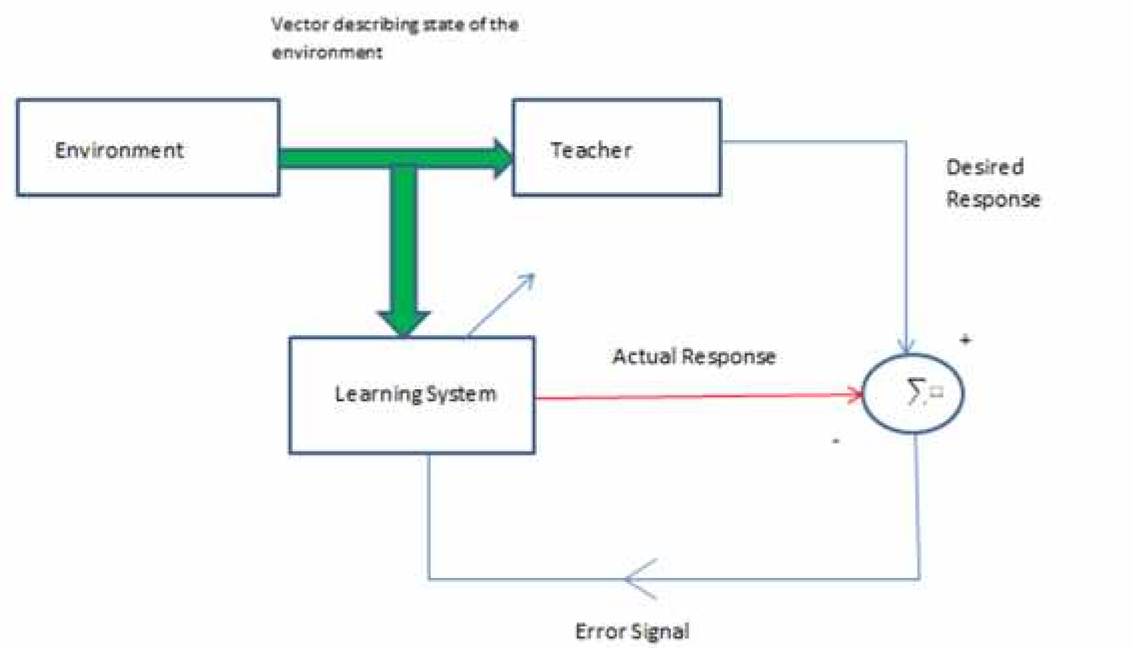


Figure 4. Working of Supervised Machine Learning

Figure 4 shows that a training vector which is dragged from the same environment is exposed to neural network and the teacher. So, for that training vector, a desired response is given by the teacher with the assistance of the possessed knowledge. Error signal shown in the Figure 4 is the difference of the actual response and the desired response. Under the combined influence of the error signal and the training vector, network parameters are adjusted. This step by step adjustment is carried out further which makes proper transfer of information of the environment possessed by the teacher to the neural network.

3.2 Unsupervised Learning

Unsupervised machine learning is a self-organized learning process in which there is no involvement of external person or teacher to look after or observe the training process. The working of the unsupervised machine learning process is shown in the Figure 5. In order to carry out unsupervised machine learning task, a competitive learning rule is used. Just take an example of a neural network consisting of two layers i.e. an input layer and a competitive layer. The available data is received by the neural network. If we talk about the competitive layer, it consists of various neurons which compete against each other for the opportunity for responding the features contained in the input data as per the given learning rule.

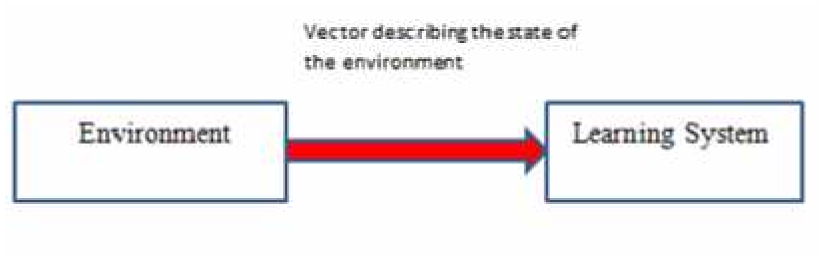


Figure 5. Working principle of Unsupervised Machine Learning

3.3 Reinforcement Learning

Reinforcement learning is a semi-supervised machine learning method which trains the models to make a sequence of decisions. The working of the Reinforcement learning is shown in the Figure 6. In an uncertain, potentially complex environment agent learns to achieve a particular goal. An artificial intelligence is subjected to a game-like situation where the computer employs trial and error method to come up with a solution to the given problem. The main objective of the Reinforcement Learning is the maximization of the total reward. Reinforcement Learning works on the rewards and penalties scheme. The Reinforcement Learning model tries to figure out the method to perform the given task in order to maximize the reward, starting from totally random trials and finishing with advanced tactics and superhuman skills.

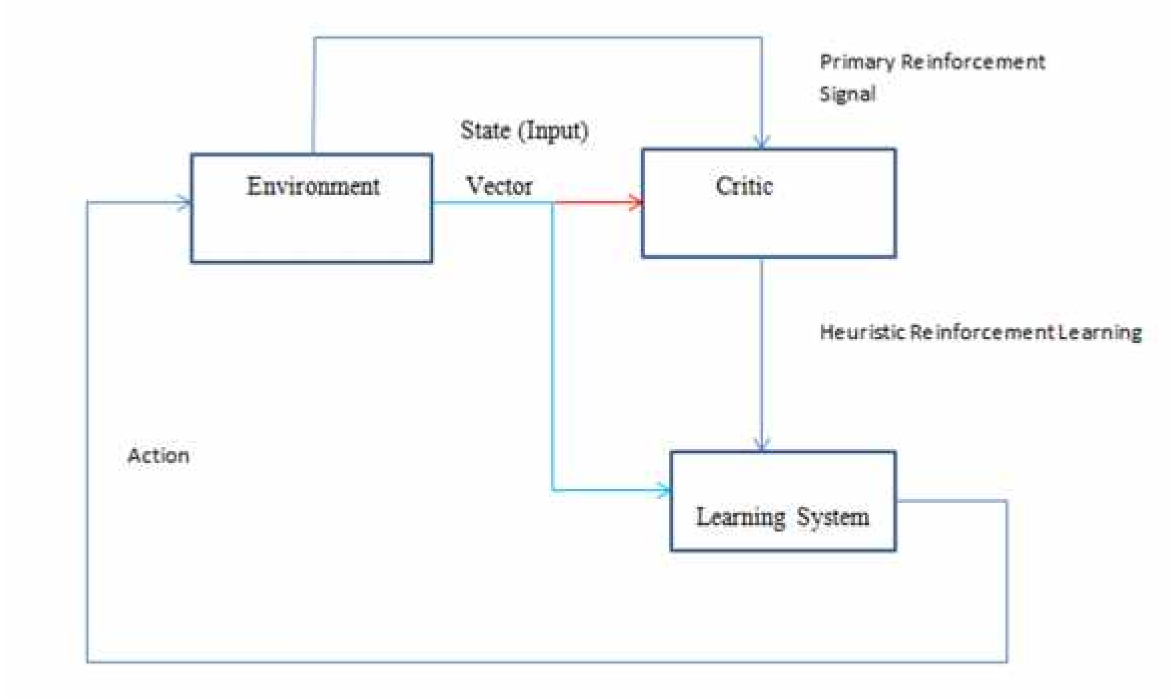
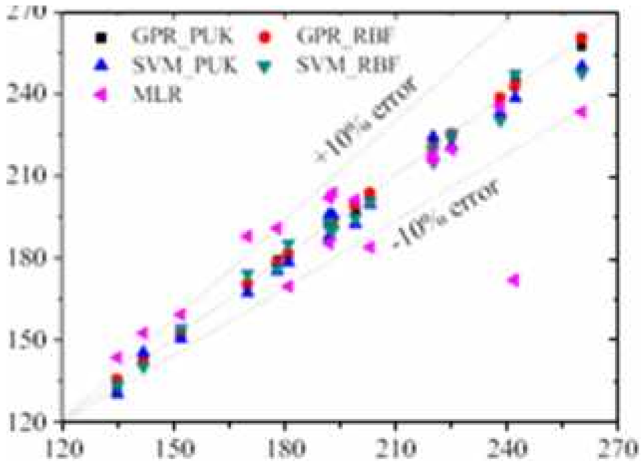


Figure 6. Working principle of Reinforcement Learning

4. Application of Machine Learning in Friction Stir Welding Process

Verma et al. [9] used various sophisticated machine learning approaches like . Support Vector Machining (SVM) , Gaussian Process (GP) regression, and multi-linear regression (MLR) for evaluating the friction stir welding process.

Predicted UTS (MPa)



Actual UTS (MPa)

Figure 7. Predicted vs actual values of Ultimate Tensile Strength (UTS) using SVM, GP, and MLR using training data [9].

As shown in Figure 7 it is observed that in comparison to the SVM and MLR models, the GPR approach works better. Therefore, GPR approach is generally used successfully for prediction of the UTS of Friction Stir welded joints.

Debroy et al. [10] studied the conditions for void formation using a Bayesian Neural Network and a decision tree. Schematic representation of the research is shown in the Figure 8. The study showed that the neural network and the decision tree predicted void formation with 96.6% accuracy by computing the causative variables like temperature, strain rate, torque, and maximum shear stress on the tool pin.

Celik et al. [11] investigated the correlation between the friction welding parameters and tensile strength of both AISI 316 austenitic-stainless steel and Ck 45 steel by developing an Artificial Neural Network (ANN) model. Figure 9 represents the artificial neural network architecture used in the study.

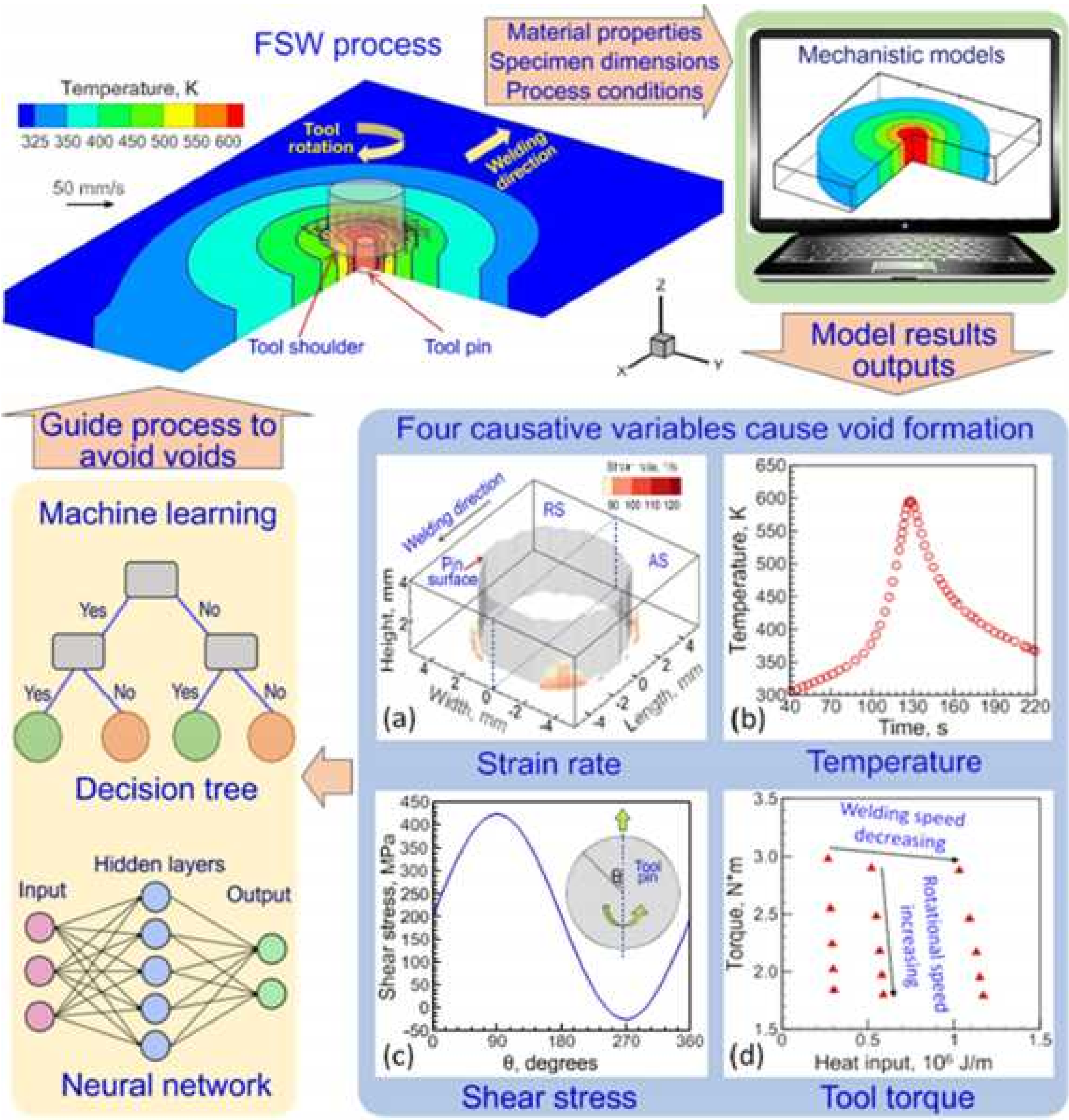


Figure 8. The components are FSW process, mechanistic models, and machine learning methods (neural network and decision tree) [10].

