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RESEARCH ARTICLE

ETPPDMRL: A novel approach for prescriptive analytics of customer reviews via enhanced text parsing and reinforcement learning

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Abstract

Necessity is the mother of invention; likewise, understanding the customer's requirements is the key to creating a successful product. Customer reviews are one of the vital essentials of fine-tuning products towards perfection. Extracting useful information from text reviews is the primary objective for prescriptive analysis. Modern science has introduced several novel methods, including Artificial Intelligence (AI) through machine learning (ML) and data mining (DM). The introduction of artificial neural networks (ANN) is driving the predictive analysis process towards being more beneficial for both customers and manufacturers. An exclusive text parser is introduced in this work to make more compatible inputs for reinforcement learning (RL). C4.5. Prescriptive Decision Maker is introduced to achieve higher Accuracy and Precision. The new modules' Exclusive Text Parser for Reinforcement Learning' and 'C4.5. Prescriptive Decision Makers' are the functional blocks used to construct the proposed method named as Enhanced Text Parser for Prescriptive Decision-Making using Reinforcement Learning (ETPPDMRL). Exclusive Text Parser and RL-based C4.5. Classifiers are submitted here as the novel contribution. Amazon customer feedback dataset is used to evaluate the performance of the proposed method during the experiments. Benchmark metrics, including accuracy, precision, sensitivity, specificity, F-score, and average process time, are used to evaluate the performance of the proposed method.

Keywords: Artificial intelligence, Artificial neural network, C4.5. classification, Data mining, Machine learning, Prescriptive analytics, Reinforcement learning.

Introduction

Prescriptive analytics is the ensemble of predictive and descriptive analytics. Predictive analytics is used to analyze and predict a certain outcome based on historical and current data. Descriptive analytics is used to epitomize the features extracted from a collection of data. Prescriptive analytics combines both methods, involving a set of statistical techniques, data mining procedures, mathematical modeling, and machine learning procedures [Sarker, 2021]. The extensive exploration in modern sensing and communication technologies such as Internet-of-Things (IoT) makes it possible to collect data from any industry in massive quantities [Brincat, F. Pacifici, S. Martinaglia and F. Mazzola,2019][Adi, E., Anwar, A., Baig, Z. et al., 2019]. Widely employed cloud servers are used to store and share massive data in an economical way [Patil, N. M., Krishna, P. M., Deena, G., Harini, C., Gnanamurthy, R. K., & Srinivas, R. V., 2023].

Predictive analytics is applicable in multiple data-intensive domains such as adaptive learning recommendation systems, behavior-based advertising, credit scoring, customer retention, direct marketing, e-mail targeting, fundraising, healthcare management, insurance pricing, portfolio management, Product recommendations and Ticket booking systems [Jouhar, M. J. K. K., & Aravinthan K., 2024; Patil, N. M., Krishna, P. M., Deena, G., Harini, C., Gnanamurthy, R. K., & Srinivas, R. V., 2023]. Commonly used variables for prescriptive analytics are amount of capital,

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application response, customer interested advertisements, and customer response [Jagannathan, J., Rajesh, K. A., Labhade-Kumar, N., Rastogi, R., Unni, M. V., & Baseer, K. K., 2023], customer response rate, debtor risks and optimal resource availability [Liye Ma, Baohong Sun,2020].

This work is intended to improve the quality of Product recommendations based on customer reviews [Liye Ma, Baohong Sun, 2021]. The positive and negative reviews about a product can impact its sales and market value. The pandemic situation a couple of years ago dramatically intensified online sales [Roszi Naszariah Nasni Naseri, 2021]. Brand value and Customer reviews are the primary considerations of the majority of online buyers when determining choices among aggregated products.

Machine Learning is the fundamental mechanism that exists behind the Prescriptive analytics process. Discovering the concealed relationships and patterns in statistical data is the central refinement of prescriptive analytics [Notz, P. M., 2023]. This work introduces a novel machine learning approach to generate product recommendations based on user reviews.

Existing Methods

Some of the existing prescriptive analysis methods are studied here to understand their methodologies and merits. The limitations of these methods are also thoroughly analyzed in this section to understand the underlying challenges and to proceed with improvement. Machine learning for predictive and prescriptive analytics of operational data in smart manufacturing [Lepenioti K. et al., 2021], machine learning for supply chain's big data: State of the art and application to social networks' data [Radouane El-Khchine, Amine Amar, Zine Elabidine Guennoun, Charaf Bensouda and Youness Laaroussi, 2018], human-machine collaboration in online customer service–a long-term feedback-based approach [Graef, R., Klier, M., Kluge, K. et al., 2021], The impact of big data analytics on company performance in supply chain management [Oncioiu, I.; Bunget, O.C.; Türkeş, M.C.; Căpuşneanu, S.; Topor, D.I.; Tamaş, A.S.; Rakoş, I.-S.; Hint, M.Ş.,, 2021] and New Business Models from Prescriptive Maintenance Strategies Aligned with Sustainable Development Goals[Grijalvo Martín, M.; Pacios Álvarez, A.; Ordieres-Meré, J.; Villalba-Díez, J.; Morales-Alonso, G., 2021] are the existing methods taken here for keen assessments.

