Development of an Ensemble Modeling Framework for Data Analytics in Supply Chain Management

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Abstract—**The application of Data Analytics (DA) in Supply Chain Management (SCM) provides a plethora of opportunities for improving the performance, efficiency, and resilience of organizations by predicting the behaviour of the supply chain network. In this regard, the use of complex DA approaches that involve the combination of multiple Machine Learning (ML) models such as the ensemble approaches have shown to be highly effective in improving prediction accuracy and model performance. Still, the application of these ensemble approaches has not yet been properly explored in SCM analytics. Thus, this paper presents an ensemble model framework specifically designed for SCM issues by exploring problem types and use cases where ensemble approaches can be applied in SCM. The developed framework enables the selection of the right ensemble models for specific SCM DA tasks. Thus, this paper contributes to the scientific body of knowledge by presenting a systematic approach to ensemble modelling in SCM analytics by outlining suitable ensemble model compositions for different SCM use cases and data analytics problems. Hence the results of this paper provide a potential tool for DA practitioners in SCM to further improve the performance of their Supply Chain (SC) networks by selecting appropriate ensemble elements for different SCM analytics problems.**

Keywords—**data analytics, ensemble model, consensus algorithm, supply chain analytics, predictive analytics, machine learning**

I. Introduction

Supply Chain Management (SCM) encompasses the complex interactions of different entities and organizations that perform different roles to foster value creation. Thus, SCM comprises multiple processes ranging from, manufacturing and distribution to sales for example. In this process, lots of data are generated, which can be analyzed using Data Analytics (DA), thus improving the efficiency of SCM activities [1]. In this regard, previous research has shown that the integration of DA and ML algorithms in SCM can result in a considerable improvement in performance and efficiency in the (SC) [2–4]. Still, the application of advanced analytics approaches for addressing different DA problems is limited by several challenges [5, 6]. The use of data analytics techniques to improve organizations' competitiveness and efficiency is affected by the fact that limited research has been done to date on the use of advanced DA techniques in SC planning and execution [5]. Mohamed *et al.* [6] identified a lack of well-defined techniques and the need to alter existing analytics methods to address the complexities of SCM operations as the challenges affecting the use of advanced analytics in SCM.

The hybrid combination of multiple algorithms is an advanced DA technique that has shown promising results in improving the quality and accuracy of predictions in SCM. For example, recent work has shown the combined application of clustering and forecasting ML algorithms to predict product sales in PoS retail [7]. Results indicate that the combination of multiple algorithms in a hybrid manner produces better results in forecasting sales compared to using models separately. Ensemble modelling is an example of hybrid analytics that involves the use of multiple models in parallel with an algorithm that combines the results from multiple models into one [8]. These types of modelling approaches have been shown to improve the prediction accuracy and performance of ML models dealing with supervised classification problems. In addition, in unsupervised clustering, the robustness, stability, and accuracy of unsupervised problem classification models could be increased [9, 10].

Previous research has shown the application of ensemble approaches in SC-related analytics and recently, due to Covid-19-related disruptions, the application of DA in SCM has received growing attention [11, 12]. The research studies [12–17] show the application of ensemble approaches in different use cases in SCM. However, there is still a lack of research into a systematic approach to applying the ensemble model and corresponding model constituents for addressing data analytics problems and use cases in SCM analytics. This research gap is expanded on further in the literature review section. In line with the previous work in [18], we consider DA problems in SCM as business issues that occur in different processes of SCM which analytics and ML algorithms are employed to solve.

Manuscript received March 30, 2023; revised May 5, 2023; accepted July 25, 2023; published November 27, 2023.

doi: 10.12720/jait.14.6.1289-1300

Thus, the focus of the current paper is to systematically develop an ensemble modelling framework for addressing DA problems that occur in the context of SCM. Hence, this paper contributes to the scientific body of knowledge by presenting the development of an ensemble modelling approach specifically for problems encountered in SCM. Furthermore, since ensemble approaches have been shown to perform better than single ML models [9, 10], this paper provides a model selection tool to help practitioners in SC analytics in choosing the right ensemble constituents for different analytics tasks, thereby, improving the general performance of their models. The main research question for this paper is how to design an ensemble modelling framework for addressing DA problems in SCM? To answer the main research question, this paper examines related articles that have developed ensemble approaches for different problem types and use cases. In the paper, the main DA problems in SCM according to [18] are considered as the input for generating an ensemble modelling framework. Thus, the ensemble framework for SCM is developed by mapping the general context of DA problems and use cases to SCM contexts. Additionally, the framework is demonstrated with selected SCM problems which are represented by data questions. For clarity, the main research question of this paper is divided into three sub-questions as follows:

1. What are DA problem types and use cases that can be addressed by ensemble modelling?
2. What are the ensemble approaches and consensus algorithms that are commonly used for the identified problem types and use cases?
3. What are the adaptations necessary for the development of an ensemble modelling framework for SCM?

The first research question provides an understanding of different DA problem types that are addressed using the ensemble approaches and shows the use cases for which custom ensemble approaches were developed in previous work. The second question helps in understanding the ensemble approaches adopted for different use cases and the consensus algorithms used in combining the individual ensemble models' results. The third question elaborates on which parts of the analyzed ensemble approach modifications and adaptations were made to generate a custom ensemble modelling framework for SCM.

The rest of the paper is structured as follows. Section II provides a literature review and theoretical foundations of the ensemble approach and its elements. Section III describes/defines the scientific methodology used in answering the research questions developed for this paper. Section IV presents the results of the conducted literature review, covers the development and demonstration of the SCM ensemble model selector framework and discusses the results. Section V, the conclusion highlights the studies limitations and provides an outlook for future research.

II. BACKGROUND

This section presents the literature review, relevant data analytics problems in SCM and the theoretical foundations for defining the concepts of ensemble modelling approaches.