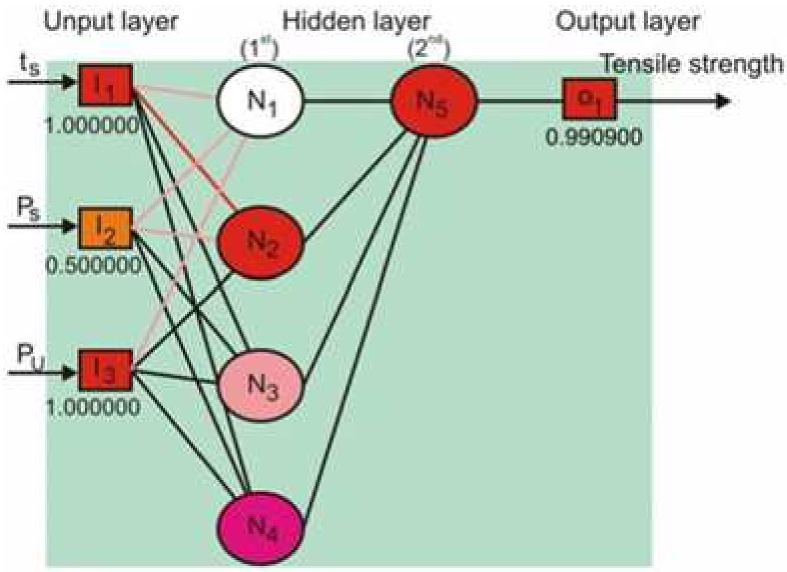


Figure 9. Four layered neural network architecture [11]

Figure 10 shows that a good correlation was obtained between the Artificial Neural Network predicted values and the experimental values.

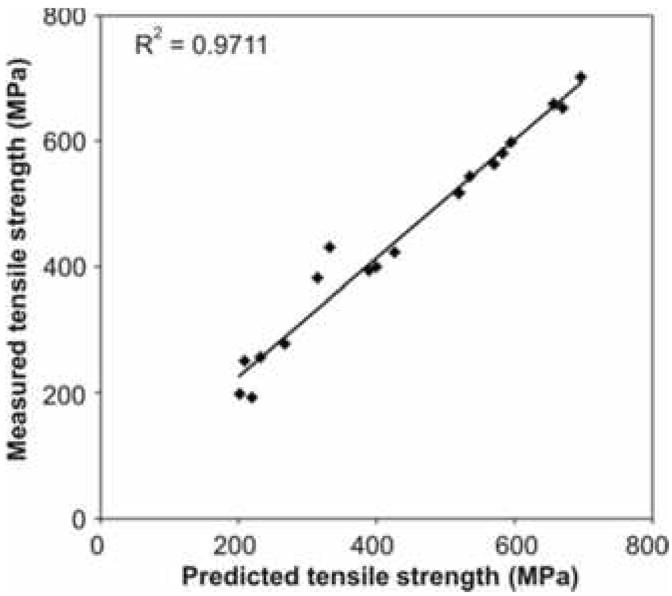


Figure 10. Comparison of measured and predicted outputs for tensile strength [11]

Maleki et al. [12] developed Artificial Neural Network based on backward propagation algorithm for predicting the yield strength, tensile strength, notch-tensile strength and hardness of friction stir welded AA 7075-T6 joints. The Neural Network architecture used in the study is shown in the Figure 11.

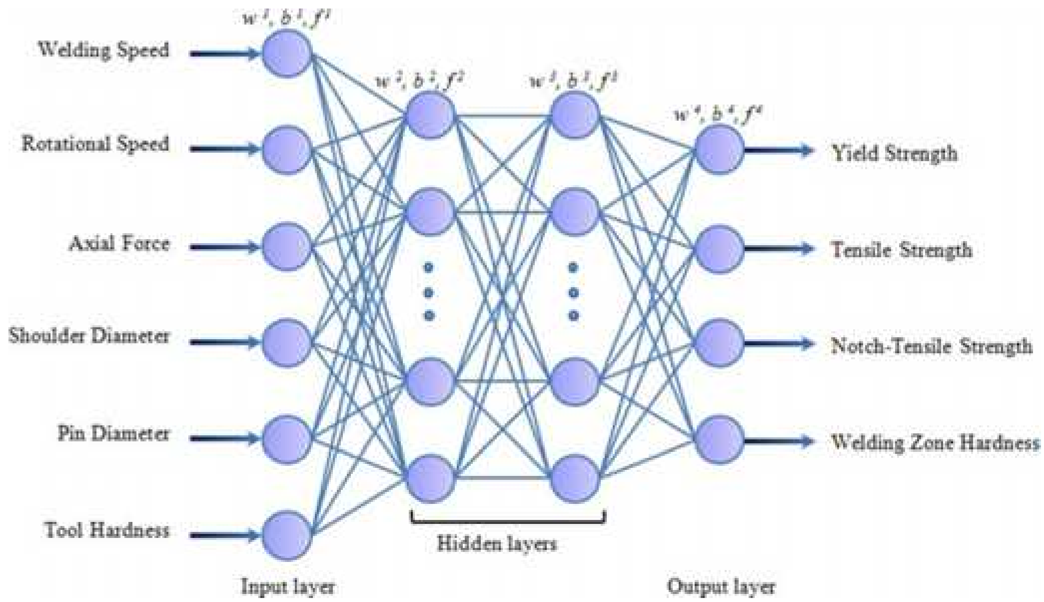


Figure 11.Schematic representation of Neural Network architecture used by Maleki et al. [12]

Figure 12 shows the comparison of the predicted and the experimental results. The results show that the if neural networks are adjusted carefully then it can be used for modeling of various Friction Stir Welding parameters.

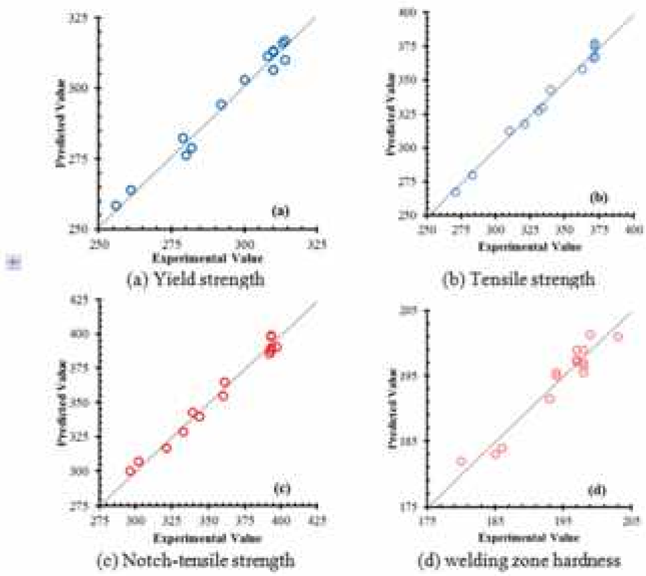


Figure 12. Experimental values plotted against predicted values [12]

Mishra et al. [13] implemented the Convolutional Neural Network for identification of the texture of Friction Stir Welded joints and Conventional Welded joints. Macias et al. [14] established a correlation between the acoustic emission signals and the various main parameters of friction stir welding process based on artificial neural networks (ANNs) trained on Levenberg-Marquardt algorithm. Figure 13 and 14 shows the methodology and the development of Artificial Neural Network architecture respectively.

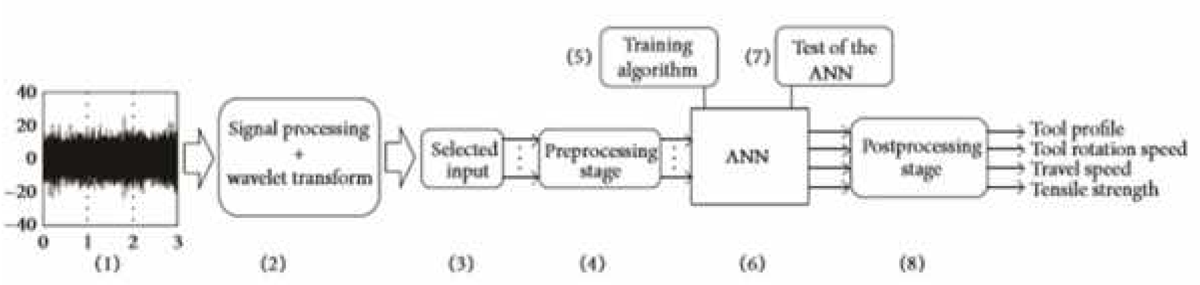


Figure 13. Artificial Neural Network development methodology [14]

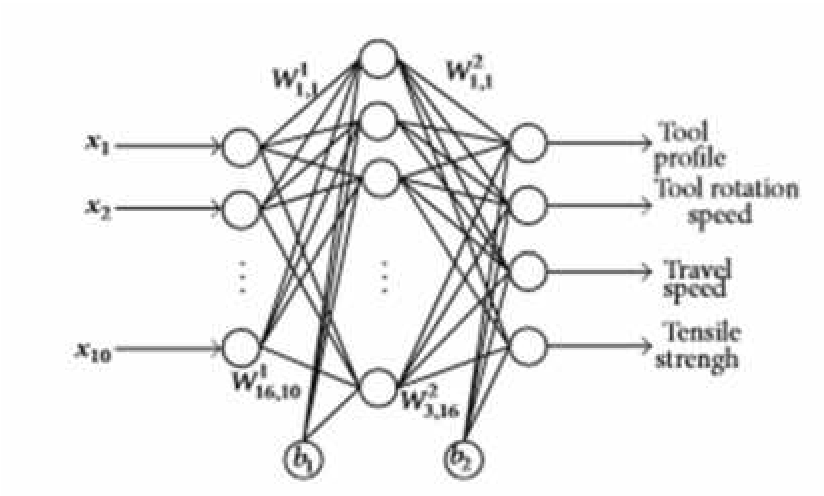


Figure 14. Artificial Neural Network architecture [14]

Figure 15 shows the predicted and measured results on the given dataset. It is clearly observed that the results obtained from the new model obtained, based on Neural Network architecture is an effective technique for the prediction of Friction Stir Welding process parameters and tensile strength of joint.

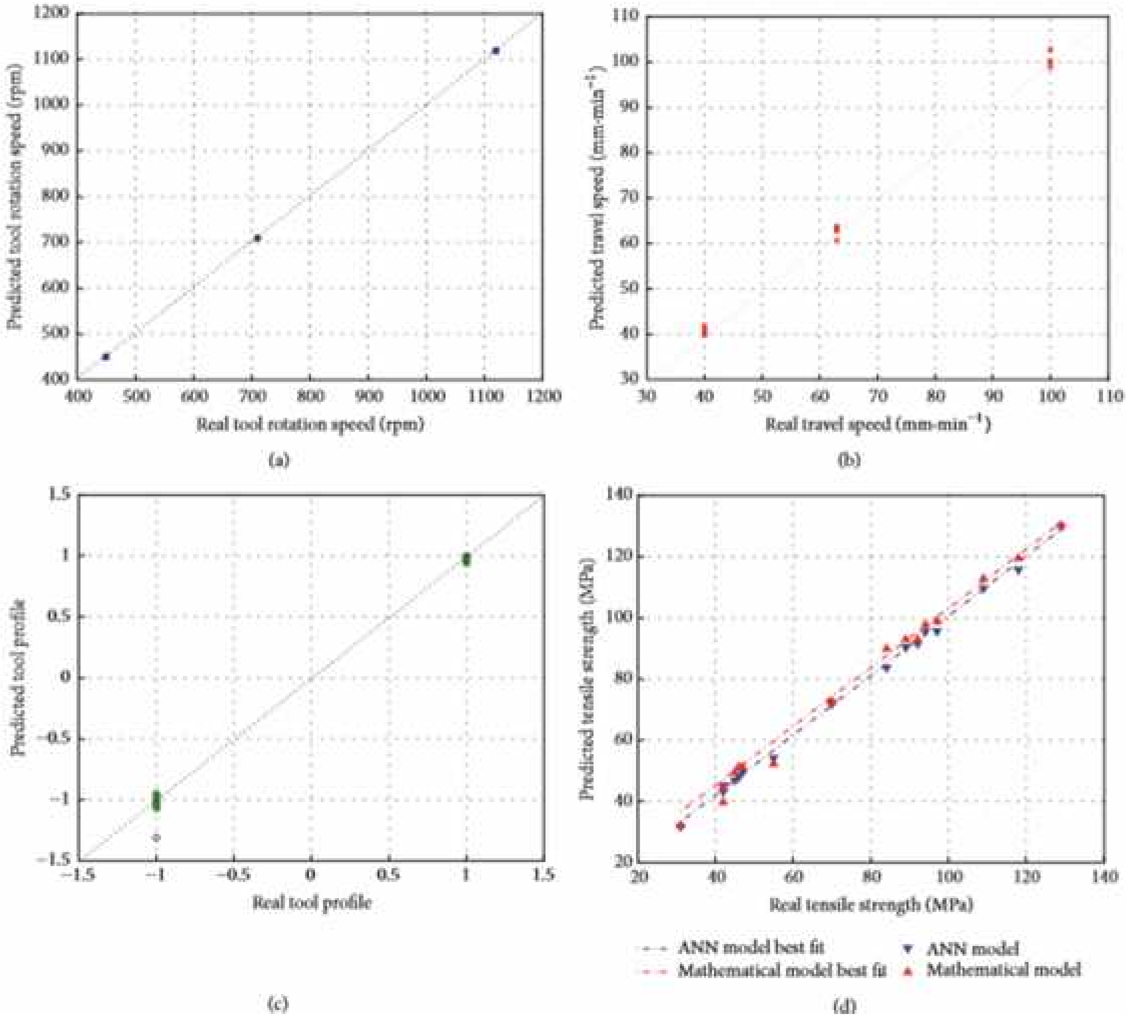


Figure 15. Predicted and Measured Values of the experimental dataset [14].

5. Designing a simple Artificial Neural Network on Google Colab by using Python coding

In this section, development of an Artificial Neural Network model by using Python Programming on Google Colaboratory platform as shown in Figure 16 will be discussed. Table 1 shows the experimental datset which shows the Ultimate Tensile Strength (MPa) value of Friction Stir Welded joints against the tool rotational speed of the tool (rpm).