Machine learning for predictive and prescriptive analytics of operational data in smart manufacturing [MLPPA]

The work of Katerina Lepenioti *et al*. is developed using a recurrent neural network (RNN) as its core. Predictive model building, predictive model deployment, prescriptive model building, prescriptive model deployment, and prescriptive model adaptation are the contributed modules introduced in the MLPPA work. MLPPA work is stated as being Industry 4.0 standard compatible. The applicability in different manufacturing industries, such as textiles, furniture, and metal processing, is an advantage of MLPPA work. However, lack of accuracy and precision in the prescriptive process is the perceived limitation of this work.

Machine Learning for Supply Chain's Big Data: State of the art and application to Social Networks' data [MLSCBD]

MLSCBD leverages social media data to perform prescriptive analytics, promoting supply chain efficiency. Since social media data comes under big data category, it is understood that the MLSCBD work is capable of handling large volumes of data. K-nearest neighbor, support vector machine and logistic regression methods are used as the base for MLSCBD work. Social media data serves as the input for MLSCBD work, enabling the visualization of the impact of price, quality, supplier, color, packaging, and delivery modes. Based on the prescriptions generated by MLSCBD work, from manufacturing industries to marketing agencies, the entire supply chain can benefit the gain. A complete analysis of the different properties of the products is performed in MLSCBD work, which is the main advantage. However, the accuracy and precision of MLSCBD are not up to mark, as the dependability of social media user reviews is always questionable.

Human-machine collaboration in online customer service–a long-term feedback-based approach [HMCOCS]

HMCOCS introduces an Adapted textual Case-based Reasoning to perform the prescriptive analytics. Pertinent data from long-term reviews obviously improves the accuracy and precision of HMCOCS work. The customer problem is fed to the neural network-based context generator, which, based on the context clustering-based learning model, determines the problem's adaptability based on human knowledge. Then, the adapted customer problems are processed through a sequence of case-based retrieval, case-base reuse, case-base revision, and case-based retention. The experiments were carried out by using Quora website. Improved accuracy is the main advantage of HMCCS method, at the same time, higher processing time is the observed limitation.

The impact of big data analytics on company performance in supply chain management [BDASCM]

BDASCM method is designed to perform prescriptive analytics by handling big data to boost company performance. The prescriptive results generated by the sampling survey are applicable to supply chain management. There are six objectives covered in BDASCM work: Discovery of companies' experience in supply chain management, Identification of strategy adaptation in large data analytics, Determination of professional capability existence, Discovery of companies' available supply chain management tools, Pinpointing companies' ability to follow big data analytical results and Estimation of experience in professional strategies applicability. These objectives are addressed based on a set of 9 basic hypotheses. Mass data handling capacity with higher processing speed is an advantage of the BDASCM method, whereas moderate accuracy achieved using fundamental statistics is identified as a limitation.

New Business Models from Prescriptive Maintenance Strategies Aligned with Sustainable Development Goals [PMSSDG]

PMSSDG's work approached the prescriptive analytics process from different perspectives, including organizational, innovation, and sustainability. Different levels of viewpoints, namely micro, meso, macro, and mega, are used to approach distinct processes, such as Data acquisition, Construction of structural information, knowledge processing, and decision-making based on the knowledge base. The Business Model Canvas, Technology Roadmap, and Information and Communication Technology strategic tools are used to develop the business model of PMSSDG. Dedicated procedures are applied in this work for Innovative content creation, Organizational design and to identify Sustainable development goals. Nominal accuracy and precision of prescriptive results are the stated advantages of this method. At the same time, domain specificity is distracted due to the adoption of diversified perspectives.

A crisp outline about the existing methods, methodologies used, advantages and limitations are enumerated in Table 1.

Related Works

Reinforcement Learning and C4.5 classification algorithms are essential components used to design the proposed method. Comprehension about Reinforcement Learning and C4.5 Classification Algorithm is provided in this section to describe the proposed system in an ameliorated way.