A. *Ensembles in Supply Chain Management (SCM)*

Safara [12] shows the application of classification ensemble models for predicting consumer behavior during the Covid-19 pandemic period. The use of ensemble classification has also been applied in forecasting product sales in Inedi *et al*.'s previous research [13]. Vasavi *et al*. [14] explored the application of ensemble models comprising two neural network algorithms in predicting the state of delivery vehicles. Zhu *et al*. [15] provides an ensemble approach for improving the ordering system and production priority in supply chains. The proposed approach involves the use of Radial Basis Function (RBF), Kriging, and Support Vector Regression (SVR) models in obtaining a predictor priority for a new order and thereby assigning the order schedule in the production. Haque and Moscato [16] provides a systematic review of trends in ensemble modelling in business applications. The result identified the following areas of business analytics for the successful application of ensemble modelling, including purchase and marketing analytics, predictive analytics, business process management analytics and customer churn analytics. Liu *et al*. [17] proposed an ensemble approach for demand forecasting using a balanced sampling method based on support vector regression.

Although research works [12–15, 17] show various SCM use cases and applications of ensemble modelling, they do not provide a general context of DA ensemble within the various processes in SCM. Brandtner *et al*. [18] identified SCM processes such as customer activities, procurement, forecast and planning, packaging and handling, transportation, warehousing and inventory management with their data problems that can be addressed with ML analytics. The ensemble approaches in Inedi *et al*. [13] and Haque *et al*. [16] focused on forecast and planning SCM activities, while Safara [12] focused on customer activities. None of the papers provides a systematic ensemble approach that covers the majority of SCM activities. Although Haque and Moscato [16] identified potential business areas for applying ensemble, it does not provide specific ensemble models and ensemble model constituents applicable to the identified business analytic use cases.

B. *Data Analytics Problems in Supply Chain Management (SCM)*

Various problems and uncertainties are encountered in the processes of SCM, and predictive data analytics provides the possibility for solving these problems. These problems range from understanding the future demands of a product, predicting product availability during different seasons of the year, ensuring on-time delivery of goods, *etc*. Brandtner *et al*. [18] already explored the main activities of SCM and systematically identified the main problems that can be addressed with DA. The problems are represented as important data questions for predicting risks, uncertainties, and abnormalities that can occur in an SC. The DA questions relevant to SCM are presented in

Table I. This table thereby provides the initial input for developing an ensemble model selector framework for the SCM domain by mapping question types to general Machine Learning (ML) problems and corresponding ensemble models for predicting a given dependent outcome.

The SCM DA problems addressed in previous studies [12–14] can also be mapped to the data questions outlined in Table I. The analyses of consumer behavior during the Covid-19 period in [12] can be mapped to data question number 12, which seeks to understand the loss of customers due to disruptive events. The application of the ensemble approach in [13] to predict the number of product sales in retail can be mapped to data question number 4, which seeks to understand product availability in a store. Vasavi *et al*. [14] applying the ensemble approach to monitoring the state of logistics vehicles can be mapped to data question number 2 that seeks to ensure the on-time delivery of products in retail.

C. Theoretical Foundations in Ensemble Modeling

The main elements of an ensemble approach are the model generators that produce the prediction models and the consensus algorithm that unifies the models' outputs into a single prediction [8]. Therefore, the theoretical foundation of this work focuses on ensemble model generators and consensus algorithms.

TABLE I. DATA QUESTIONS IN SCM [18].

No.	Data Questions
1	Which cost and time factor combinations have the highest impact on SCM cost and sales?
2	How do delivery paths (procurement or transport) result in early/late deliveries?
3	What group of suppliers and what cases (of timing, locations, transportation types *etc*.) will most likely have (what levels of) full deliveries?
4	What groups of products will always be available/out-of-stock in the inventory?
5	What are the most critical cost/time factors that affect supply chain revenue?
6	What are the sustainability-related costs/time factors that have the most impact on operational costs?
7	Does the use of sustainable transport/delivery paths affect operational costs and delivery time?
8	What is the most efficient sustainable (procurement and transport) delivery path?
9	Does practicing sustainable warehousing result in the non-availability of products or increased op. costs?
10	How does customer satisfaction due to sustainable activities (packaging, products or transportation) attract? new customers?
11	What disruptive events will result in the loss of customers?
12	How does unsupplied material resulting from a disruption affect total revenue/out-of-stock rate?
13	What group of suppliers will likely deliver supplies late because of a particular disruptive event?
14	What are the supply/delivery paths or transportation types that are the most efficient during disruptions?
15	How much does disruption of deliveries affect sales/revenue in SCM?

1) Ensemble generation: Ensemble generation shows how the ML models are generated, combined and organized to address a given problem [8, 10]. Since the different types of ML models are used in predicting the results for different problem types, the model composition in an ensemble approach involves the aggregation of similar models for the given prediction problem. There are many models for different problem types such as supervised classification algorithms, unsupervised clustering models etc. Thus, it is important to combine the models in a systematic way to generate the best prediction results. The models can be combined by growing or pruning. Growing and pruning involve systematic increments and decrements in the model combinations respectively [19]. The goal is to find the optimal model combinations that produce the best performance/result.

In a hybrid ensemble approach, models are organized parallel to each other, however, the variations that exist show how data inputs are fed into the models and the results aggregated across each model. The three common approaches for combining ensemble models are bagging, stacking, and boosting [20]. In bagging, different records of a dataset are provided as input to the same ML model. In stacking and boosting, the same data input is provided for a similar type of ML model, however, for boosting, the errors/performance of each model are considered when computing the final prediction result.

2) Ensemble consensus: The consensus ensemble provides the algorithm for combining the different predictions produced by each of the individual ensemble models into a single result [8, 10]. Similar to the ensemble generator, different consensus algorithms are commonly applied for different ML problem types, supervised and unsupervised problems.