Table 1. Experimental Dataset

Tool Rotational Speed (RPM)	UTS (MPa)
425	465
575	444
350	440.6
650	415
500	448

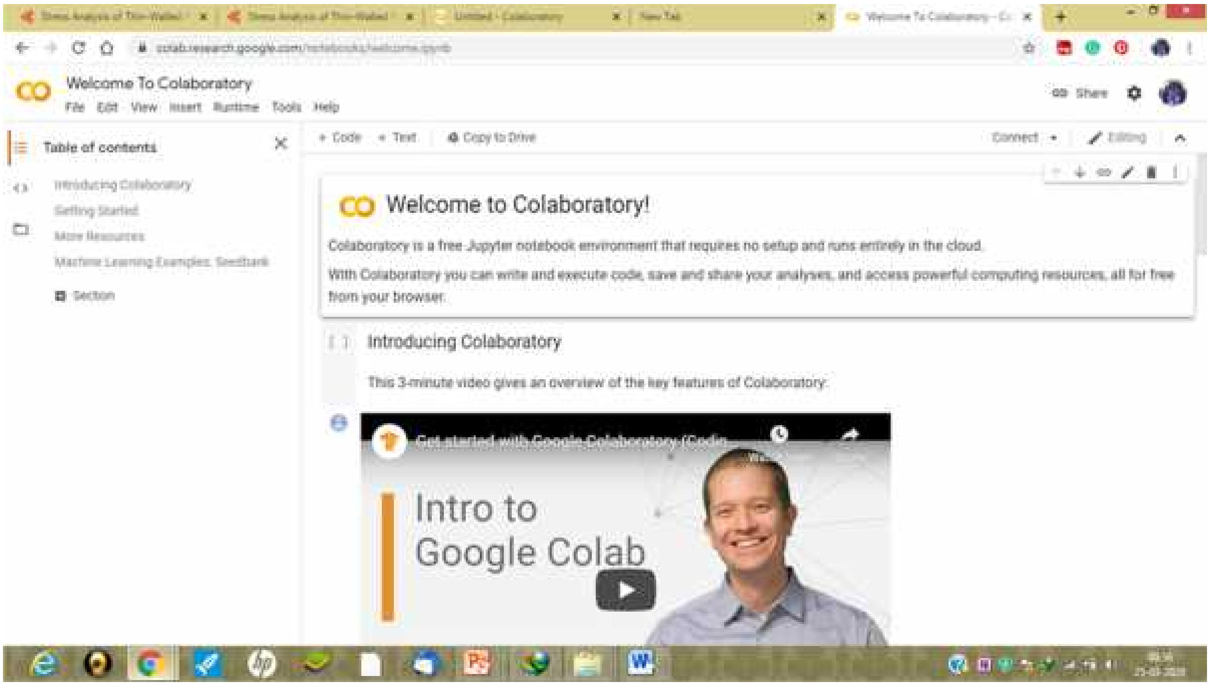


Figure 16. Google Colaboratory Platform

First we will start with our imports. Here we are importing TensorFlow and calling it tf for ease of use. We then import a library called numpy, which helps us to represent our data as lists easily and quickly. The framework for defining a neural network as a set of Sequential layers is called keras, so we import that too as shown in the Figure 17.

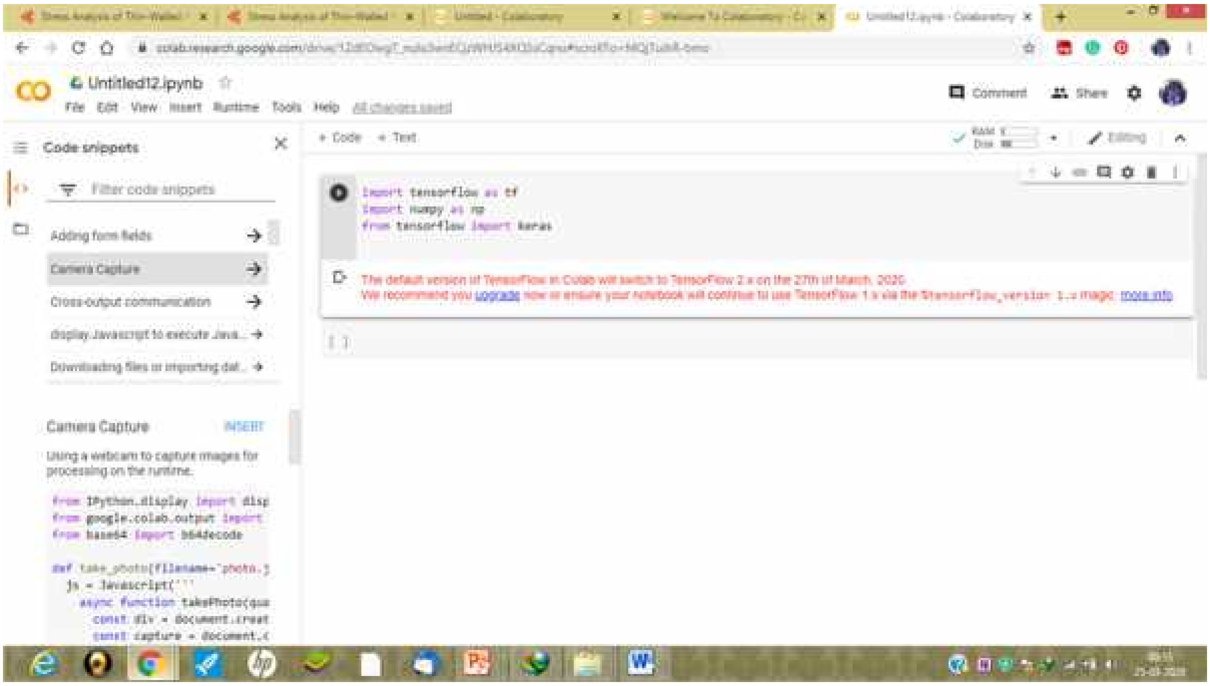


Figure 17. Importing process

Next we will create the simplest possible neural network. It has 1 layer, and that layer has 1 neuron, and the input shape to it is just 1 value as shown in the Figure 18.

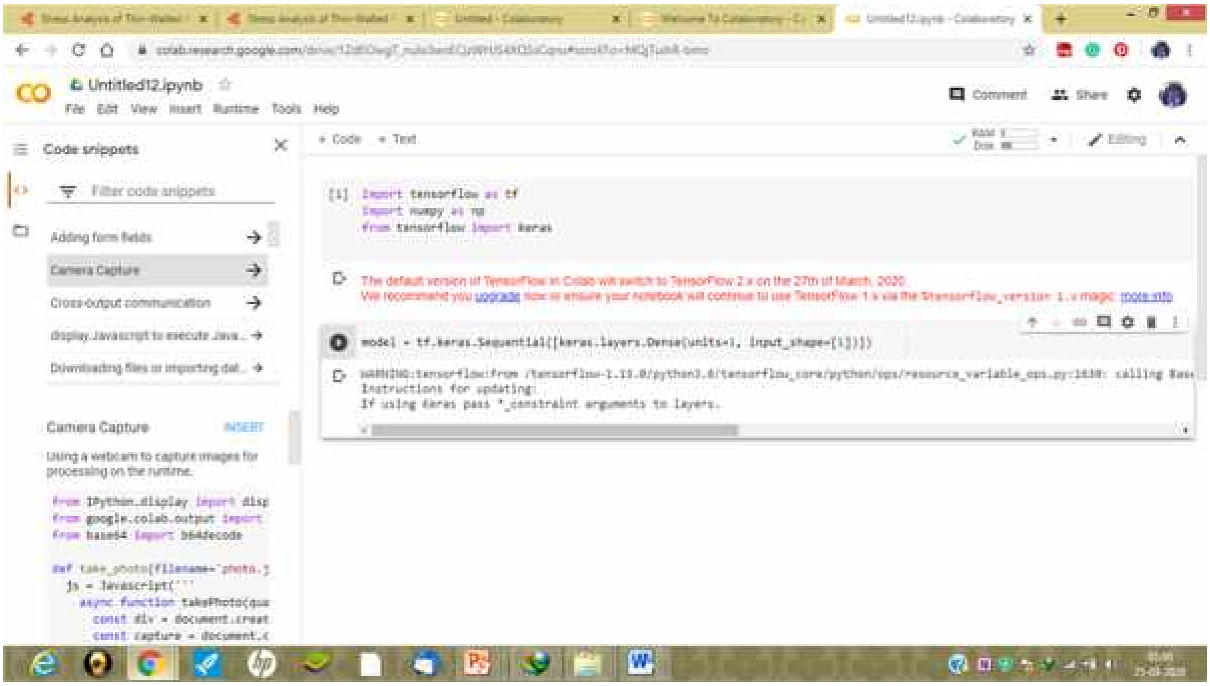


Figure 18. Defining the Neural Network

Now we compile our Neural Network as shown in Figure 19. When we do so, we have to specify 2 functions, a loss and an optimizer. The LOSS function measures the guessed answers against the known correct answers and measures how well or how badly it did. It then uses the OPTIMIZER function to make another guess. Based on how the loss function went, it will try to minimize the loss. It will repeat this for the number of EPOCHS which you will see shortly. But first, here's how we tell it to use 'MEAN SQUARED ERROR' for the loss and 'STOCHASTIC GRADIENT DESCENT' for the optimizer.

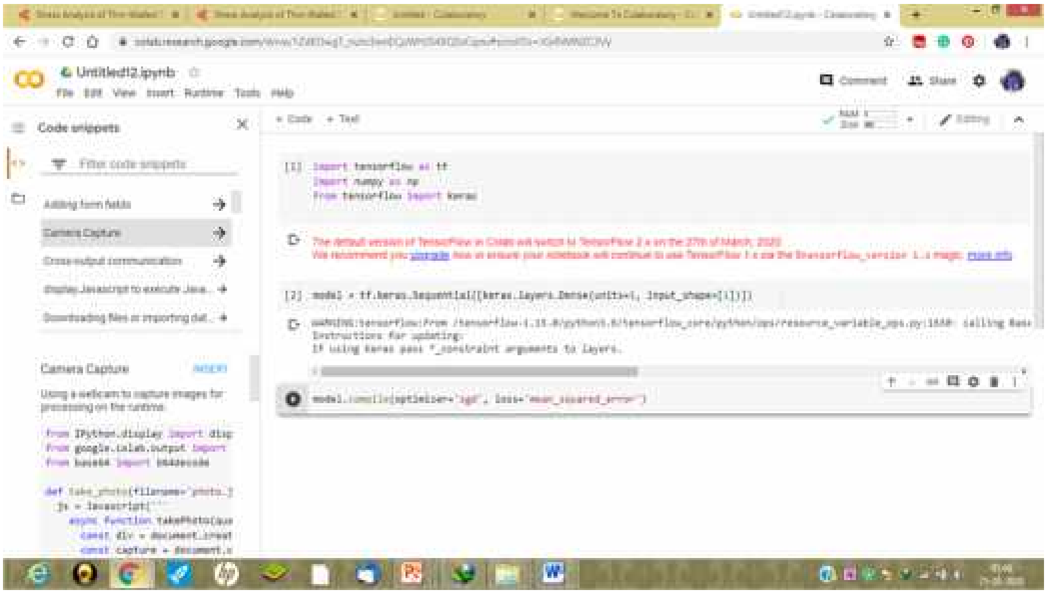


Figure 19. Compiling the Neural Network

Next up we'll feed in some data as shown in the Figure 20. A python library called 'Numpy' provides lots of array type data structures that are a defacto standard way of doing it. We declare that we want to use these by specifying the values as an np.array[].

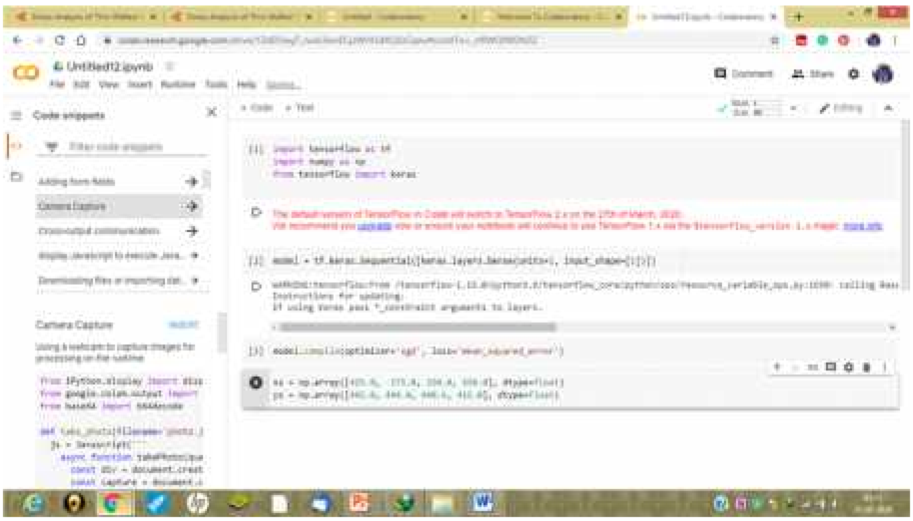


Figure 20.Providing the data

The process of training the neural network, where it 'learns' the relationship between the Xs and Ys is in the model.fit call which is shown in Figure 21. This is where it will go through the loop we spoke about above, making a guess, measuring how good or bad it is (aka the loss), using the opimizer to make another guess etc. It will do it for the number of epochs you specify. When you run this code, you'll see the loss on the right hand side.

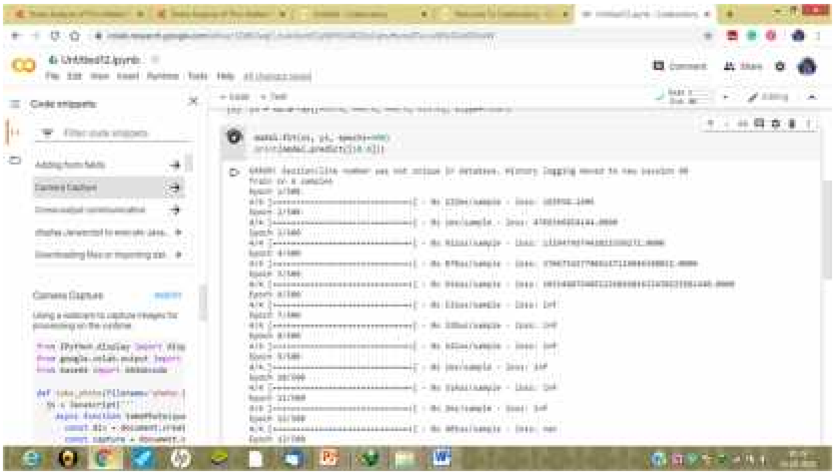


Figure 21. Training and Testing the Neural Network

6. Conclusion

There is a loss of time and materials if the optimization of the Friction Stir Welding parameters is done through experimental studies which further leads to increase in the cost of the experiment. Machine Learning approach like Artificial Neural Network and image processing overcome these issues. So, it can be concluded that the mechanical and microstructure properties can be predicted and also the defects formation can also be observed by the implementation of various Machine Learning tools in the Friction Stir Welding process.