Reinforcement Learning (RL)

The incorporation of RL in designing the proposed works for its inimitable characteristics in handling massive unlabeled data [K. Jaskie and A. Spanias, 2019][Shoush, M., & Dumas, M., 2023]. In sentiment analysis or for prescriptive analytics, the availability of labeled data in huge volumes is quite limited. Therefore, the property of RL in learning from unlabeled data is a boon to prescriptive analytics. Moreover, fast convergence, producing uncommonly accurate results, and bias resistance are the additional qualifications that make RL the best choice for prescriptive analytics. The long-term projection is one of the essential requirements for prescriptive analytics, which RL can seamlessly achieve. The ability to autocorrect the errors and the self-finetuning property of RL has great benefits in foretelling the ordinance.

The RL comprises two essential entities: the Agent and the Environment. The general notations used in RL are action (A), State (S), Reward (R), Policy (π), Value (V) and Action Value (Q). The Action A refers the possible moves that the agent can perform, S is the current state of the environment, R is the reaction of the environment based on the last performed action, π is the decision-making policy used by the agent to take the subsequent action based on the current state [Lucian Buşoniu, Tim de Bruin, Domagoj Tolić,

Table 1: Existing methods' methodologies, advantages and limitations

Author	*Work*	*Methodology*	*Advantages*	*Limitations*
Lepenioti K. et al	Machine learning for predictive and prescriptive analytics of operational data in smart manufacturing	Recurrent Neural Network	Multi-industry applicability	Less Accuracy
Radouane El-Khchine et al	Machine Learning for Supply Chain's Big Data: State of the art and application to Social Networks' data	K-Nearest, SVM, Logistics Regression	Multiple product property consideration	Less accuracy and precision
Graef R. et al	Human-machine collaboration in online customer service–a long-term feedback-based approach	Neural network based Context Generator	High Accuracy	More processing time
Oncioiu I. et al	The impact of big data analytics on company performance in supply chain management	Sampling Survey	Massive data handling	Moderate Accuracy
Grijalvo Martín M. et al	New Business Models from Prescriptive Maintenance Strategies Aligned with Sustainable Development Goals	New perspective maintenance model	Nominal Accuracy	Domain specificity

Jens Kober, Ivana Palunko, 2018], V is the expected long-term value, Q is similar to V with action as the additional parameter. The RL organization is illustrated in Figure 1.

In Figure 1, t is the current timestamp otherwise referred as Initial time. S_t is the state at timestamp t, R_t is the current reward. The action A_t is performed by the agent on the environment that causes new state S_{t+1} at timestamp $t+1$ and the reward R_{t+1}.

State-Action-Reward-State-Action (SARSA) on-policy algorithm is one of the types of RL state update algorithms used in the proposed method [. Alfakih, M. M. Hassan, A. Gumaei, C. Savaglio and G. Fortino, 2020][R. Li et al., 2018]. The state update equation of SARSA is

$$Q(s_t,a_t) \Leftarrow Q(s_t,a_t) + \alpha\left[r_{t+1} + \gamma Q(s_{t+1},a_{t+1}) - Q(s_t,a_t)\right]$$

Equation (1)

SARSA Algorithm

Algorithm 1: SARSA (λ): Learn function $Q: S \times A \to \mathbb{R}$

Step 1: Initialize States $S = \{1,2\cdots n_s\}$

Step 2: Let the Actions be a set of $A = \{1,2\cdots n_a\}$

Step 3: Let the reward function $R: S \times A \to \mathbb{R}$

Step 4: Define Probabilistic transition function $T: S \times A \to S$

Step 5: Let the learning rate $\alpha \in [0,1]$

Step 6: Let the discounting factor $\gamma \in [0,1]$

Step 7: Let $\lambda \in [0,1]$: Tradeoff between Temporal Difference and Monte Carlo Prediction

Step 8: Start Q-Learning($S, A, R, T, \alpha, \gamma, \lambda$)

Step 9: Initialize $Q: S \times A \to \mathbb{R}$ with arbitrary

Step 10: Initialize Eligibility Threshold $e: S \times A \to \mathbb{R}$ with 0

Step 11: While $\neg Converged(Q)$

Step 12: Select $(s,a) \in S \times A$ arbitrarily

Step 13: While $\neg Complete(s)$

Step 14: $r \Leftarrow R(s,a)$

Step 15: $s' \Leftarrow T(s,a)$

Step 16: Update π based on Q

Step 17: $a' \Leftarrow \pi(s')$

Step 18: $e(s,a) \Leftarrow e(a,s) + 1$

Step 19: $\delta \Leftarrow r + \gamma . Q(s',a') - Q(s,a)$

Step 20. $\forall(\tilde{s},\tilde{a}) \in S \times A := Q(\tilde{s},\tilde{a}) \Leftarrow Q(\tilde{s},\tilde{a}) + \alpha \cdot \delta \cdot e(\tilde{s},\tilde{a})$, $e(\tilde{s},\tilde{a}) \Leftarrow \gamma \cdot \lambda \cdot e(\tilde{s},\tilde{a})$