In supervised classification, the consensus algorithms are easier to implement and understand since the results produced by the ensemble models are mostly similar. Consensus algorithms developed for classification problems are referred to as group decision making algorithms and are commonly generated from variations of individual voting produced by each ensemble model [9].

In unsupervised problems, the consensus is that algorithms are more complex since clusters produced by each model can be entirely different from the other model clustering models. As a result, consensus algorithms that seek to combine these different clusters into one result are usually considered an optimization problem of finding the optimal cluster configuration that maximizes the performance and stability of the ensemble prediction models [10].

III. MATERIALS AND METHODS

To describe the methodology of this paper, first, we present the steps used in collecting relevant data for the analyses conducted in this work. Then, we show the analysis method, capturing the phases of the analyses and items used in presenting the results.

A. Data Collection

A systematic literature review of relevant papers was conducted in accordance with [21] to provide answers to the three research questions defined in the initial part of this paper. Selected literature articles are examined to understand the problem types and specific use cases, where the ensemble approach was developed to address a custom problem.

The keywords "consensus" and "ensemble" were used for searching and initially selecting relevant papers from the Scopus database. The Scopus database is selected for searching relevant articles for systematic review because this database is superior to all other academic databases, and it also covers over 99% of articles indexed in the web of sciences [22]. First, selected papers were analyzed based on their abstracts and were selected for further analyses if an ensemble modelling approach was developed and applied to a specific and elaborated use case. Thus, only articles that developed and applied customized ensemble approaches and also applied them in a clear use case are considered relevant. General review papers are ignored. The initial search returned 85 documents. After filtering by the mentioned criteria, 15 articles were selected for final analysis.

B. Analysis Method

A quantitative analysis was conducted based on the data collected to provide answers to the research questions. Three high-level properties are used in analyzing the selected articles. The first property is the ensemble properties, the second is the use case properties and the last category is the specific ML models. These three high-level analytic properties, representing the stages of analyses conducted, will help to provide the necessary understanding to answer the research questions for this paper.

1) Ensemble properties: The following items are examined under ensemble properties: DA problem type, ML model type, consensus approach, ensemble model organization and modifications made. The problem type maps each paper into supervised and unsupervised ensemble applications. The ML model type examines the type of machine learning models that are comprised in the ensemble model such as classification, regression, anomaly detection or clustering models. The consensus approach identifies and classifies how the consensus algorithm that combines the models' results works. The ensemble model organization shows how the individual ensemble models are organized, such as bagging, boosting, and stacking [20]. The modification shows the improvement applied to the conventional ensemble approach to developing the custom approach presented in the respective paper. Understanding the modifications and improvements to the traditional ensemble methods will provide useful input for developing our custom ensemble modelling framework for SCM-related problems.

The justification for selecting the items is as follows. The "DA problem type" is selected because it is specifically mentioned in the first research question. Thus, this item helps in mapping general DA problems to SCM-specific contexts captured in [18]. The "ensemble model organization" and "consensus approach" are selected as analysis items because they are important properties for describing any new or customized ensemble approach [8, 10]. The property "ML model type" is used because it provides a class for logically grouping similar models in each custom approach since ensemble approaches generally involve the parallel use of similar ML models [8]. The property "modifications" is used to identify the changes made in conventional ensemble approaches in the development of the custom approach.

2) Use case properties: The following items are included in this category: organizational domain and purpose. The organizational domain shows the business application for which the custom ensemble approach is developed. The purpose identifies the objective for applying the ensemble model in the use case. The objective could be to predict the unwanted risky situation in a business use case or to detect a behavioral anomaly in a particular network. Understanding these objectives and model types used in the ensemble will be useful in mapping SCM data-related problems to different ML ensemble algorithms for a similar type of analytics objective, for instance, objectives related to identifying the anomalies in the SC network or predicting unwanted risky behavior such as supply delays and product unavailability.

The justification for the selection of these two items "organizational domain" and "purpose" for the use case properties is that in describing a use case of new technology (e.g., custom ensemble approaches), it is necessary to understand the different types of organizations and businesses to which the technology is applicable and the purpose of such applications.

3) Machine learning models: This property examines the frequency count of different ML algorithms used in the different papers analyzed for custom ensemble approaches. This will help in understanding the appropriate models that can be used in similar SCM analytics based on DA problem types and use cases identified in the first and second stages of the analyses respectively. The justification for the selection of this property is that it helps to present the actual ML models subsumed by different ML model types identified in the first stage of the analyses (Ensemble properties -> ML model types). Thus, the most frequently reoccurring ML model types identified in the first stage of the analysis provide the analysis items for ML models.

IV. Result and Discussion

This part of the paper presents the results and discussions of the results. The findings of this paper are presented in two parts. The first is the presentation of the result analysis of ensemble properties from the literature, the second the development and demonstration of the ensemble framework for supply chain analytics.

A. Result Analyses of Ensemble Properties in Literature

Table II contains the quantitative summary of the analyzed papers. The first column shows the numbering of items from the high-level properties (such as ensemble properties, use case properties and ML models) used in presenting the analyses from this work. The second column shows the actual labels of the analysis items' use case. The third column shows the results of the analysis items for each of the high-level properties. The fourth column shows the article count for each result. The last column contains the references of the related articles for each analyzed item.

1) Problem types and use cases

The results show that the articles that developed a custom ensemble approach for their given use case are equally divided between supervised and unsupervised learning problem types.