References

[1]. Haykin, S.S., 2009. *Neural networks and learning machines*/Simon Haykin.

[2]. Zurada, Jacek M.``Introduction to Artificial Neural System". *West Publishing Company*, St. Paul, MN, 1992

[3]. Arbib, Michael A. ``Brains, Machines, and Mathematics: Second Edition". *Springer-Verlag*, New York, NY, 1987.

[4]. Alpaydin, E., 2020. *Introduction to machine learning*. MIT press.

[5]. Mitchell, T.M., 1997. *Machine learning.*

[6]. Marsland, S., 2015. *Machine learning: an algorithmic perspective*. CRC press.

[7]. Michie, D., Spiegelhalter, D.J. and Taylor, C.C., 1994. *Machine learning. Neural and Statistical Classification,* 13(1994), pp.1-298.

[8]. Quinlan, J.R., 2014. C4. 5: *programs for machine learning.* Elsevier.

[9]. Verma, S., Gupta, M. and Misra, J.P., 2018. Performance evaluation of friction stir welding using machine learning approaches. *MethodsX*, 5, pp.1048-1058.

[10]. Du, Y., Mukherjee, T. and DebRoy, T., 2019. Conditions for void formation in friction stir welding from machine learning. npj *Computational Materials*, 5(1), pp.1-8.

[11]. Ersozlu, I. and Celik, S., 2019. Artificial Neural Network application to the friction welding of AISI 316 and Ck 45 steels. *Kovove Materialy-Metallic Materials*, 57(3), pp.199-205.

[12]. Maleki, E., 2015. Artificial neural networks application for modeling of friction stir welding effects on mechanical properties of 7075-T6 aluminum alloy. *In IOP Conference Series: Materials Science and Engineering* (Vol. 103, No. 1, p. 012034). IOP Publishing.

[13]. Mishra, A. and Nagpal, K., 2019. Convolutional Neural Network for Image Processing of Friction Stir Welded and Conventional Welded Joints Texture. *Int. J. Hum. Comp. Inter. Data Min,* 2(1&2), pp.5-9.

[14]. Jiménez-Macías, E., Sánchez-Roca, A., Carvajal-Fals, H., Blanco-Fernández, J. and Martínez-Cámara, E., 2014. Wavelets application in prediction of friction stir welding parameters of alloy joints from vibroacoustic ANN-based model. *In Abstract and Applied Analysis* (Vol. 2014). Hindawi.

Author'sBiography

Akshansh Mishra received his graduation degree in Mechanical Engineering from SRM Institute of Science and Technology in 2017 & he is now admitted to MS in Mechanical Engineering degree in Politecnico Di Milano (QS world rank 9 in Mechanical Engineering). He also founded a research and development firm known as Stir Research Technologies which works on the collaborative research in Artificial Intelligence and Friction Stir Welding. His main research interests are Machine Learning, Reinforcement Learning, Advanced Manufacturing Process, and Friction Stir Welding.

How to Cite

Mishra. Akshansh(2019). Understanding Machine Learning for Friction Stir Welding Technology, *International Journal of Machine Learning and Networked Collaborative Engineering*, Vol. 03 No. 3, 2019, pp.143-158.

doi : https://doi.org/10.30991/IJMLNCE.2019v03i03.003

Vol. 03, No. 3,(2019), 159-167, **ISSN:2581-3242**

IJMLNCE JOURNAL

International Journal of Machine Learning and Networked Collaborative Engineering

Journal Homepage: http://www.mlnce.net/home/index.html

DOI : https://doi.org/10.30991/IJMLNCE.2019v03i03.004

Knowledge Graph-based Recommendation Systems: The State-of-the-art and Some Future Directions

[a]Sajisha P.S., [b]Anoop V.S[*], [c]Ansal K.A

[a]*Indian Institute of Information Technology and Management- Kerala (IIITM-K), Thiruvananthapuram, India - 695581*
[b]*Data Engineering Lab, Indian Institute of Information Technology and Management- Kerala (IIITM-K), Thiruvananthapuram, India – 695581*

[c]*Saintgits College of Engineering, Kottukulam Hills, Pathamuttam P. O, Kottyam, Kerala, India - 686532*

[a]*sajisha.mpcs19@iiitmk.ac.in,* [b]*anoop.res15@iiitmk.ac.in,* [c]*ansal.ka@saintgits.org*

Abstract

The unprecedented growth of unstructured data poses many challenges in semantic computing, which is an active research area for many years. While unearthing interesting patterns such as entities, relationships, and other metadata are important, it is equally important to represent them in an efficient, easy to access manner. Knowledge Graphs (KGs) are one such mechanism to represent facts extracted from unstructured text. KGs represent entities as nodes and relationships as edges. Such a representation may find applications in many meaning-aware computing applications such as question answering, summarization, etc., to name a few. Very recently, knowledge graph-based recommendation systems have become popular which has many advantages over traditional recommendation engines. This survey is an attempt to summarize and critically evaluate some of the very recent approaches to knowledge graph-based recommendation approaches.

Keywords

Knowledge Graphs,

Recommendation Systems,

Knowledge Representation,

Semantic Computing,

Machine Learning

1. Introduction

The astounding rate of generation of unstructured text data demands efficient algorithms and other methodologies to represent, analyze and extract useful patterns. Unearthing such patterns is crucial for businesses to generate actionable insights for key decision-making processes. Being a mechanism to represent entities and relationships using nodes and edges, knowledge graphs find applications in areas such as question answering, summarization, to name a few. When closely analyzing, it is found that knowledge graph-based recommendation systems are becoming popular and widely adopted, where recommendation systems are sub-classes of information filtering systems that suggest items to users based on certain features and conditions. These items can be as simple as books to read, films to watch and apparel to buy or even more complex suggestions in industries such as suggesting what to do next on the failure of a specific component. In the last few decades, we have witnessed a rise in web services including e-commerce portals such as Amazon, video portals such as YouTube and Netflix, etc. These platforms heavily use recommendation systems to suggest items to their users, which is unavoidable in our daily life.

[*] Corresponding Author

Anoop V.S.

Email: anoop.res15@iiitmk.ac.in

Most recommendation systems such as traditional collaborative filtering based approaches use simple user ratings done on items. These predefined information sources pose some constraints and thus the quality of the recommendation engines in many cases is degraded. While content-based and collaborative filtering based approaches are popular, there are approaches reported that use hybrid methodologies for recommendation tasks. Very recently, knowledge graph-based recommendation systems are found to be extremely useful when dealing with large sets of data. The ease in representing and suggesting contents makes the knowledge graph-based approaches very popular and we may find many production-level implementations nowadays. The advantage of graph-based recommendation systems is that heterogeneous data sources can be used for providing better recommendation results. Very recently, techniques using external knowledge bases for supplementing more contextual information are also introduced in the graph-based recommendation systems literature. Thus it is undoubtable that it is highly necessary to have systematic research in knowledge graph-based recommendation systems and this paper is an attempt in this direction.

This survey attempts to review some of the very recently reported approaches to knowledge graph-based recommendation algorithms. The major contributions of this survey are outlined as follows:

(a) Introduces knowledge graphs and some of the interesting areas where knowledge graphs may find applications.

(b) Critically review some of the prominent approaches that have been reported very recently in the literature that uses knowledge graphs for recommendation systems.

(c) Towards the end of this survey, the authors discuss some interesting research dimensions on knowledge graphs for recommendation algorithms.

Organization of this article: The remainder of this article is summarized as follows: Section 2 gives a brief introduction to semantic computing using knowledge graphs. Section 3 outlines a detailed survey on some of the very recent approaches for building recommendation systems using knowledge graphs. In Section 4, the authors highlight some of the future research trends in this dimension and Section 5 concludes the survey.

2. Knowledge Graphs and Semantic Web

With the seminal approaches to “semantic computing”, the researchers represent the knowledge using graphs consisting of nodes and edges. Such a representation mechanism has many advantages both in organizing and retrieving knowledge. The entities and concepts are represented as nodes and the relationships connecting these nodes are denoted by edges. For example, consider the sentence “A recommendation system is a subclass of information filtering system that seeks to predict the rating or preference”. In this case, entities such as “recommendation system”, “information filtering system”, “rating”, “preference” will be represented as nodes and possible relationships such as “subclass of”, “predict” will be represented as the edges connecting these entities.

The term “knowledge graph” was first introduced by Google in the year 2012 when they started to introduce the notion of semantics into their search algorithms. But now the term is widely used by other knowledgebase providers such as DBPedia. Anyhow, we consider any knowledge base as a knowledge graph if it exhibits (1) represents entities and their relationships in nodes and edges (2) the classes and/or concepts and their relationships in a schema or ontology (3) has wide coverage on various domains and (4) potentially link entities with other knowledge bases or graphs. There were several attempts reported in constructing knowledge graphs that resulted in various types of knowledge graph systems and tools introduced in this area. Some of such prominent systems are outlined in the subsequent sections.

(a) Cyc Knowledge Graph

Cyc Knowledge Graph [7] is one of the very early artificial intelligence projects that is treated as a long-living one that aims to integrate a comprehensive ontology and knowledge base. A miniature version of Cyc is also available, known as OpenCyc which is a curated knowledge graph with API end-points for the users to explore it. Cyc focuses on implicit knowledge that other AI platforms may use for their operations and enhancing knowledge [7].

(b) Freebase

Freebase is a publicly available crowdsourced method of creating knowledge graphs. It supports many of the real-world entity types in its schema but the organization maintaining Freebase, was acquired by Google and the Freebase was shut down in 2015. According to recent statistics, The last known version of Freebase contains nearly fifty million entities and three billion facts acquired over time.

(c) DBPedia

DBPedia is one of the most prominently used knowledge graphs that has wide coverage[8]. It is constructed by extracting structured information and facts available in Wikipedia. DBPedia contains millions of entities and their relationships that were primarily extracted from Wikipedia infoboxes. Text mining and natural language processing researchers and practitioners are heavily using DBPedia[8].

(d) Never Ending Language Learning (NELL)

NELL is a project by CMU[9] that attempts to solve the research question “Can computers read?” and from 2010, NELL is continuously running to extract facts from the unstructured text available in web pages. In addition to this, it also tries to improve its text understanding competence, so that it can extract more and more facts from the web, with high accuracy[9].

(e) Google Knowledge Graph

Introduced to the public in the year 2012, Google attempts to construct a large knowledge graph. Even though it is unclear how Google collects the facts and converts into a knowledge graph, practitioners often commented that they use resources such as Wikipedia to extract knowledge. Google’s knowledge graph contains billions of entities and their relationships and is still evolving.

3. Knowledge Graph-based Recommendation Systems

We use many applications on a daily basis where recommendation engines play a major role in recommending appropriate items to us based on our previous pattern of interaction with the system. For example, based on the articles you read, the recommendation engine can suggest other articles you are interested in or based on your purchase history, the items we are interested in, or music or playlist based on our previous interactions. A recommendation engine uses a large amount of data that has been generated by user interactions, analyzes it, extracts patterns and then personalized suggestions are made to satisfy the user's needs. While referring to the literature on recommendation systems, one can easily identify that Collaborative Filtering (CF) is one of the widely used and popular recommendation techniques. This approach makes use of the old interactions of a particular user and suggests or recommends contents based on their preferences. On the other hand, there are techniques that use comparison between items that have similar properties along with the past user interactions with the system for recommending items. This technique is called Content-Based Filtering (CBF). In a nutshell, CBF will recommend those items to the users, which have similar properties to those items the user has already bought or clicked. Researchers and practitioners of recommendation systems always attempt to device algorithms that leverage external knowledge for improving content-based recommendations. In a content-based recommendation engine, the features are normally available for both the users and the items. For users, these are typically their details such as age, location, etc,. For items like books, the features may be the author, year of publication, name of the publisher, etc. In the recent past, there were several approaches proposed in the recommendation literature that uses content for recommendation, but a very few approaches have attempted the use of the interconnections between the content and external knowledge sources, which is referred to as a knowledge graph (KG).

Knowledge Graph is considered as a heterogeneous graph consisting of Nodes and Edges. Nodes correspond to entities and edges represent the corresponding relation. When comparing with approaches that do not use knowledge bases, the approaches that use KG into the recommendation has the following benefits[12]:

(1) A knowledge graph always exhibits a rich semantic relatedness among items that can be used to explore the hidden connections and thereby improve the accuracy of the recommendation results.

(2) The different types of relations in a KG helps to extend the user's interest, which will increase the diversity of recommended items;

(3) KG connects items which are previously liked by a user which enables the explainability to the recommender systems.

In this direction, there are many recent approaches reported in the recommendation system literature and this survey attempts to critically evaluate and summarize some of those prominent approaches. Yixin Cao et.al. recently proposed an approach [1] that unifies knowledge graph learning and recommendation. In this, the authors proposed an approach that has the capability of learning the model of recommendation and knowledge graph completion. The authors contributed a new recommendation model which is based on a translation-based approach, which considers several preferences in connecting a user to an item. The approach then trains it with a knowledge graph completion model by integrating different transfer schemes [1]. Their experiments on benchmarked knowledge graph datasets showed that their proposed approach significantly outperforms state-of-the-art knowledge graph-based recommendation systems. Another recent approach called KGAT [2], was proposed by Xiang Wang et. al., that models the connectivities which are high-order, in a knowledge graph, in a complete manner. It sends or transfers the embeddings from a node's neighbors recursively to refine the node's embedding. It also uses an attention mechanism that deals with discriminating the importance of the neighbors [2]. The authors have compared the performance of their proposed method with state-of-the-art approaches, such as Neural FM and RippleNet and found that the proposed approach significantly outperforms the state-of-the-art approaches [2].