Step 21: $s \Leftarrow s'$

Step 22: $a \Leftarrow a'$

Step 23: End do

Step 24: End 30

Step 25: Return Q

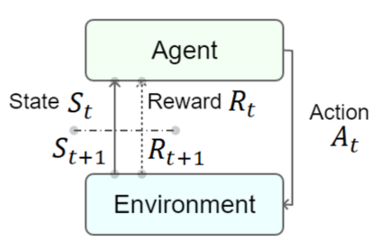

Figure 1: Reinforcement Learning

C4.5 Classification Algorithm

C4.5 is a statistical decision tree classification algorithm that comes with some advantages such as Single pass pruning technique to alleviate overfitting, ability to handle both continuous as well as discrete data, and the tolerance against incomplete data. C4.5 inherits the advantages of Iterative Dichotomiser 3 (ID3) algorithm with an additional quality of independence in declaring features into categorical [Anis Cherfi, KaoutherNouira& Ahmed Ferchichi, 2018].

Algorithm 2: C4.5(D)

Step 1: Read attributed dataset D as input

Step 2: Initialize an empty set $T = \{\}$

Step 3: If $Stopping\ Criteria = TRUE$ OR $PureSet(D) = TRUE$ return

Step 4: $\forall a \in D$ compute information-theoretic criteria where a is the attribute of members of D

Step 5: Select a_{best} based on step 4

Step 6: Initialize T with a_{best} as the root node

Step 7: Extract subsets d_v of D based on a_{best}

Step 8: $\forall d_v \in D := T_v = Call\, C4.5(D)$ and attach to corresponding branch

Step 9: return T

Node construction process of C4.5 classification procedure is given in Figure 2.

C4.5. technique uses post pruning process to simplify the tree [J. -S. Lee, 2019]. This simplification process takes place once the node construction phase is complete. Elimination of non-beneficial branches during the pruning stage improves the memory efficiency of the algorithm. The pruning process beings with the calculation of parent and child pessimistic error rates. The error rates arecalculated using Equation 2 and the need for pruning is determined by Equation 3.

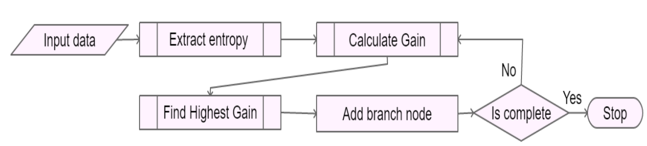

Figure 2: C4.5 Node construction

$$e = \frac{r + \frac{Z^2}{2n} + Z\sqrt{\frac{r}{n} - \frac{r^2}{n} + \frac{z^2}{4n^2}}}{1 + \frac{Z^2}{n}} \quad \text{Equation (2)}$$

where r is the error rate comparison threshold, n is the number of acquired samples and $Z = \phi^{-1}(confidence\,level)$

$$Prunning = \begin{cases} Required\ if\ (pessimistic\ error > parent) \\ Not\ required\ otherwise \end{cases} \quad \text{Equation (3)}$$

Proposed Method

ETPPDMRL Method consists of two major modules to support the performance enhancements. They are Enhanced Text Parser for Reinforcement Learning (ETPRL) and C4.5 Prescriptive Decision Maker (CPDM). ETPRL module is used to convert the input into numerical weighted data and CPDM method is used to make decisions based on the data received from ETPRL.

Enhanced Text Parser using Reinforcement Learning (ETPRL)

ETPRL is responsible for interpreting user reviews into eloquent data operable by RL. Specialized Lexical Analyzer, Symbol Table, User review lexicon and Parser are the main ingredients of ETPRL. Sentences, Clauses, Phrases and words are the major components processed by a standard parser whereas, Sentences, Noun Phrase, Determiner, Verb Phrase, Prepositional Phrase Verb and Noun are the contents processed by the ETPRL module. It is also designed in a way to handle multiple lexicons in a symbol table for better accuracy. The illustration of ETPRL is given in Figure 3.

General Language Lexicon (L_G), Product Lexicon (L_P), Location Lexicon (L_L) and Bias Lexicons (L_B) are the four types of lexicons are provided to the ETPRL module. L_G is the standard English language lexicon used to refer the common natural language entities such as Nouns, Verbs and Phrases. Product Lexicon L_P contains the information about the product names, category, model number. Location Lexicon contains information about the place names, origin, climate and territory information. Bias lexicon L_B consists information related to sentiment analysis to perceive the feedback of the user. A clear hierarchy sequence of L_P , L_B , L_L and L_G is assigned from highest preference to evade ambiguity conditions in the ETPRL module. For example, the term 'Dove' exists in both L_P and in L_G . The term is common for a kind of bird and a cosmetic product manufacturing company. In such case, higher priority L_P takes advantage and search for supporting keywords from the input text such as product name and properties. Content of L_G will be utilized only in the absence of product supporting words in the input text.