TABLE II RESULT ANALYSIS OF ENSEMBLE PROPERTIES FROM LITERATURE

A	**Ensemble properties**	**Items**	**Article count**	**Articles**
1	DA problem type	Supervised learning	8	[9, 23–29]
		Unsupervised learning	7	[23, 27, 30–34]
2	ML model type	Classification	6	[9, 23, 25–27, 29]
		Clustering	5	[23, 31–33, 35]
		Anomaly detection	2	[30, 31]
		Others	3	-
3	Consensus approach	Distance/ similarity matrix	4	[23, 25, 31, 32]
		Weighted voting	3	[24, 26, 31]
		Majority voting	3	[23, 26, 27]
		Graph cut-based consensus	2	[34, 35]
		Others	4	-
4	Ensemble models organization	Stacking	8	[9, 23, 26, 28, 29, 31, 33, 36]
		Boosting	4	[24–26, 29]
		Bagging	3	[29, 31, 32]
		Combined (Ba+Bo) or (Ba + St)	2	[31, 35]
5	Modifications	Ensemble models selection	8	[23–26, 29–31, 35]
		Feature selection	4	[27, 28, 32, 33]
		Consensus algorithm	3	[9, 31, 34]
		Others	3	-
B	**Use case properties**	**Items**	**Article count**	**Articles**
1	Organizational Domain	Healthcare	6	[27, 28, 31–33, 35]
		Information security	4	[25, 26, 29, 30]
		Others	4	-
2	Purpose	Risk prediction	6	[9, 25–27, 29, 35]
		Network structure/ behaviour	5	[24, 28, 21–33]
		Abnormal behaviour	2	[30, 31]
		Categorization	2	[30, 31]
C	**ML Models**	**Items**	**Article count**	**Articles**
1	Supervised classification	SVM	6	[9, 23–27]
		RF	5	[9, 23, 25, 26, 29]
		NN-MLP	5	[9, 23, 25–27]
		LR	3	[23, 25–27]
		DT	4	[9, 23, 25, 26]
		BN	4	[9, 23, 25, 29]
2	Unsupervised clustering	K-means	2	[23, 32]
		SOM	2	[23, 35]
		Others	4	-
3	Anomaly detection	Isolation forest	2	[30, 31]
		Local outlier factor	2	[30, 31]

NB: only repeated properties are listed, and non-repeated items are categorized under 'others'
Ba+Bo is bagging and boosting combined
Ba+St is bagging and stacking combined

Supervised learning is an ML problem type for which the dataset can be divided into training and test data, whereas in unsupervised learning, a single dataset is provided as input [37].

Refining the supervised and unsupervised learning problems further shows the ML model types commonly used in custom ensembles, including classification, clustering and anomaly detection algorithms. Classification algorithms are used in supervised learning problems while clustering and anomaly detection are used in unsupervised learning.

Healthcare and information security are the common business domains for which custom ensemble approaches are developed. This could imply that these are the sectors where increased model performance and accuracy are in high demand. Complex ensemble modelling is applied to these use cases for risk prediction, predicting network structure or behavior and predicting abnormal behavior. These types of objectives also exist in SCM. Due to the complexity of a given SC network, it could be necessary to apply an ensemble approach to predict the risk of delays in the delivery of a product or predict abnormal behavior that is occurring in the network in a specific time interval.

2) Application of ensemble and consensus approaches

The results show that the ensemble models are usually organized in the traditional method of stacking, boosting, and bagging, representing the order in which they are commonly used. There is a combination of bagging and either the stacking or boosting methods as shown in [31, 35]. The findings also show that boosting is commonly used in supervised problems. This is because boosting methods are used for calculating the weight of each model in contribution to the final result, which is usually not the case in unsupervised learning.

The consensus methods commonly used in the articles are distance or similarity matrix, weighted voting, majority voting and graph partitioning in the order in which they are commonly used in the analyzed articles. Similarity matrix and graph partitioning are commonly used in unsupervised clustering problems while weighted voting and majority voting are commonly applied to supervised classifications. The similarity matrix involves mapping partitions produced by cluster ensemble into an intermediate representation. Graph-based consensus transforms cluster combination problems into graph problems such as hypergraphs and bipartite graphs [38]. Majority voting requires more than 50% of the ensemble models to give the same prediction label. Weighted voting considers the error produced by each ensemble model in training when combining the models' results [39].

3) Adaptations necessary for SCM-focused ensemble approaches

The results show that for custom ensemble approaches analyzed, most modifications and improvements are applied to the ensemble model generator part of the ensemble composition. The other areas of improvement are feature selection and consensus algorithms. For most improvements, different methods were developed for pruning the ensemble models into an optimal number of models that results in improved model performance. For the feature selection, these ensemble approaches are developed to reduce the high dimensional dataset into a reasonable number of features that results in improved ensemble performance. Feature bagging is used in [35] to show the application of different features of a dataset to the same model which are then stacked across similar models. The generation of a custom consensus algorithm is the area where modifications were recorded the least in the examined papers.

B. Development and Demonstration of SCM Ensemble Modeling Framework

Using the results presented in the first part of Section IV as input, this section describes the ensemble model selector framework developed for SCM analytics and provides a simulation demonstrating the use of the ensemble framework to address SCM data problems.

1) Development of SCM ensemble model selector framework: Reflecting on our results shows that in developing a custom ensemble approach for SCM-related problems, the focus must be placed on the ensemble model composition while common consensus approaches for supervised and unsupervised learning are used for the problem type predicted by the ensemble model. Thus, mapping SCM data questions (as shown in Section II-A of this paper) to ML problem types (supervised and unsupervised learning), to objectives (risk prediction, network behavior prediction and abnormal behavior prediction), to ML models (classification, clustering and anomaly models) systematically provides the basis for an ensemble modelling framework for SCM.