A system that learns rules which are explainable for recommendation tasks, with knowledge graphs is reported very recently which was proposed by Weizhi Ma et. al.[3]. Majority of the previous approaches attempted to incorporate side information to get better recommendation results. But these approaches have their own disadvantages such as difficulties with explainability and debugging, requiring a heavy amount of human intervention and knowledge of the domain, to name a few. The authors claim that their proposed approach is an approach that uses a joint learning framework that induces explainable rules that are available in the knowledge graph that guides to building a neural recommendation model which is rule-guided[3]. Systematic experiments on a benchmarked dataset showcased the significant performance of the proposed approach in recommendation [3]. Another approach that uses a multi task feature learning framework for knowledge graph enabled recommendation is proposed by Hongwei Wang et. al. [4]. As collaborative filtering-based approaches usually exhibit issues such as sparsity and cold start problems with recommendations. Keeping these in mind, the authors proposed a multi-task feature learning approach (MKR) for knowledge graph enhanced recommendation. It is an end-to-end framework that makes use of KG embeddings to assist recommendation tasks[4]. The authors have demonstrated that their approach achieved better gains in real-world recommendation tasks such as recommendations in movies, books, music, and news recommendations, when compared with the prominent approaches in recommendation. The authors further claimed that MKR is successful to generate better recommendations even if it has to deal with sparse user-item interactions [4].

Another notable work reported was a knowledge-aware graph neural network based approach that incorporates label smoothness regularization for recommender systems [5]. To overcome the issue of manual feature engineering while developing knowledge graph-based recommendations, the authors proposed an approach that incorporated knowledge graph neural networks with label smoothness regularization for providing better recommendations for the users [5]. The authors first convert the knowledge graph into a weighted graph. Then they applied a graph neural network which is capable of computing item embeddings which preserves personalization features. A rigorous experiment has been conducted on four different datasets and the proposed system showed better performance compared to this method. A new approach called the Knowledge-aware Path Recurrent Network (KPRN) that uses KGs for recommendation was introduced by Xiang Wang et. al. [6]. The advantage of KPRN is that it can provide path representations by combining the semantics entities and relationships. By considering the dependencies within a path which are sequential in nature, the authors conducted reasoning on these paths to leverage the available user-item interaction[6]. The authors have conducted experiments on movie and music datasets and demonstrated that their approach outperformed the state-of-the-art approaches in recommendations.

Very recently, an approach for learning knowledge graph embedding for products in e-commerce was reported by Da Xu et. al.[10]. In this work, the authors proposed a novel knowledge graph embedding approach for learning the product relations as product knowledge for the electronic commerce domain[10]. They have constructed a new approach called a self-attention-enhanced distributed representation learning model that was capable of capturing embeddings from customer activity data from electronic commerce websites. The proposed approach was executed on some real-world dataset and the performance was evaluated for knowledge completion, search, ranking and recommendation processes[10]. Another approach that introduced a fine-grained knowledge graph for providing better personalized recommendations called DUSKG[11] was another approach that attempted incorporating multiple types of service data considering their logical relations. The authors proposed a compact data representation model incorporating different sorts of logical relations between the data. The five major relationships such as "FocusOn", "BelongTo, "USimilar", "SSimilar" and "FSimilar" are considered for their experiment and it showed that their proposed approach showed better recommendation performance with least computation time[11].

Another recent approach that explored the higher order user preference on KGs for recommendation engines [12] was reported in the recommender system literature by Hogwei Wang et. al. The authors stated that to avoid cold start problems, researchers normally use side information for building recommendation algorithms and in the proposed approach, the authors used a knowledge graph as the side information. They have proposed RippleNet which is a complete framework that uses a knowledge graph into the recommendation system[12]. The authors claim that this has brought more explainability in the recommendation engine and the real-world experiments showed that their proposed approach outperforms some of the state-of-the-art approaches for recommendation. A very notable and interesting work that explored the potential of using a knowledge graph specifically for movie recommendation, HI2Rec[13], was introduced by Ming He et. al. Their proposed system used a mechanism that incorporated multiple information that is capable of learning the vector representations of users and items with the aim of providing top-N recommendations to the users[13]. The authors stated that this will solve the issue of earlier approaches which give less consideration about the properties or demographics of the users.

Zhu Sun et. al. proposed an approach for learning KG embedding that can automatically learn meaningful representations of both entities and paths (relationships) between entities for representing an and taking into consideration, the preferences of the users towards items[20]. The proposed approach uses recurrent neural network architecture with a pooling operator. The duty of the pooling operator is to make sure the saliency of different edges in finding out the user preferences towards items. The authors have extensively validated the proposed approach on different real-world datasets which showed that their proposed approach significantly outperformed the state-of-the-art methods [20]. A deep network for news recommendation which makes use of the knowledge-aware feature was introduced by Hogwei Wang et. al.[21] in which the authors address the problem of extended reasonability of the existing knowledge graph based-approaches. Their proposed approach, known as DKN, is a deep recommendation framework based on contents which can perform click-through rate predictions[21]. By conducting systematic experiments on real online news platforms, the authors were successful in showcasing the significant performance of their proposed approach[21]. A notable work that explored the possibility of using node2vec[22] for generating item recommendations by fusing machine learning with knowledge graph embeddings was introduced by Enrico Palumbo et. al.[23]. The authors applied node2vec on a knowledge graph generated from the famous MovieLens 1M dataset and DBpedia and used the node relatedness to generate item recommendations. When compared with the traditional collaborative filtering-based approaches, the proposed method significantly outperformed them[23].

An approach called RippleNet[24] was reported in the recommendation systems literature recently. The system was developed keeping an aim of incorporating preferences of the users on knowledge graphs for recommendation systems. This approach stimulates the dissemination of preferences of users over a set of entities by extending a user's potential interests along links in a KG[24]. Experiments conducted on benchmarked recommendation datasets show the RippleNet is capable of providing better recommendations when compared with the state-of-the-art approaches[24]. Most of the collaborative filtering based recommendation approaches only use the user-item rating matrix and do not consider semantic information. Ruihui Mu and Xiaoqin Zeng proposed an approach based on a knowledge-graph to solve this issue[25]. They have used representation learning mechanisms on knowledge graphs to embed existing semantics into a vector space which is low-dimensional. Their proposed approach combines the semantics of items into the recommendation task by computing the meaning-aware similarity between items[25]. The authors have claimed that their proposed approach could significantly outperform some of the state-of-the-art approach in knowledge graph-based recommendation engines.

There are other interesting approaches very recently reported in the knowledge graph based recommendation literatures such as unifying task oriented knowledge graph learning and recommendation[14], differentiated fashion recommendation using knowledge graph and data augmentation[15], a semantics driven knowledge graph for food recommendation[16], an attention-enhanced, knowledge-aware user preference model for recommendation[17], a graph augmented memory network for recommending medication combination[18], location embeddings for next trip recommendation[19], etc. which are worth mentioning in this paper.

4. Knowledge Graph-based Recommendation – Future Research Dimensions

Since technological advancements are still fueling and acting as a catalyst, the amount of unstructured text data that will be generated in the coming years will be highly exponential. Being an efficient knowledge representation mechanism, knowledge graphs will have huge potential in the coming years. Recommendation systems that need side information and augmented knowledge will heavily make use of knowledge graphs. This poses many challenges and research opportunities among text mining communities to devise better meaning-aware algorithms that can operate on knowledge-graphs for personalized recommendations. In this section, we discuss some of the potential research opportunities and avenues the recommendation system researchers and practitioners can look into.

One of the most interesting research dimensions on knowledge graph-based recommendation is to incorporate more side information into the recommendation engine so that better personalized recommendation is possible. For instance, bringing in more user information (say, demographic information) may improve the quality of recommendations. Also, connecting social network interactions would open new avenues to explore how social influence affects the recommendation. A very recent research trend in the recommendation system is the explainable recommendations. Integrating information propagation and decision processes, the explainability of recommendation engines may significantly improve, which is an area worth looking at. Graph Neural Networks (GCN) is one recent approach that got significant attention among recommendation system researchers and active research is happening in this dimension as well. Since earlier approaches face issues related to cold start problems in recommendation, it is worth experimenting on that dimension to eliminate the issues by bringing in techniques like zero-shot learning and reinforcement learning.

5. Conclusions

This survey outlined some of the very recent approaches in knowledge graph-based recommendation systems. As knowledge graph is one of the effective representation mechanisms for knowledge that has been unearthed from unstructured text, it got wider acceptance among research communities. A knowledge graph represents entities and relationships as nodes and edges respectively and a large number of meaning-aware applications and algorithms can operate on this graph. One such application is recommendation systems that suggest a user with items based on their previous interactions with the system. Knowledge graph based recommendation systems became very popular recently primarily due to its ability to supply side information for augmenting data and thus enhancing the quality of recommendations. This paper discusses some of the very prominent approaches reported very recently in the recommendation literature. Some interesting research dimensions are also discussed towards the end of this paper. This survey will be useful for the researchers and practitioners who wish to work on entity knowledge graphs based recommendation systems.

References

[1]. Cao, Y., Wang, X., He, X., Hu, Z., & Chua, T. S. (2019). Unifying knowledge graph learning and recommendation: Towards a better understanding of user preferences. In The world wide web conference (pp. 151-161).

[2]. Wang, X., He, X., Cao, Y., Liu, M., & Chua, T. S. (2019). Kgat: Knowledge graph attention network for recommendation. *In Proceedings of the 25th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining* (pp. 950-958).

[3]. Ma, W., Zhang, M., Cao, Y., Jin, W., Wang, C., Liu, Y., ... & Ren, X. (2019). Jointly learning explainable rules for recommendation with knowledge graph. *In The World Wide Web Conference* (pp. 1210-1221).

[4]. Wang, H., Zhang, F., Zhao, M., Li, W., Xie, X., & Guo, M. (2019). Multi-task feature learning for knowledge graph enhanced recommendation. *In The World Wide Web Conference* (pp. 2000-2010).

[5]. Wang, H., Zhang, F., Zhang, M., Leskovec, J., Zhao, M., Li, W., & Wang, Z. (2019). Knowledge-aware graph neural networks with label smoothness regularization for recommender systems. *In Proceedings of the 25th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining* (pp. 968-977).

[6]. Wang, X., Wang, D., Xu, C., He, X., Cao, Y., & Chua, T. S. (2019). Explainable reasoning over knowledge graphs for recommendation. *In Proceedings of the AAAI Conference on Artificial Intelligence* (Vol. 33, pp. 5329-5336).

[7]. Douglas B Lenat. CYC: A large-scale investment in knowledge infrastructure. *Communications of the ACM*, 38(11):33–38, 1995. http://dx.doi.org/10.1145/219717. 219745

[8]. Auer, S., Bizer, C., Kobilarov, G., Lehmann, J., Cyganiak, R., & Ives, Z. (2007). Dbpedia: A nucleus for a web of open data. *In The semantic web* (pp. 722-735). Springer, Berlin, Heidelberg.

[9]. Mitchell, T., Cohen, W., Hruschka, E., Talukdar, P., Yang, B., Betteridge, J., ... & Krishnamurthy, J. (2018). *Never-ending learning*. Communications of the ACM, 61(5), 103-115.

[10]. Xu, D., Ruan, C., Korpeoglu, E., Kumar, S., & Achan, K. (2020). Product Knowledge Graph Embedding for E-commerce. *In Proceedings of the 13th International Conference on Web Search and Data Mining (*pp. 672-680).

[11]. Wang, H., Wang, Z., Hu, S., Xu, X., Chen, S., & Tu, Z. (2019). DUSKG: A fine-grained knowledge graph for effective personalized service recommendation. *Future Generation Computer Systems*, 100, 600-617.

[12]. Wang, H., Zhang, F., Wang, J., Zhao, M., Li, W., Xie, X., & Guo, M. (2019). Exploring high-order user preference on the knowledge graph for recommender systems. *ACM Transactions on Information Systems (TOIS)*, 37(3), 1-26.

[13]. He, M., Wang, B., & Du, X. (2019). HI2Rec: Exploring knowledge in heterogeneous information for movie recommendation. *IEEE Access*, 7, 30276-30284.

[14]. Li, Q., Tang, X., Wang, T., Yang, H., & Song, H. (2019). Unifying task-oriented knowledge graph learning and recommendation. *IEEE Access*, 7, 115816-115828.

[15]. Yan, C., Chen, Y., & Zhou, L. (2019). Differentiated fashion recommendation using knowledge graph and data augmentation. *IEEE Access*, 7, 102239-102248.

[16]. Haussmann, S., Seneviratne, O., Chen, Y., Ne'eman, Y., Codella, J., Chen, C. H., ... & Zaki, M. J. (2019). FoodKG: A Semantics-Driven Knowledge Graph for Food Recommendation. *In International Semantic Web Conference* (pp. 146-162). Springer, Cham.

[17]. Tang, X., Wang, T., Yang, H., & Song, H. (2019). AKUPM: Attention-enhanced knowledge-aware user preference model for recommendation. *In Proceedings of the 25th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining* (pp. 1891-1899).

[18]. Shang, J., Xiao, C., Ma, T., Li, H., & Sun, J. (2019). GAMENet: graph augmented memory networks for recommending medication combination. *In Proceedings of the AAAI Conference on Artificial Intelligence* (Vol. 33, pp. 1126-1133).

[19]. Dadoun, A., Troncy, R., Ratier, O., & Petitti, R. (2019). Location Embeddings for Next Trip Recommendation. *In Companion Proceedings of The 2019 World Wide Web Conference* (pp. 896-903).

[20]. Sun, Z., Yang, J., Zhang, J., Bozzon, A., Huang, L. K., & Xu, C. (2018). Recurrent knowledge graph embedding for effective recommendation. *In Proceedings of the 12th ACM Conference on Recommender Systems* (pp. 297-305).

[21]. Wang, H., Zhang, F., Xie, X., & Guo, M. (2018, April). DKN: Deep knowledge-aware network for news recommendation. *In Proceedings of the 2018 world wide web conference* (pp. 1835-1844).