ETPRL is equipped with combinational context analysis to eliminate the mutual interpretation perplexities while handling L_B .For example, the word 'Good' is set as the positive bias category, at the same time the presence of a 'not' will make into negative bias category. Positive, Positive with slight corrections, Positive with major corrections and Negative are the different sentiment recommendation categories used in ETPRL. The sentiment of the given input review is analyzed in this phase and they are labelled under any of the above-mentioned category.

A Product table is maintained for ETPPDMRL in which each product has an unique Product Identification Number (PID). The product table format is given in Table 2, in which m referes the maximum number of properties of a product and n refers the number of products included for the prescriptive analytics.

A prescription set ρ is initialized as $\rho = \{\rho_0, \rho_1, \rho_2, \rho_3\}$ in which each member denotes the entropy gain of Positive, Positive with minor modifications, Positive with major modifications and Negative categories respectively. The user review dataset is fed to the ETPRL system to calculate ρ using the following algorithm.

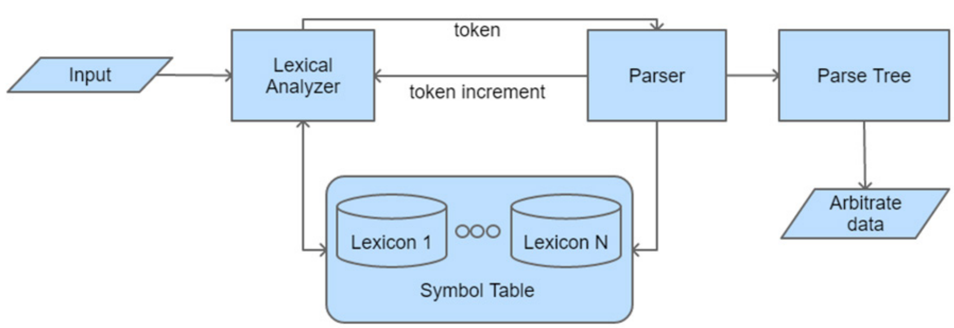

Figure 3: Enhanced Text Parser

Algorithm 3: ρ Bias Boost

Input: Review dataset

Step 1: Initialize ρ as $\forall \mathrm{i} = 0 \to 3 := \rho_i = 0$;

Step 2: for $\mathrm{i} = 0 \to n$ do

Step 3: Apply sentiment analysis for i^{th} Review

Step 4: If review type = positive, Increment Bias for ρ_0 by 1

Step 5: If review type = positive with recommendations, Increment Bias for ρ_1 by 1

Step 6: If review type = positive with complaints, Increment Bias for ρ_2 by 1

Step 7: If review type = Negative, Increment Bias for ρ_0 by 1

Step 8: Determine ρ_{max} as $\max(\rho_0, \rho_1, \rho_2, \rho_3)$

Step 9: Normalize bias set ρ to 0 to 1 as

$$\forall \mathrm{i} = 0 \to 3 := \rho_i = \frac{\frac{\rho_{max}}{100} \times \rho_i}{100}$$

Step 10: return ρ

By this way, ETPRL fetches each record from input, parse the content and generate context sentiment bias for prescription set which will be fed to CPDM Module

C4.5 Prescriptive Decision Maker (CPDM)

CPDM constructs a decision tree by using Algorithm 2 for different types of prescriptions. The CPDM Tree construction is performed based on the Positive/Negative comments with/without references to achieve the prescription as illustrated in Figure 4.

The Amazon user review dataset is split into 10% chunks and the prescription is made for every chunk individually. Different types of prescriptions are made such as Increase production (Δ_I), Sustain production along with review referral to technical team (Δ_S), reduce product along with review referral to technical team (Δ_R) and Drop production (Δ_D) to the minimum boundary as per equation 4.

$$Prescription_{P_i} = \begin{cases} \Delta_I \; if \; \rho_0 > \frac{3}{4} \; AND \; \rho_0 \neq \rho_1 \neq \rho_2 \neq \rho_3 \\ \Delta_S \; if \; \rho_1 > \frac{3}{4} \; AND \; \rho_0 \neq \rho_1 \neq \rho_2 \neq \rho_3 \\ \Delta_R \; if \; \rho_2 > \frac{3}{4} \; AND \; \rho_0 \neq \rho_1 \neq \rho_2 \neq \rho_3 \\ \Delta_I \; if \; \rho_3 > \frac{3}{4} \; AND \; \rho_0 \neq \rho_1 \neq \rho_2 \neq \rho_3 \\ \varnothing \; otherwise(No \; Prescriptions) \end{cases}$$

Equation (4)

Where P_i is the particular product specified in the review.