With the mapping approach presented above, different ML algorithms are preselected for the SCM data question investigated. Also, considering whether the data question is mapped to supervised or unsupervised learning, specific consensus algorithms suitable for these types of problems are recommended. Thus, with this approach, ensemble problems are not treated differently and independently as either clustering problems or classification problems. Rather, data analytics problems related to the SCM domain are considered holistically, where a question mapper is used to map the question into supervised or unsupervised learning, and model generators consider the objective of the analysis in recommending suitable ML algorithms. Lastly, a common consensus suitable for either supervised or unsupervised learning is recommended. Therefore, the necessary modifications necessary for developing a custom ensemble approach for SCM include an SCM data question generator, question mapper, model selector based on the objective of the analyses and the supervised/unsupervised learning consensus selection.

2) Description of SCM ensemble modeling framework: Fig. 1 shows the structure of the SCM ensemble modelling framework, covering supervised classification, unsupervised anomaly prediction and unsupervised clustering. Using the results of the analyses conducted in the previous section, the main elements of the developed framework include the question mapper and ensemble recommender.

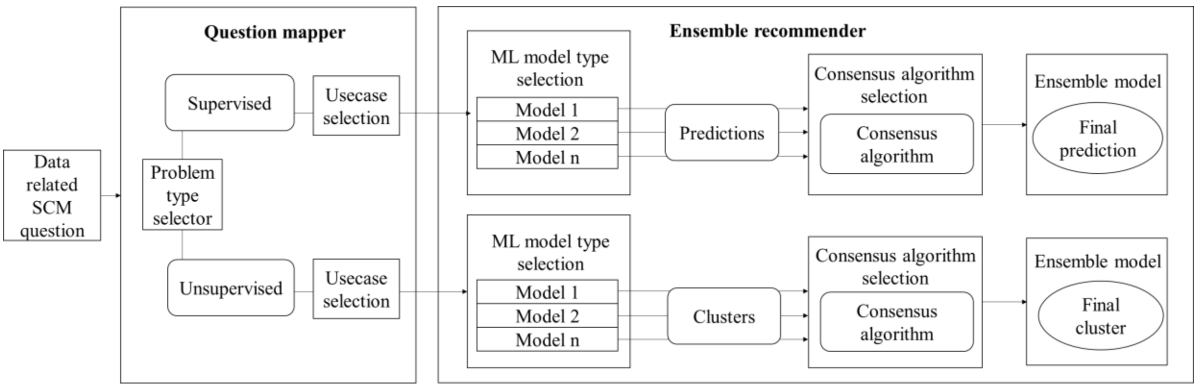

Figure 1. Ensemble modeling framework for DA in SCM.

Question Mapper: this element helps in identifying the problem type and derived use case SCM data analytics questions can be mapped to. As in a real-world application this mapping can be done using multiple approaches (e.g., if-then else rules, lookup matrix, machine learning), we do not specify a mapping method which must be applied. How we applied the mapping, in a first demonstration of the framework, can be seen in Section IV-C.

- Problem type selection: The analyses conducted in the previous section identify two problem types and include supervised learning and unsupervised learning. Thus, the sample data analytics questions presented in Section II-A can be mapped into supervised and unsupervised learning problems.
- Derived use case selection: four derived use case properties are generated from the examined articles. They are risk prediction, categorization, network behavior, anomaly detection. DA questions related to the prediction of the structure or behavior of the SC network are mapped to network behavior prediction use cases. Questions related to predicting unwanted behavior in the SC are mapped to risk prediction use cases. Questions related to predicting different classes of results are mapped into categorization use cases. Lastly, questions involving abnormal occurrences in the SC are mapped to abnormal behavior use cases.

Ensemble recommender: this element provides recommendations on ensemble members such as, which ML Model type to select, which consensus algorithm to choose, and which ensemble model to create for the given SCM DA questions:

- ML Model type selection: three model types are repeatedly used in ensemble problems based on the findings of this paper and they include classifications, clustering, and anomaly detection, models. By providing a DA question and mapping the question to the respective supervised/unsupervised learning problem type and selecting the derived use case, the relevant model type is recommended.
- Consensus algorithm selection: based on the findings, the common consensus for unsupervised learning is the similarity matrix algorithm. For supervised learning, majority voting and weighted voting are common but they are also applicable to unsupervised problem types.
- Ensemble models: by analyzing the related articles, commonly used ensemble models for specified problem types, derived use case and ML model types are identified. Risk prediction is a binary classification of unwanted situations. The following are identified for supervised risk classification models: Linear Regression (LR), Support Vector Machine (SVM) and Neural Network Multilayer Perceptron (NN-MLP). Categorization is a prediction of multiple classes or levels of the outcome. The following are identified for supervised categorization classification models: Decision TreE (DT), Random Forest (RF), Bayesian Network (BN), Neural Network (NN) etc. Anomaly prediction is a cluster of unusual events. The following are identified as unsupervised abnormal behavior models: isolation forest and local outlier factor: Network behavior prediction is a cluster of multiple categories. The following are identified as unsupervised network behavior clustering models: Self-Organizing Maps (SOM), k-means and fuzzy k-means.

C. Demonstration of SCM Ensemble Modeling Framework with DA Questions

To illustrate how our framework works, we provide an example of how a user can find a suitable ensemble method for their data analysis task. Since this is a prototype, the user has to select from a pre-defined group of questions that cover the most encountered scenarios in SCM mentioned in Section II-A.

First, the user must identify if the used data set is suitable for supervised or unsupervised learning, based on the availability and quality of the available data. Second, the user must identify which use case the problem belongs to (network behavior, categorization, risk prediction and abnormal behavior prediction). Third, the user is offered a choice of machine learning model types suited to the selected use case (classifications, clustering, or anomaly detection). Fourth, the user can choose a consensus algorithm suited to the selected machine learning model type (e.g., similarity matrix algorithm, majority voting, weighted voting, *etc*.). Fifth, the user is presented with a list of machine learning models (e.g., LR, SVM, DT, BN, *etc*.) that can be used in an ensemble model based on the selected consensus algorithm.