[22]. Grover, A., & Leskovec, J. (2016). node2vec: Scalable feature learning for networks. *In Proceedings of the 22nd ACM SIGKDD international conference on Knowledge discovery and data mining* (pp. 855-864).

[23]. Palumbo, E., Rizzo, G., Troncy, R., Baralis, E., Osella, M., & Ferro, E. (2018). *Knowledge graph embeddings with node2vec for item recommendation. In European Semantic Web Conference* (pp. 117-120). Springer, Cham.

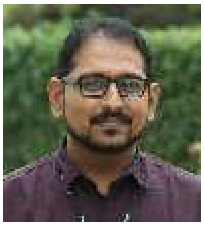
[24]. Wang, H., Zhang, F., Wang, J., Zhao, M., Li, W., Xie, X., & Guo, M. (2018). Ripplenet: Propagating user preferences on the knowledge graph for recommender systems. *In Proceedings of the 27th ACM International Conference on Information and Knowledge Management* (pp. 417-426).

[25]. Mu, R., & Zeng, X. (2018). Collaborative filtering recommendation algorithm based on knowledge graph. *Mathematical Problems in Engineering*, 2018.

Author's Biography

Sajisha P.S. is currently pursuing her research leaning to Master of Philosophy (M.Phil.) from Indian Institute of Information Technology and Management – Kerala (IIITM-K), Thiruvananthapuram, India. She has completed her Masters and Bachelors in Computer Science from Mahatma Gandhi University, Kottayam, Kerala. Her research interests include recommendation systems and knowledge graph-based machine learning applications.

Anoop V.S. has completed his Doctor of Philosophy (Ph.D) and Master of Philosophy (M.Phil) in Computer Science, both with specialization in Text Mining, Natural Language Processing, and Information Retrieval, from Indian Institute of Information Technology and Management - Kerala (IIITM-K), Thiruvananthapuram, India. Anoop is currently working as a Senior Scientist and Head of Training with Kerala Blockchain Academy (KBA) He is a passionate and active teaching professional with seven years of experience with Indira Gandhi National Open University, New Delhi. His major research interests include Applied Artificial Intelligence using Text Mining and Natural Language Processing (NLP) and Blockchains. He has several publications in his credit including international and national journals, book chapters and conference proceedings in major venues of Artificial Intelligence and Knowledge Management.



Ansal K A has completed his B.Tech in Electronics and Communication from Mahatma Gandhi University in 2007 with a University 3rd rank, and completed his post graduation in M.Tech Communications Systems from Anna University Gundy, Chennai with University Gold Medal. He has completed his Doctoral Degree from Pondicherry Central University in the area of Miniaturized Antennas with UGC JRF. He has an awardee of various fellowships like UGC MANF, DST Inspire , Research excellence award from IEAE, and young researcher award from IEI. He has more than 40 journals and 35 international conference publications in his credit. His area of interest belongs RF system design, Microwave and Millimetre wave, Wireless Communications, Digital image Processing, Machine and Deep learning. He has awarded International Engineering Educators Certification from IUCEE USA, and is an active member of IEEE,IEAE,IEI,ISTE,IETE and IAENG.

How to Cite

S. Sajisha P., S. Anoop V, A. Ansal K.(2019). Knowledge Graph-based Recommendation Systems: The State-of-the-art and Some Future Directions. *International Journal of Machine Learning and Networked Collaborative Engineering*, 3(03) pp 159-167.

doi : https://doi.org/10.30991/IJMLNCE.2019v03i03.004

Vol. 03, No. 3 ,(2019), 168–181 , **ISSN:2581-3242**

IJMLNCE JOURNAL

International Journal of Machine Learning and Networked Collaborative Engineering

Journal Homepage: http://www.mlnce.net/home/index.html

DOI : https://doi.org/10.30991/IJMLNCE.2019v03i03.005

Performance Evaluation of LAR protocol using real dataset on Highway and City Scenario

[a]Amrit Kaur Saggu, [b]Shivani Agarwal

[a]Department of Computer Science and Engineering, [b]KIET School of Management

KIET Group of Institutions, Delhi-NCR, Ghaziabad - 201206, India

[a]amrit.saggu@kiet.edu, [b]jindal.shivani24@gmail.com

Abstract

Vehicular ad-hoc networks have gained immense popularity as a research domain as more and more vehicles interact with each other to communicate information. This paper is aimed at evaluating the performance of Location Aided routing protocol (LAR) for Vehicular Ad-hoc networks (VANETs) using NS2 and SUMO. This protocol is evaluated under highway and city scenarios obtained from Open Street Map (OSM) and Bologna Ringway dataset respectively. The performance metrics considered for these scenarios are throughput, packet delivery ratio (PDR), routing overhead. The above mentioned parameters are calculated by varying the simulation time and number of vehicles. The results obtained are graphically plotted and analyzed.

Keywords

LAR;
VANETs;
routing protocols;
city scenario;
real dataset;
highway scenario;
open-street map

1. Introduction

Vehicular Ad-hoc network (VANET) is an extension of Mobile ad-hoc network (MANET) wherein vehicular nodes communicate with each other as opposed to mobile devices communicating with each other in MANETs. In VANETs vehicles communicate in either of the two modes: vehicle-to-vehicle (V2V) or vehicle-to-infrastructure (V2I) [1]. These networks are characterized by high vehicular density and highly dynamic nature of vehicles wherein vehicles keep moving in and out of the network. Based on their modes of communication VANETs find wide applicability in several safety related applications wherein a driver can be notified prior to occurrence of some crash or other hazardous road related conditions. A large number of entertainment and comfort applications such as gaming, advertisements to attract customers to their stores or announcements like petrol pumps, highways restaurants to announce their services to the drivers within communication range are also supported by these networks [2].

In this paper a position based location-Aided Routing *(LAR)* protocol is used for analyzing the performance of VANETs. This protocol relies on location information of the nodes in order to discover routes from source node to the destination node by confining the search to a smaller request zone [3]. It leads to a considerable reduction in the routing overhead as opposed to certain topology-based routing protocols like AODV and DSR. LAR works under two schemes, as per scheme 1 the sender knows in advance the location of the destination at certain time instance and the speed with which it is moving. The sender makes use of this meta-data and begins the discovery of route up to the destination for the current time instance. RREQ packets forwarded by sender to any node not lying within the request zone are rejected by them. As per scheme 2, source node has prior information about the destination's location based on which it computes its distance up to the destination node. The computed distance and location of the destination node are forwarded to the intermediate nodes which decide whether to forward it to the next nodes or to discard it based on its own distance from the destination.

LAR scheme is evaluated by using the following performance metrics: Throughput, Packet delivery ratio and routing overhead. Rest of the paper is organized as: Section 2 is about related work, In Section 3 we present the simulation framework, Section 4 comprises experimental results and finally Section 5 presents the conclusion followed by references.

2. Related Work

In paper [4] vehicular interaction is analyzed for a road map of JNU. The whole network is partitioned into smaller sub regions. The selection of path by drivers in real time is incorporated to ensure vehicular communication. They have evaluated the performance of AODV routing protocol in terms of Delivery ratio, Packet loss and Router dropfor the above scenario. In paper [1] the performance of AODV, DSR and DSDV is evaluated for the highway scenario of China. Routing metrics such as: delivery of packet quotient, end to end delay and routing load has been measured. It was seen that these protocols could not find their suitability in such dynamic networks.

In [5] an analysis is presented for three algorithms i.e. AODV, DSR, LAR and based on the traffic situation it is decided as to which routing protocol to opt for. It is observed that LAR protocol outperforms the other two protocols in terms of all the performance metrics considered. DSR shows worst performance amongst them. In [6] a performance evaluation scheme is presented to monitor the traffic conditions in the city of Rome. The location of taxis moving around in the city are captured and analyzed for the bottleneck caused by them. They compare the results with classic mobility models and observe the effect on information exchange by both the models.

In [7] an extension to the existing LAR protocol is provided which is a direction based strategy. This protocol improves the performance of routing by applying the concept of selective forwarding of packets. For this purpose, a specific area is selected beforehand in which the packets will be forwarded and also the node sender of such a packet will be selected a priori. This scheme works well for highly populated environment. In [8] performance evaluation of urban environment is presented with respect to different routing protocols namely GPSR, AODV, OLSR, DSDV and DSR. In the urban scenarios a lot of commotion is observed due to high rise towers which leads to a significant drop in the messages delivered across different vehicles. It is observed that most of the protocols mentioned above fail to produce the desired results for this scenario due to the interference caused by obstacles. The GPSR protocol however produces better results than other protocols.

3. Simulation Framework

We have conducted the simulation for analyzing the performance of LAR protocol under two different environment scenarios. The first scenario which is a highway region is obtained from Open Street Map (OSM) as depicted in Figure 1. We have taken the highways around Delhi, in particular NH-24, NH-34, NH-9, and NH-44. The traffic is randomly generated on this network with the help of randomTrips tool present in the traffic simulator SUMO. Second we take a real world data set of the city of Bologna wherein the network is already present and there exists a predefined route and communication link between vehicles. The traces of traffic for Bologna city are obtained from the peak hour traffic i.e. between 8 am to 9pm [9]. The traffic flows for both the scenario can be visualized using GUI of SUMO as depicted in Figure 2 (a) and Figure 2 (b) respectively. Further Figure 3 presents the working flow of our implementation.

Figure 1. Extracted image of Delhi highway from OSM

Figure 2(a). SUMO visualization Delhi highway map

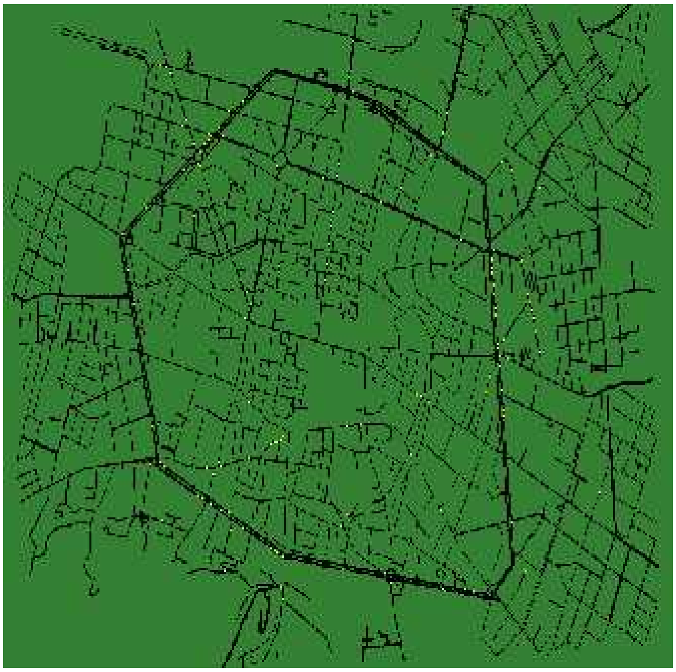


Figure 2(b). SUMO visualization of Bologna city dataset

The process begins by capturing the map from OSM or obtaining the real dataset from Bologna. For the OSM map the network and routes are created and vehicles are randomly deployed. Once the route and network are developed then mobility traces are generated for both the scenarios. The LAR protocol is then run on the mobility traces obtained in the previous steps with the help of NS2. The trace file thus generated is run with the awk scripts to measure the rate of throughput, packet delivery ratio and overhead produced while these vehicles communicate.

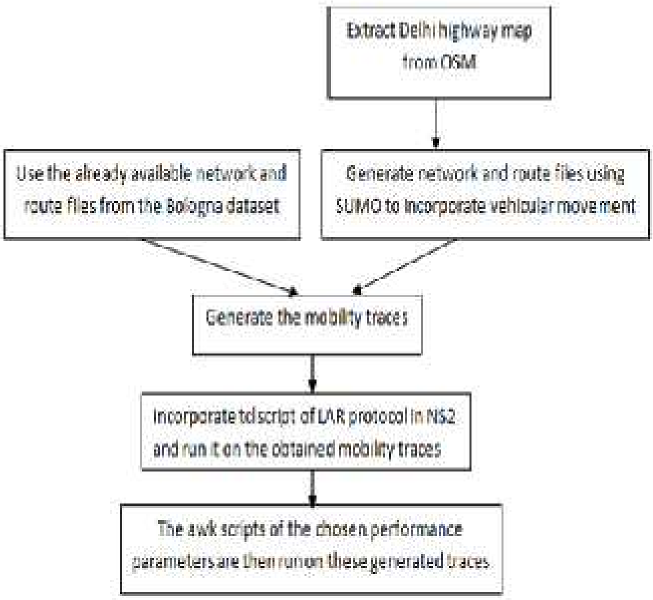


Figure 3. Working flow of the implementation

4. Simulation Framework

The experiments have been performed using the traffic simulator SUMO-0.31.0 and a network simulator NS2.32. These have been opted considering their compatibility with Ubuntu 11.04. Python 3.6 is used to generate random trips for the Delhi highway map extracted via OSM. The experiment has been carried out considering two cases under each of the chosen scenario with Table 1 providing a complete set of details for the chosen simulation parameters.

Table1. Simulation Parameters

Parameter	**Specification**
MAC protocol	IEEE 802.11 DCF
Data Type	Constant Bit Rate (CBR)
Radio Propagation Model	Two-Ray ground reflection model
Channel Type	Wireless
Antenna Model	Omni
Routing Protocol	LAR
Data Packet Size	512 Kbps
Bandwidth	2 Mbps
Simulation Time (seconds)	500,1000,1500,2000, 25000 (Highway scenario) 200,400,600,800,1000 (City scenario)
Number of vehicles	100~500

Next we discuss the metrics that have been considered for monitoring the performance of LAR protocol. Following are the metrics considered:

Throughput– it is defined as the ratio of number of packets transmitted per unit time. In our experiment the unit of throughput is considered to be kbps [10].

Packet delivery ratio- it is defined as the ratio of number of bits transferred by the sender to that received by the receiver. Congestion in the network tends to increase the value of this ratio [11].

Overhead – it is defined as the amount of extra packets that have to send during the transmission of actual information during routing [12].