Table 2: Product Table

PID	*Name*	*Model*	*Prescription Set*	*Property 1*	*Property 2*	…	*Property m*
ID1							
ID2							
…							
IDn							

The impact of prescription made for every 10% data is then investigated to determine the impact of the prescription in the environment. The increase in the market value, sales and the number of positive feedbacks is set to generate a reward to the action performed and the decrease effects in the environment is set to generate the penalty. These Rewards and Penalties are applied in the SARSA model given in Algorithm 1. By this way the probability of inappropriate prescriptions is diminished by the RL.

Experimental Setup

A computer with an i7 processor and 16GB RAM was used to develop and test the proposed modules. Visual Studio IDE [A. Svyatkovskiy, S. Lee, A. Hadjitofi, M. Riechert, J. V. Franco and M. Allamanis, 2021] was used to develop a dedicated Graphical User Interface (GUI) for fetching data from the server, evaluating method performance, and displaying logged results as comparison graphs. The function modules of the ETPPDMRL method were coded in Visual C++ to facilitate data retrieval, performance evaluation, and result visualization. The system was trained and tested using the Amazon Reviews dataset[Kaggle].

Results and Analysis

The Amazon Reviews dataset was used to evaluate and compare method performance. Accuracy measures how closely prescriptions match the exact effective prescription. It is calculated as (TP+TN)/(TP+TN+FP+FN). The dataset was divided into 10 equal parts, and True Positive, True Negative,

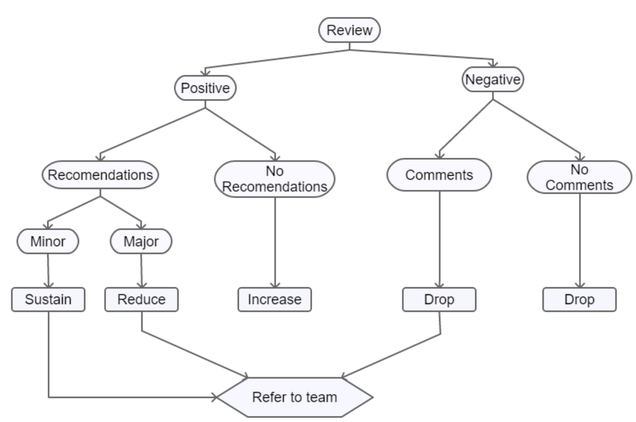

Figure 4: CPDM

False Positive, and False Negative values were logged for each. Performance metrics, including Accuracy, Precision, Sensitivity, Specificity, and F-Score, were calculated. Average Record Processing Time was also measured.

Accuracy

Accuracy is a directly proportional evaluation metric to the performance of any prescriptive algorithm. Accuracy is calculated using the formula $\frac{TP+TN}{TP+TN+FP+FN}$. Calculated Accuracy values for every 10% data chunk. As per the observed results, the Accuracy initial value of ETPPDMRL for 10% of data is 40.47%. Gradually it is increasing to the highest accuracy value 93.31% acquired for 100% data. Highest assorted accuracy of other methods is 98.1%, 97.23%, 95.81, 92.13% and 89.31 of methods HMCOCS, PMSSDG, BDASCM, MLSCBD and MLPPA respectively. An increase of 1.22% accuracy is achieved by the proposed method than the best existing method HMCOCS. This comparison graph is given in Figure 5.

Precision

Precision is one of the elementary metrics which is used to represent the closeness between the prescriptions made. It is also directly proportional to the performance of any classification of prescription algorithm. Precision is calculated using the formula $\frac{TP}{TP+FP}$.

Based on the experimental results, it is observed that the highest precision values while processing 100% data are 98.31%, 98.22%, 97.58%, 95.72%, 91.76% and 89.41% of ETPPDMRL, HMCOCS, PMSSDG, BDASCM, MLSCBD and MLPPA given in order. A performance improvement of 0.21% precision is achieved in ETPPDMRL method than the nearest performer HMCOCS method. Figure 6 provides the comparison of Accuracy.

Sensitivity

Sensitivity is also known as Recall or True Positive Rate (TPR). In the prescriptive analytics domain, sensitivity is about the measure of effective prescriptions rate over the total prescriptions. Therefore, the performance of the algorithm is directly proportional to the sensitivity score. That is, higher sensitivity refers higher quality of the prescriptive algorithm.

Sensitivity is calculated using the formula $\frac{TP}{TP+FN}$. Measured sensitivity values for every 10% data chunks for the methods used.