To practically demonstrate our conceptual ensemble modelling framework, we developed a prototype using the decision tree logic simulation in Power-BI [40]. The decision tree logic simulation uses the frequency of mentioned problem types, derived use cases model types, consensus, and ensemble models, gathered from the papers in the conducted literature review, to create an easily accessible overview of the most suggested ensemble models in literature for the specific SCM-related questions depicted in Table I. We selected four questions to exemplify all the derived use cases (risk prediction, categorization, abnormal behavior prediction, and network behavior). These are presented below.

1) Supervised risk prediction: The DA question "How do the delivery paths (procurement or transport) result in early/late deliveries?" seeks to predict the risk of late delivery by using the external data relating to SC paths as the input data. This is a binary prediction since the result of the prediction is either early or late for any given SC path parameters. Fig. 2. shows the ensemble members useful for predicting the list of late delivery. By mapping this question to supervised learning and mapping the derived use case to risk prediction, the simulation suggests the model type, consensus algorithm, and ML models for the ensemble. The suggested model type is classification, and by selecting majority voting, the following ML models are listed: LR, NN-MLP, and SVM.

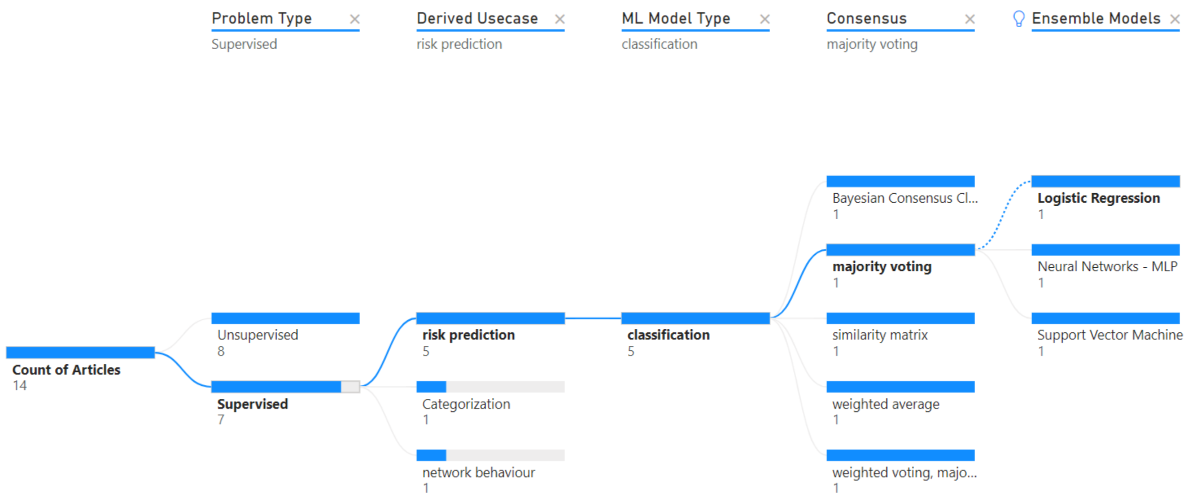

Figure 2. Supervised risk prediction ensemble.

2) Supervised categorization: The DA question "What group of suppliers and what cases (of timing, locations, transportation types etc.) will most likely have (what levels of) full deliveries?" is considered a categorization problem since the prediction result will provide a different level of product deliveries which could be categorized into, for example, empty delivery, half-full delivery, full delivery etc. Fig. 3 shows the simulation of ensemble elements for the categorization problem. By mapping this question accordingly into a supervised categorization problem, the ensemble members suggested are as follows: The model type is classification algorithms, the consensus is majority voting and models include DT, RF, NB, NN-MLP, etc.

3) Unsupervised network behavior: The DA question "What are the most critical cost/time factors that affect supply chain revenue?" is considered an unsupervised network behavior prediction since the objective is to cluster the network properties based on the time and cost behavior. By mapping this question accordingly in the simulation as depicted in Fig. 4, the following ensemble members are suggested. Model type is clustering algorithms, consensus algorithm is similarity matrix, and models are fuzzy k-means, SOM, k-means, etc.