For the highway scenario an average of five iterations for each set of nodes ranging from 100~500 has been considered to determine each of the metric. The graphical results thus obtained for each of the metric by varying the simulation time in the range 500~2500 (seconds) and plotting it against the average of results obtained for each of the performance metric, considering all the iterations of 100 and 500 nodes lie under case one. They are depicted in Figure 4(a), Figure 4 (b), Figure 4(c).

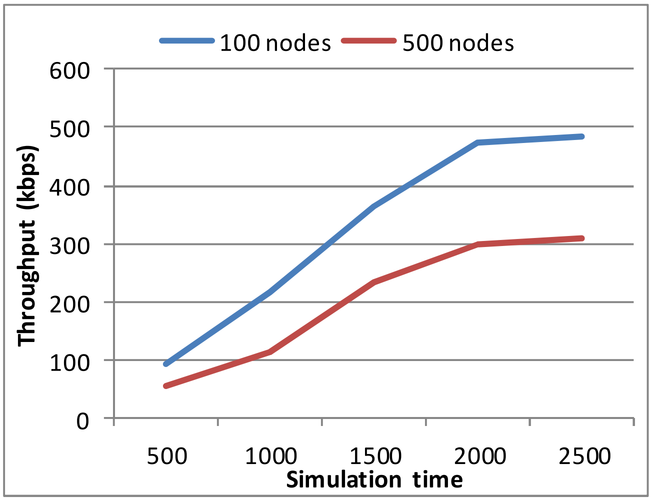


Figure 4(a). Throughput 100 and 500 nodes against the variability in simulation time

As per Figure 4 (a), it can be seen that the average throughput shows a sharp increase with the increase in simulation time till the time reaches nearly 2000 (close to the peak maximum time chosen) beyond which the throughput shows a considerably linear increase with increase in time for both the sets of 100 and 500 nodes.

In Figure 4 (b) average packet delivery ratio for the set of 100 nodes is seen to show a sharp decrease till simulation time reaches1000 seconds beyond which a linear increase till the maximum time instance i.e. 2500 seconds is observed. For the set of 500 nodesa constant increase is seen till 1000 seconds with a sharp drop beyond this value till it is increased beyond 1500 seconds. Any further increase in the simulation time till the maximum chose time instance shows a linear decrease in the PDR.

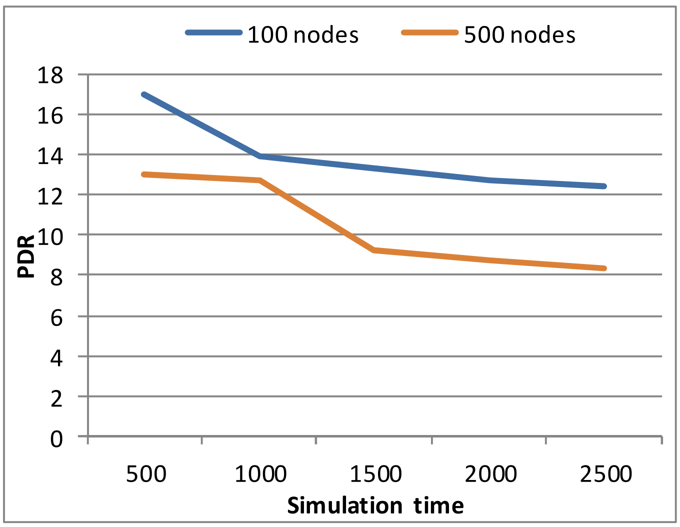


Figure 4 (b). PDR of 100 and 500 nodes against the variability in simulation time

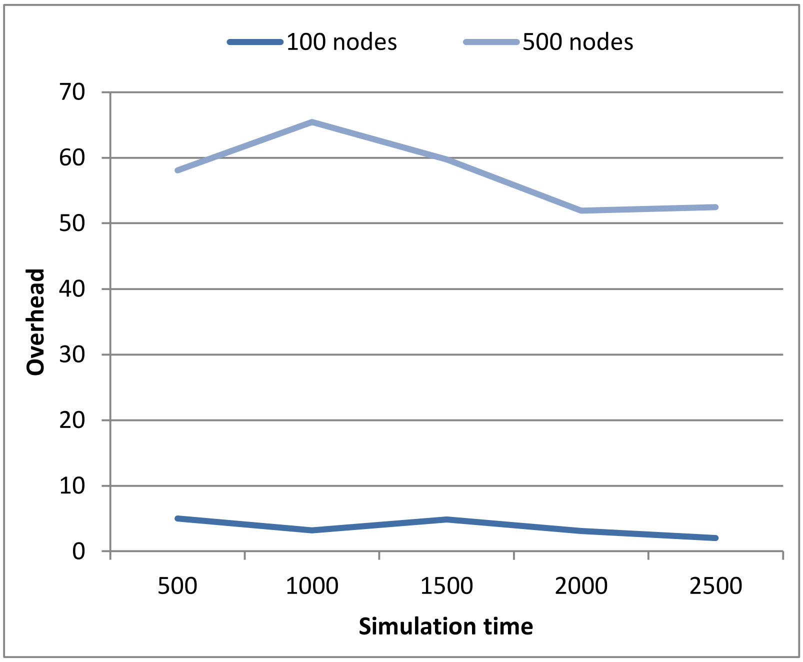


Figure 4(c).Overhead of 100 and 500 nodes against the variability in simulation time

As per Figure 4 (c) we can see that for a set of 100 nodes against all the time instances the overhead is shows a sharp increase in its values till 1000 seconds, beyond which a drastic decease in the value can be observed on further increasing the time instance till 2000 seconds. a further increase in the time up till the already set maximum allowable limit shows a linear increase in its value.

On the contrary for the set of 500 nodes, a relatively gradual decrease in values till 1000 seconds followed by a gradual increase and then a linear decrease can be seen. A smoother zigzag curve can be seen in this case.

In Figure 5 (a) the average throughput for the all the sets of nodes ranging from 100~500 for the 1000 time instance shows a very sharp decrease in its value on increasing the number of vehicles from 100 to 200. A further increase in the vehicle count shows an approximately linear increase in the throughput values.

For the 2000 time instance the throughput values are seen to show a considerable decrease on increasing the number of vehicles, followed by a sharp increase till the number of nodes are increased till 400 and till it reaches the chosen maximum set of nodes i.e. 500 a drastic decrease can be seen as opposed to a linear decrease for 1000 time instance.

An increase in number of nodes for a fixed chosen area leads to a very high chance of increase in collisions amongst these nodes thereby leading to a decrease in throughput values.

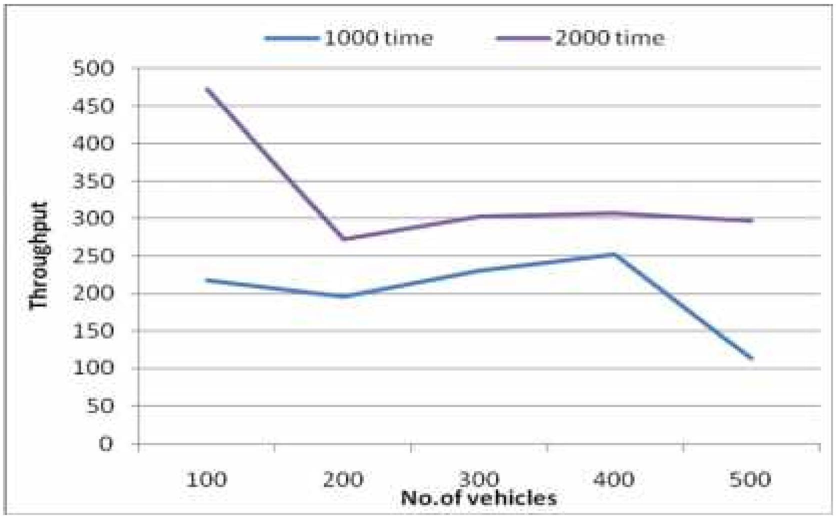


Figure 5 (a). Throughput for 1000 and 2000 time instances against the variability in number of vehicles

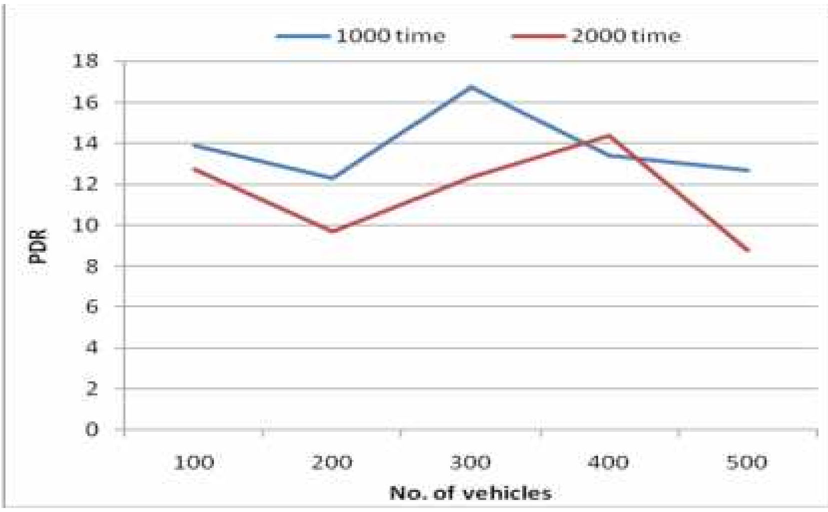


Figure 5 (b). PDR for 1000 and 2000 time instances against the variability in number of vehicles

In Figure 5 (b) the average PDR for all the five iterations of vehicles against 1000 and 2000 time instance is seen to show a sharp decrease for till 200 vehicles. On further increasing the number of vehicles we can observe a drastic increase in the PDR value till number of vehicles reach to 300 for the 1000 time instance and for 2000 time instance increase persists till 400 numbers of vehicles.

Further increase in number of vehicles leads to strong decrease in the PDR value for the 1000 time instance till vehicle count becomes 400. Increase in the vehicle count beyond this leads to a less sharper decrease in PDR values. For the 2000 time instance a severe decrease in PDR value persists as long as numbers of vehicles are increased till they reach the maximum chosen value i.e. 500.

Figure 5 (c) depicts that graphs follow a similar trend for both 1000 and 2000 time instance. An increase in a number of vehicles is represented by a sharp increase in average overhead values till the count of vehicles reach 300. Further increase in vehicle count up to 400 is observed to show a considerably smooth decrease in the average overhead values. This is followed by a sharp increase in average overhead values for an increase in vehicle count till the maximum chosen values i.e. 500.

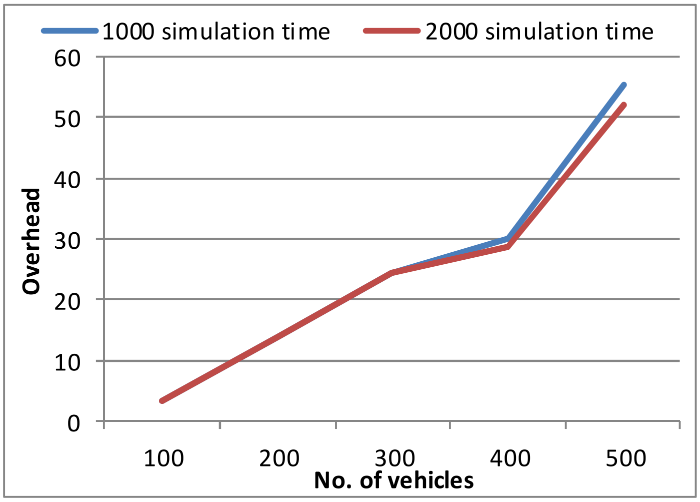


Figure 5 (c). Overhead for 1000 and 2000 time instances against the variability in number of vehicles

For the real world dataset of the Bologna city [9] scenario same cases have been considered. Case one comprises five iterations for each set of nodes ranging from 100~500. The graphical results thus obtained for each of the metric by varying the simulation time in the range 200~1000 (seconds) and plotting it against the results obtained for each of the performance metrics are depicted in Figure 6 (a), Figure 6 (b), Figure 6 (c). Case two comprises visualization of results for the values obtained by varying the number of vehicles/nodes in the range 100~500 for both two fixed time instances 200 and 1000.

Thus similar to the highway scenario case one depicts variability in terms of simulation time for two sets of nodes 100 and 500 and case two accounts of variation in number of vehicles moving in the chosen area for two fixed instances 200 and 1000 sec. The obtained results for case two are shown in Figure 7 (a), Figure 7 (b) and Figure 7 (c). Low initial simulation time for this scenario in comparison to the highway scenario is done to ensure faster execution of LAR protocol, proceeding for larger values lead to a considerable increase in the time complexity.

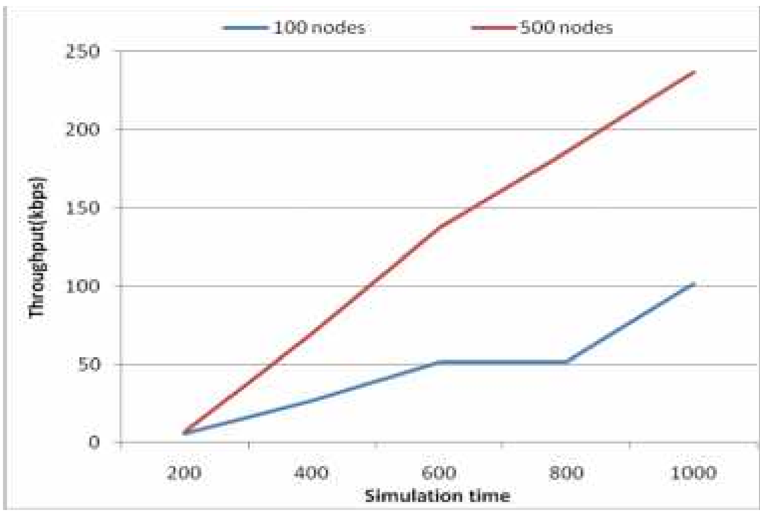


Figure 6 (a). Throughput 100 and 500 nodes against the variability in simulation time

In fig 6(a) it can be observed that as the time increases the throughput increase almost linearly for 500 nodes. For 100 nodes the increase is not exactly linear. Also it is observed that for the same time instances the throughput achieved by 500 nodes is more than that of 100 nodes because more number of packets is delivered by 500 nodes during a simulation time. In fig 6 (b) it is observed that packet delivery ratio drops considerably for 500 nodes and with a less margin for 100 nodes. Also the packet delivery ratio is less for 100 nodes as compared to 500 nodes for same simulation time. In fig 6 (c) we observe that for 500 nodes, overhead increases as the simulation time increases. The increase however is not sharp it is rather slow. For 100 nodes the overhead is very low and nearly remains constant all throughout.