Though the initial value of sensitivity of ETPPDMRL at 10% data is lesser than the PMSSDG and HMCOCS, the improvements are significantly improved after processing 70% of data. For all data quantity higher than 70%, the sensitivity score of proposed ETPPDMRL method is higher than other methods. During the experiments.

A Training-Testing Ratio of 70:30 is globally accepted extent, so that the performance of proposed method comes under the acceptable category in terms of Sensitivity parameter. A comparison graph of measured sensitivity scores is provided in Figure 7.

Specificity

Specificity is otherwise known as True Negative Rate (TNR) refers the probability of negative test. Identifying low impact

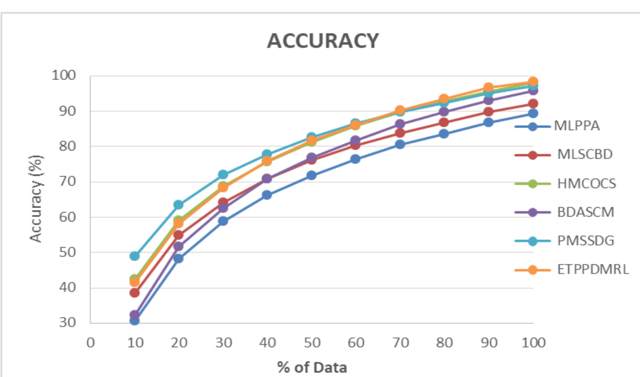

Figure 5: Accuracy

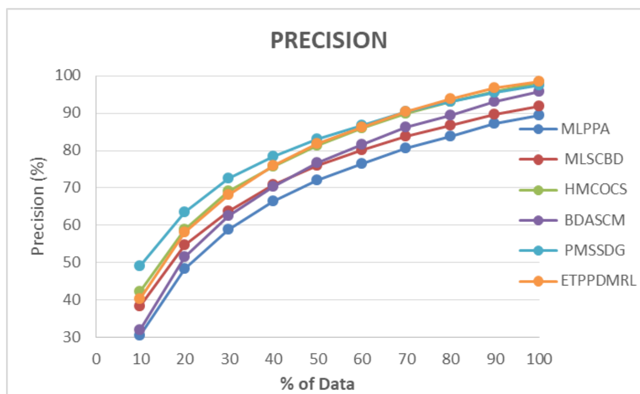

Figure 6: Precision

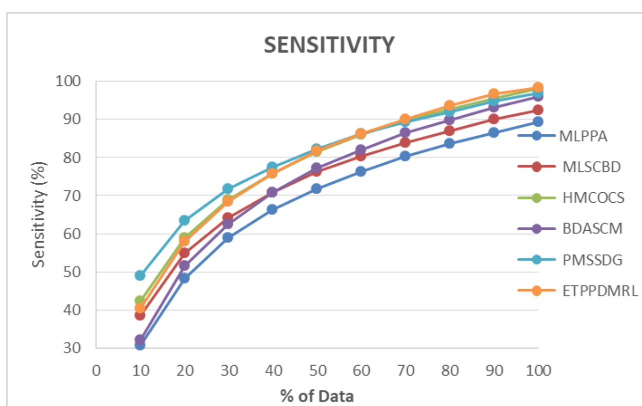

Figure 7: Sensitivity

prescriptions is very important in prescriptive analytics to reduce the false positives. Higher specificity index refers the higher quality of the classification or prescriptive analytics algorithm.

Specificity is calculated using the formula $\frac{TN}{FP+TN}$.

Enumerated specificity for 100% of data are 98.31%, 98.22%, 97.56%, 95.72%, 91.83% and 89.39% secured by ETPPDMRL, HMCOCS, PMSSDG, BDASCM, MLSCBD and MLPPA. A perceived improvement of 1.09% of specificity is consummated by the ETPPDMRL method than the nearest performer HMCOCS with the value 98.21%. A comparison of Specificity is shown in Figure 8.

F-Score

F-Score is a parameter used to measure the resonance between the Precision and Sensitivity. It is very similar to accuracy, that is, higher F-score rerefers higher quality of the prescriptions generated. The objective of measuring F-Score is to amalgamate the overall performance of both precision and sensitivity. F-Score is calculated using the formula $2\times\frac{Precision\times Sensitivity}{Precision+Sensitivity}$.

A progression of 0.22% is achieved in F-Score parameter by ETPPDMRL method over the F-Score of 98.09% which is achieved by the HMCOCS method. Since F-Score is the consolidation of both Precision and Sensitivity, it is realized that the overall performance of ETPPDMRL method is improved than the other methods. The comparison graph for F-Score is provided in Figure 9.