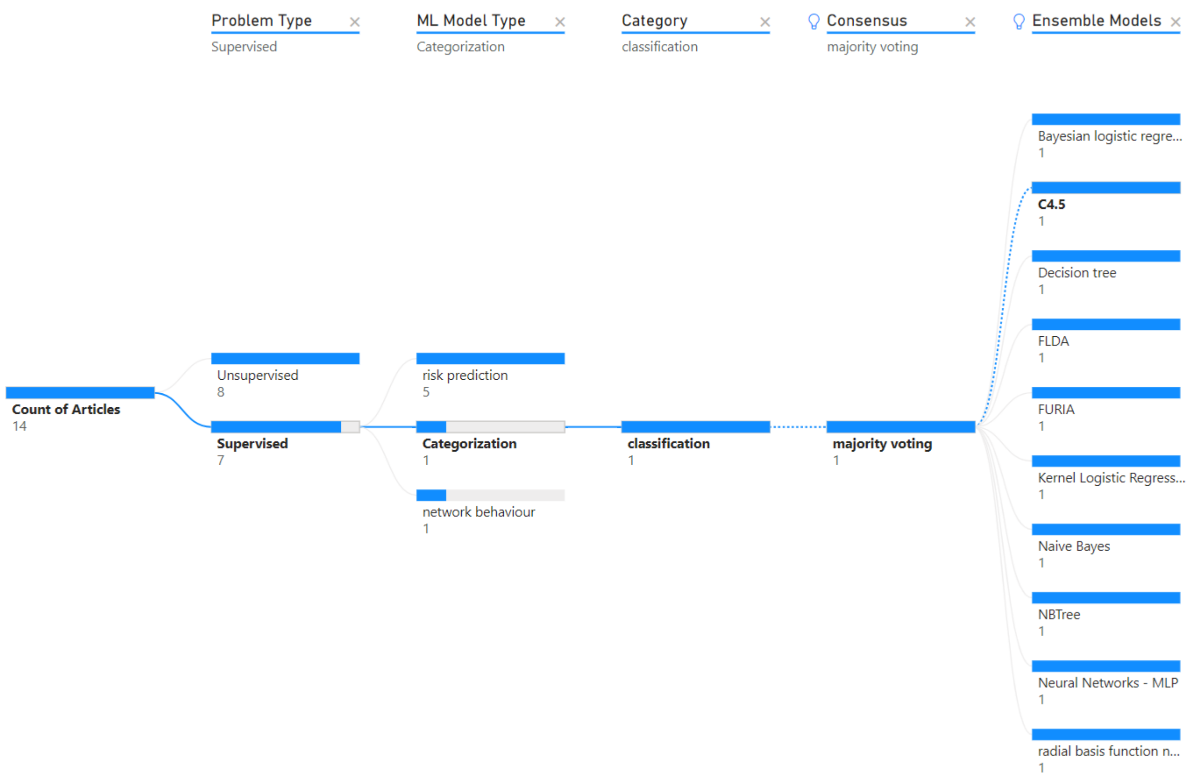

Figure 3. Supervised categorization ensemble.

Figure 4. Unsupervised network behavior ensemble.

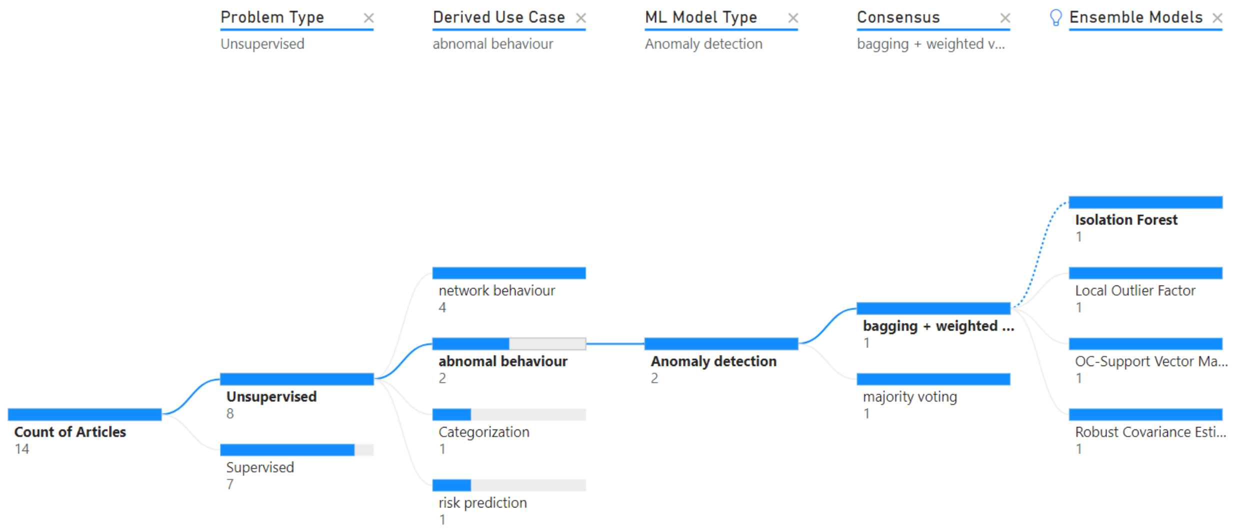

Figure 5. Unsupervised anomaly detection ensemble.

4) Unsupervised abnormal behavior

The DA question "What groups of products will always be available/out-of-stock in the inventory?" can be considered as an unsupervised anomaly prediction because the objective is to cluster out-of-stock anomalies that occur during the sale of different products. By mapping the question accordingly in the simulation as depicted in Fig. 5, the following ensemble members are suggested. The model type is the anomaly detection model, and by selecting majority voting as consensus algorithms, the models listed include isolation forest, local outlier, and elliptic envelope.

D. Discussions

The discussions resulting from this work are considered within two major themes, which are the managerial implications of the ensemble framework for SCM and the scientific implications in model selector development.

Considering the practical implications, as highlighted in an earlier study [18], the purpose of DA application in SCM is to increase efficiency by improving the performance, resilience and sustainability of SCM processes. Thus, by applying ensemble approaches, SC managers can reduce uncertainties in their network due to better prediction accuracy. Ensemble approaches have been shown to have better prediction performance than conventional methods [9, 10]. However, SC managers are limited by the lack of custom DA approaches for addressing various complexities in SCM processes [6]. Our approach contributes to SCM as a potential tool that can help SC managers to reduce the uncertainty in their network, by using our model selector tool (as demonstrated in Figs. 2–5) in choosing appropriate ensemble elements such as ML models and consensus algorithms to predict the behavior of their SC networks, identify anomalous occurrences, categorize expected outcomes and predict potential risky occurrences in the network. Thus, with our framework, common DA problems and uncertainties that occur in SCM such as out-of-stock anomalies and risk of late deliveries as shown in [18] can be addressed with the right ensemble elements with improved prediction accuracy.

Considering scientific implications, Udokwu *et al.* [41] provides a systematic analysis of research gaps and potential opportunities for the application of DA in SCM. The paper identifies the lack of skilled experts as one of the issues limiting the use of DA in SCM. A skilled expert is expected to have a good understanding of SCM processes and a technical understanding of DA approaches, techniques, and tools for addressing data problems in SCM. This work extends the previous work in [41] by developing an ensemble model selection tool that will equip DA experts to improve the performance of their various SCM analytic tasks. As such, the tool aims to provide guidance and recommendations on how to choose the appropriate ensemble models for different types of SCM questions and data sets, based on a literature review and a decision tree logic. The tool also aims to enhance the usability and flexibility of the DA methods by allowing the user to select from a pre-defined group of questions. Therefore, we expect the tool to reduce the complexity and uncertainty involved in selecting and applying DA methods in SCM and thus to improve the accessibility, accuracy, and reliability of the results. Moreover, to the best of our knowledge, this is also a first paper showing which machine learning models can be used to construct a specifically suited ensemble model based on a specific supply chain management related question.