In fig 7 (a) it is observed that the throughput initially increases as the number of nodes increase but gradually its starts falling as more nodes are added. This happens because as the number of vehicles increase the number of collisions also increases therefore less number of packets will be exchanged.

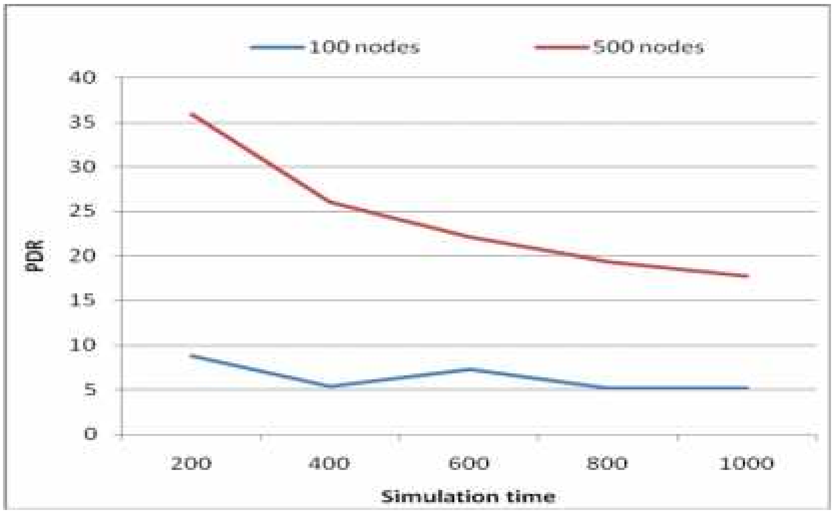


Figure 6 (b). PDR 100 and 500 nodes against the variability in simulation time

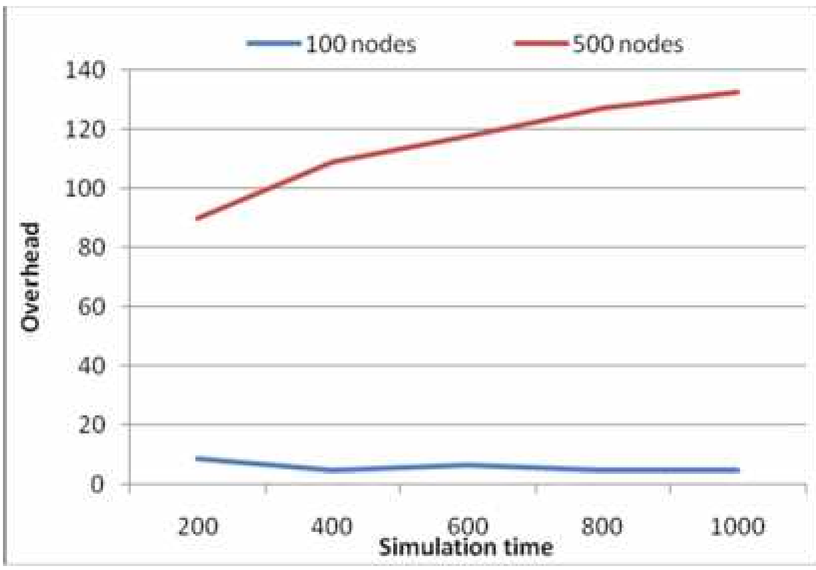


Figure 6 (c). Overhead 100 and 500 nodes against the variability in simulation time

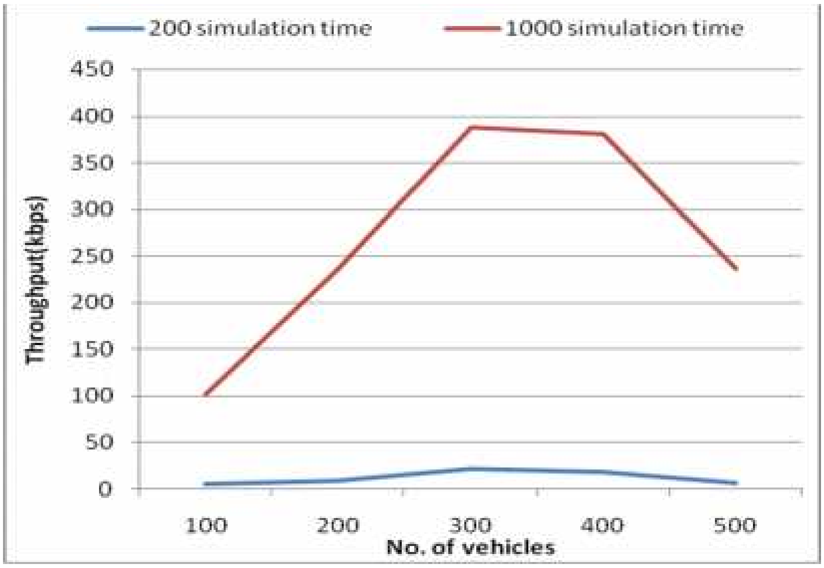


Figure 7 (a). Throughput for 200 and 2000 time instances against the variability in number of vehicles

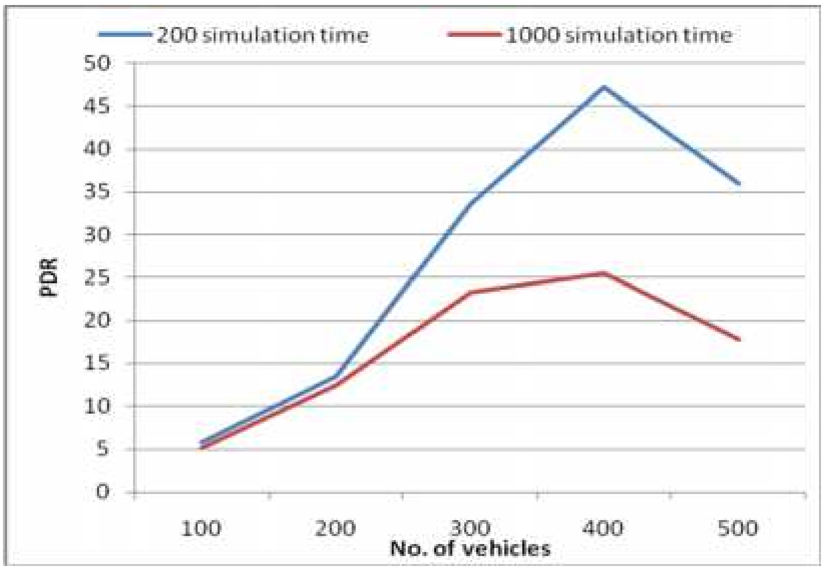


Figure 7 (b). PDR for 200 and 2000 time instances against the variability in number of vehicles

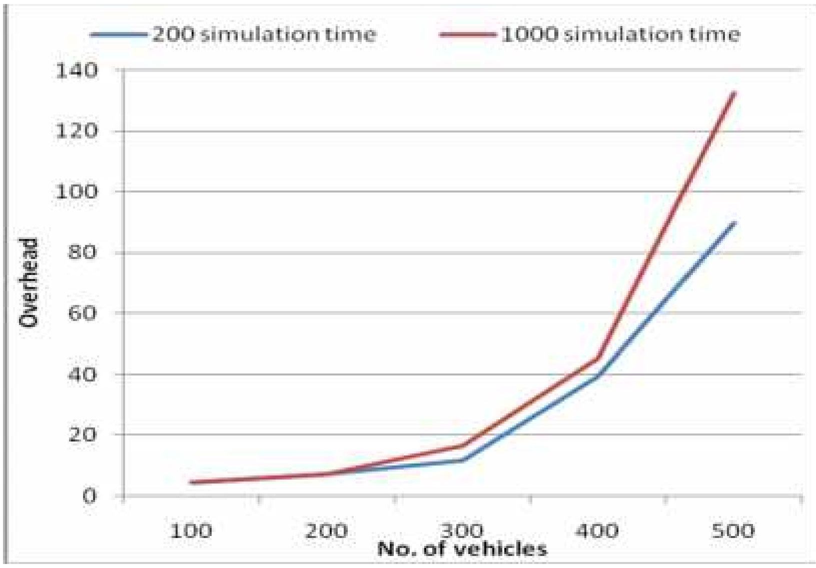


Figure 7 (c). Overhead for 200 and 2000 time instances against the variability in number of vehicles

In fig 7 (b) we observe that the packet delivery ratio increases rapidly with increase in the number of vehicles but after reaching 400 vehicles which is the highest point of increase , the packet delivery ratio starts to fall.

In fig 7 (c) it is observed that the overhead increases exponentially with the increase in the number of vehicles. The overhead is more for a higher simulation time and comparatively less for a lower simulation time.

5. Conclusion

In this work we have evaluated the performance of Location Aided Routing protocol (LAR) for Vehicular Ad-hoc Networks (VANETs) in terms of throughput, packet delivery ratio and routing overhead. We have considered two scenarios namely highway and city scenario. For highway we have taken Delhi highway data from OSM map and for city scenario we have taken real traces of Bologna Ringway dataset. For each of these scenarios the performance is evaluated by considering variation in terms of number of vehicles and simulation time.

We observe that with the increase in simulation time the throughput increases for both highway and city scenario. The packet delivery ratio and overhead tend to decrease with increase in simulation time.

References

[1]. Gurumoorthi, E., & Ayyasamy, A. (2019). Cache agent based location aided routing protocol using direction for performance enhancement in VANET. *Wireless Personal Communications*, *109*(2), 1195-1216.

[2]. Rana, K. K., Tripathi, S., & Raw, R. S. (2018). Analytical analysis of improved directional location added routing protocol for VANETS. Wireless Personal Communications, 98(2), 2403-2426.

[3]. Manohar, M. P., & Setty, S. P. (2018). Performance Analysis of Reactive Routing Protocols AODV, DYMO, DSR, LAR in MANETs. International Journal on Future Revolution in Computer Science & Communication Engineering, 4(3), 01-07.

[4]. Xiong, W., & Li, Q. Q. (2015). Performance evaluation of data disseminations for vehicular ad hoc networks in highway scenarios. The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences, 37.

[5]. Dixit, M., Kumar, R., & Sagar, A. K. (2016, April). VANET: Architectures, research issues, routing protocols, and its applications. In Computing, Communication and Automation (ICCCA), 2016 International Conference on (pp. 555-561). IEEE.

[6]. Ko, Y. B., &Vaidya, N. H. (2000). Location-aided routing (LAR) in mobile ad hoc networks. Wireless networks, 6(4), 307-321.

[7]. Lobiyal, D. K. (2012). Performance evaluation of realistic vanet using traffic light scenario. arXiv preprint arXiv:1203.2195.

[8]. Pandey, K., Raina, S. K., &Rao, R. S. (2015, June). Performance analysis of routing protocols for vehicular adhoc networks using NS2/SUMO. In Advance Computing Conference (IACC), 2015 IEEE International (pp. 844-848). IEEE.

[9]. Amici, R., Bonola, M., Bracciale, L., Rabuffi, A., Loreti, P., & Bianchi, G. (2014). Performance assessment of an epidemic protocol in VANET using real traces. Procedia Computer Science, 40, 92-99.

[10]. Raw, R. S., Lobiyal, D. K., Das, S., & Kumar, S. (2015). Analytical evaluation of directional-location aided routing protocol for VANETs. Wireless Personal Communications, 82(3), 1877-1891.

[11]. Bouras, C., Kapoulas, V., &Tsanai, E. (2015).Performance evaluation of routing mechanisms for VANETs in urban areas. In Algorithms, Probability, Networks, and Games (pp. 133-153). Springer International Publishing.

[12]. Bedogni, L., Gramaglia, M., Vesco, A., Fiore, M., Härri, J., & Ferrero, F. (2015). The Bologna Ringway dataset: improving road network conversion in SUMO and validating urban mobility via navigation services. IEEE Transactions on Vehicular Technology, 64(12), 5464-5476.

Author's Biography

Ms. Amrit Kaur Saggu has done B.Tech from ABES-EC and her master's from JIIT (Noida) with major interests in the field of Networks. She is currently working as Assistant professor in CSE Department, KIET Group of Institutions. She has attended several workshops and conferences. She has also published in reputed journals.

Dr. Shivani Agarwal is an Assistant Professor in KIET School of Management at KIET Group of Institutions, Ghaziabad, India. She has earned her PhD from Indian Institute of Technology (IIT, Roorkee) in Management. Prior to his current role, she was associated with Institute of Technology & Science, Ghaziabad, UP, India, HRIT Group of Institutions, Ghaziabad, UP, India; IIT Roorkee, UK, India and Center for Management Development, Modinagar, UP.

She has attended several short term course at Indian Institute of Technology Roorkee, India, IIT Delhi, India; earned NPTEL certificate for Research Writing and Human

resource Management.

She has authored or co-authored more than 10 research articles that are published in journals, books and conference proceedings. She teaches graduate & post graduate level courses in management.

She received Ph.D in Organization Behaviour (Psychology) from IIT Roorkee, India in 2015 and MBA from Guru Gobind Singh University, New Delhi, India in 2009 and a bachelor's degree in Science from Chaudhary Charan Singh University, Meerut, India in 2007.

She is the Book Series Editor of Information Technology, Management & Operations Research Practices, CRC Press, Taylor & Francis Group, USA, She is guest editor with IGI-Global, USA. She is the corresponding author. She can be contacted at jindal.shivani24@gmail.com .

How to Cite

Saggu, Amrit Kaur, and Agarwal, Shivani(2019). Performance Evaluation of LAR protocol using real dataset on Highway and City Scenario. *International Journal of Machine Learning and Networked Collaborative Engineering*, 3(03) pp 168-181.

doi : https://doi.org/10.30991/IJMLNCE.2019v03i03.005**.**