Average Processing Time

Processing time is one of the notorious parameters in the evaluation of any algorithm. It is getting furthermore precedency while processing large volume of data. Processing time is a inversely proportional parameter to the performance. That is, the higher processing time indicates the lower processing speed of the algorithm. In general, the unit of the Processing time is measured in milliseconds (mS) unit.

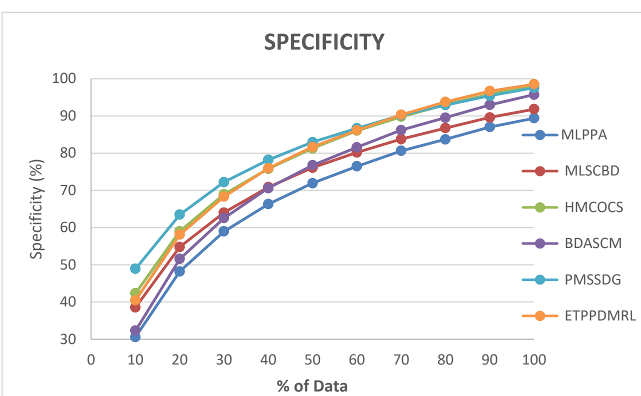

Figure 8: Specificity

Average processing time is calculated using the formula

$$\frac{1}{N}\sum_{i=1}^{N}(\tau_{c_i}-\tau_{s_i})$$

where τ_{c_i} is the completion time of i^{th} event and τ_{s_i} is the starting time of i^{th} event.

As per the experiments conducted, it is observed that the minimum average record processing time is 2004mS which is consumed by ETPPDMRL while processing 60% data. The performance rank wise sequence of existing and proposed method is ETPPDMRL, MLPPA, BDASCM, MLSCBD, PMSSDG and HMCOCS with the overall average record processing times 2021mS, 2078 mS, 2142mS, 2254mS, 2532mS and 2696mS.

Based on the average record processing time parameter, existing MLPPA method performs closely with the best performance ETPPDMRL. The HMCOCS method secured the 2nd position in the parameters such as Accuracy, Precision, Sensitivity, Specificity and F-Score. But while considering processing time, this method consumed very high processing time of 2717mS while processing 30% data chunk. The Average Processing time comparison is illustrated in Figure 10.

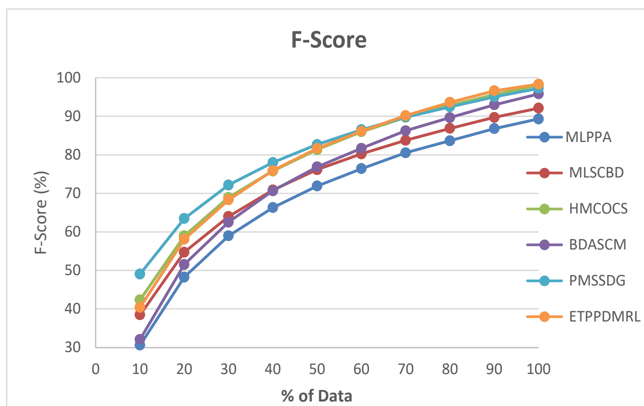

Figure 9: F-Score

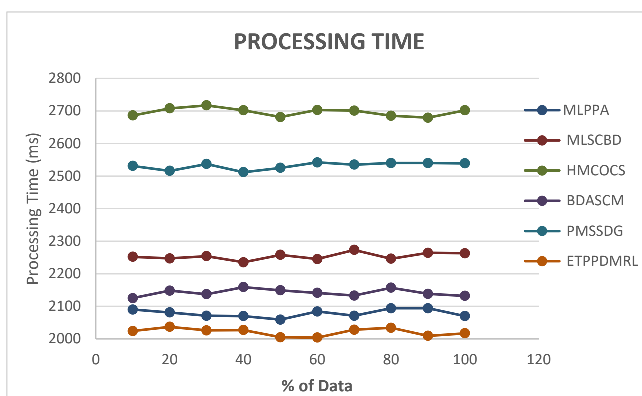

Figure 10: Average Record Processing Time

Conclusion

A prescriptive analyzing method named as ETPPDMRL is developed for product manufacturing and supply chain management in this work. ETPPDMRL operates based parsing and by sentiment analyzing of the user reviews. A dedicated parser with multiple lexicons is developed for RL in particular. C4.5 Decision Tree based prescriptive generator is also introduced in this work. Both Enhanced Text Parser for Reinforcement Learning and C4.5 Prescriptive Decision maker are submitted here as the novel contributions of ETPPDMRL work. Based on the experiments carried out and the outcome results, it is understood that the performance of the introduced modules working in harmony with each other and the overall performance is improved to the mark. The lowest processing time ensures that the ETPPDMRL method could be recommended to apply in real-time to improve the supply chain management considerably.

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Conflict of Interest

None

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