To provide comparative discussions of results obtained with our work and other similar works, we provide examples of SCM DA use cases that applied ensemble models. Safara [12] applied ensemble models to predict the risk of customer loss due to Covid disruption and used models such as SVM, DT, Artificial Neural Network (ANN) and NB. Considering a similar use case of risk prediction (See Fig. 2), our framework suggests binary classifiers such as LR, SVM and MLP. The models suggested by our framework are mostly similar because MLP is a type of ANN, and it is represented in both cases. Also, SVM which is also a binary classifier is represented in both cases. Also, two ensemble models comprising KNN and ANN are used in [14] to predict the risk of damage for logistic vehicles. Although there is a similarity in the use of ANN and MLP suggested by our framework for similar use cases, unlike our work, Vasavi *et al.* [14] does not consider risk prediction as a binary classification due to the absence of binary-only classifier models such as LR and SVM.

A lot of research has focused on developing ML model selectors and various support tools for DA in different domains. The purpose of applying automated tools such as model selectors in data analytics is to speed up the analytic process [42]. Le *et al.* [43] and Ahsan *et al.* [44] developed an automated modelling tool for feature selection in the areas of bioinformatics and information security respectively. Lindauer *et al.* [45] developed a model selector that uses automated algorithm configuration for different input datasets which are not specific to any domain. The output of this work is an ensemble model selector tool that is developed by mapping the general contexts of ensemble approaches to SCM-specific contexts. Our model selector tool provides suggestions for ensemble model organizations and ML algorithms that are suitable for different problem types and use cases encountered in SCM. Providing model selection support to SCM analysts addresses an urgent gap in practice, i.e., a high level of uncertainty in which ML models, and even more, the combination of ML models in ensemble approaches is needed for different SCM use cases [46]. The developed framework is the first instance of a framework that highlights which SCM-related problems can be solved best with which specific ensemble approaches. Thus, our paper provides a good starting point for future research in mapping additional data-related problems to the best-suited ensemble model approaches which can solve them.

V. Conclusion

The main objective of this paper is to develop an ensemble modelling framework for addressing DA problems in SCM. This is achieved by analyzing relevant articles that developed ensemble approaches for different business domains to understand the modifications and improvements necessary for developing custom ensemble approaches. By building on ensemble approaches applied in specific use cases across different application domains, the developed ensemble modelling framework for SCM combines findings from a variety of ensemble applications. From an SCM perspective, this approach provides new insights into how to select appropriate ensemble models for SCM-related data questions.

As such, the problem types and use cases of different ensemble approaches are identified. The identified problem types and use cases include supervised risk prediction and categorization and unsupervised network behaviour and anomaly detection. Furthermore, machine model types and consensus suitable for these problem types and use cases are then derived. Mapping problem types and use cases into different machine learning model types and consensus algorithms provided the basis for the development of the SCM ensemble modelling framework. The developed framework was then simulated to show different ensemble model combinations and consensus algorithms suitable for addressing sample SCM DA questions. The developed framework and its implementation in the form of the Power-BI decision tree allow practitioners to select appropriate ensemble model combinations based on the specific SCM use case and the respective SCM data questions they want to address. Although the actual applicability of the framework has not yet been evaluated in practice, we deem it to be potentially useful as it has been developed based on thoroughly selected ensemble approaches with comparable problem types and question configurations.

However, the main limitation of this paper is the possible problem of generalization. We identified four use cases, such as risk prediction, categorization, network behaviour, and anomaly detection, where custom ensemble approaches are applied based on the examined papers. Since the examined papers are limited to 15 articles from the Scopus database only, more use cases may be derived if the scope of paper selection is expanded to include more articles. It also has to be considered, that the current prototype relies on conducting the literature review to determine, which machine learning model is suited for an ensemble to solve a specific data related question in SCM. This means that the system is not able to generate an entirely new combination of machine learning models that might not be present in the literature. Another limitation of this work is the lack of evaluation to examine the improvement of prediction accuracy observed when the developed ensemble approach is applied to an actual SCM DA problem. Thus, the future work of this paper is to apply the developed ensemble approach and assess the improved prediction accuracy recorded by applying the method to real-life data in a current research project. In addition, the designed framework could be improved if it considered the user's particular dataset to form a decision. This would allow the system to provide more tailored and accurate recommendations based on the characteristics of the data, such as the number of rows and columns, the distribution of values, the presence of missing values, *etc*. Also, this might help select the appropriate hyper-parameters that should be used for the ensemble (e.g., number of trees, max tree depth, number of layers, *etc*.).

Conflict of Interest

The authors declare no conflict of interest.

Author Contributions

Conceptualization, C.U.; Methodology, C.U. and P.B and R.Z.; Formal analysis, C.U. and P.B.; investigation, C.U. and R.Z. and P.B. and T.O.; Data curation, R.Z.; writing—original draft preparation, C.U. and R.Z. and P.B.; writing—review and editing, C.U. and R.Z. and P.B; supervision, P.B.; project administration, P.B.; funding acquisition, P.B. All authors had approved the final version.

Funding

The financial support by the Austrian Federal Ministry for Digital and Economic Affairs and the National Foundation for Research, Technology and Development and the Christian Doppler Research Association is gratefully acknowledged.

Acknowledgement

Open Access Funding by the University of Applied Sciences Upper Austria.

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