SUPPLIER SELECTION USING XAI

A PROJECT REPORT

Submitted by

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in the partial fulfillment for the award of the degree of

BACHELOR OF ENGINEERING

IN

COMPUTER SCIENCE AND ENGINEERING

DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING

RAJALAKSHMI ENGINEERING COLLEGE

ANNA UNIVERSITY, CHENNAI

MARCH 2021

ANNA UNIVERSITY, CHENNAI

BONAFIDE CERTIFICATE

Certified that this project report titled **“SUPPLIER SELECTION USING XAI”** is the bonafide work of **RHEA SUDESH (170701181), RITU BANSAL (170701186), ROSHIKA (170701190)** who carried out the project work under my supervision. Certified further that to the best of my knowledge the work reported herein does not form part of any other thesis or dissertation on the basis of which a degree or award was conferred on an earlier occasion on this or any other candidate.

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This project is submitted for Viva Voce Examination to be held on / /**2021**.

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ABSTRACT

Supplier Selection under Procurement remains a relatively unexplored issue in Supply Chain Management. It is a key factor that overlooks the enforcement of good buying decisions, satisfying stakeholders, minimizing maverick spending and hitting performance targets. Through supplier selection, an organisation examines, assesses and engages with suppliers. The Supplier Selection process utilizes an exorbitant amount of a company's assets and is frequently the pivotal factor in the profitability of any firm.

Up to this point, the scope of deploying AI backed supplier selection models have been limited to the procurement of C-type products. This is due to the presence of undetected bias in the system, inability of AI models to consider qualitative parameters, lack of substantial datasets and ambiguity regarding the decision made by the algorithm.

Having said that, with the rise of Explainable AI, we presently have a set of tools and frameworks to comprehend and interpret the predictions made by Machine Learning models with greater confidence, and by extension, build more interpretable and inclusive AI. Furthermore, recent studies have presented a significant correlation between qualitative parameters(like market reputation of a supplier) and weighable statistics. Hence, in this project, a combination of mathematical, statistical and AI approaches are employed to gauge the performance and suitability of a supplier based on objective and subjective attributes. Subsequently, a post-hoc Explainable AI structure is added to help detect and resolve bias, drift and other gaps in the data while simultaneously growing end-user trust by improving transparency with human-interpretable explanations.

ACKNOWLEDGEMENT

Initially we thank the Almighty for showering us with his constant blessings through the endeavor to put forth this report. Our sincere thanks to our Chairman **Dr. S. MEGANATHAN, B.E., F.I.E.,** and our revered and respected Chairperson **Dr. (Mrs.) THANGAM MEGANATHAN, Ph.D.,** for providing us with the requisite infrastructure and sincere endeavoring educating us in their premier institution. Our sincere thanks to **Dr. S.N. MURUGESAN, M.E., Ph.D.,** our beloved Principal for his support and facilities provided to complete our work in time. We express our sincere thanks to **Dr. R.G. SAKTHIVELAN, M.E., Ph.D.,** Head of the Department of Computer Science and Engineering for his guidance and encouragement throughout the project work. We convey our sincere and deepest gratitude to our internal guide, **Mr. P.V. RAJARAMAN, M.E.,** Assistant Professor(SS), Department of Computer Science and Engineering, Rajalakshmi Engineering College for his guidance throughout the project. We want to thank our project coordinator, **Dr. PRIYA VIJAY, M.E., Ph.D.,** Professor, Department of Computer Science and Engineering for her useful tips during our review to build our project. We would like to extend our hearty thanks to our industry consultant, **Mr. MANISH AGARWAL, Procurement Head, Armstrong Engineering,** for his constant support and guidance. Finally we express our gratitude to our parents and classmates for their moral support and valuable suggestions during the course of the project.

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TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF ABBREVIATION

XAI	Explainable Artificial Intelligence
SHAP	SHapley Additive exPlanations
ML	Machine learning
TOPSIS	Technique for Order of Preference by Similarity to Ideal Solution
MCDM	Multiple criteria decision-making
AHP	Analytical Hierarchy Process
ANP	Analytic Network Process
ANN	Artificial Neural Network

CHAPTER 1

INTRODUCTION

1.1 GENERAL

A key function of supply chain management is to methodize and orchestrate the flow of components from various suppliers to manufacturers for the objective of engineering products that must meet customers' value conventions. Arguably, in the current international marketplace described by globalization, thriving customers' standards, growing regulatory monotony and cut-throat competitive pressure, organizations must choose and maintain core suppliers to cope and prosper. Hence, supplier selection and evaluation represents one of the most important functions of purchase and supply management roles.

When it comes to the application of smart algorithms in Supplier, it's presence is already well known for C-type products. C-type products are usually bought in small quantities and at lower prices. However, for A-type and B-type products which are comparatively expensive and are significant to the quality of the finished product, the tenets of AI are largely unknown. The motivation of this research originates from two critical roadblocks in deploying Mathematical, Statistical and AI models for supplier selection: The blackbox nature of algorithms and lack of human interpretability. In recent years, with the development of Explainable AI algorithms, an avenue of newer possibilities opens up where we bottlenecks like these can be overcome.

1.2 OBJECTIVES

- Reduce purchase risk and maximize the overall value of the purchaser by typically involving evaluating, at a minimum, supplier quality, cost competitiveness, potential delivery performance and technological capability.
- Use qualitative and quantitative measures to rank suppliers through a combination of ML, Mathematical and statistical approaches.
- Deploy a post-hoc XAI model on top of the rank algorithm to understand the decisions made by the machine and minimise the chance of bias.

1.3 EXISTING SYSTEM

Up to this point, the scope of deploying AI backed supplier selection models have been limited to the procurement of C-type products. This is due to the presence of undetected bias in the system, inability of AI models to consider qualitative parameters, lack of substantial datasets and ambiguity regarding the decision made by the algorithm. Bias, Fairness, Transparency and Causality are all major concerns with existing systems.

1.4 PROPOSED SYSTEM

In this project, we aim to integrate XAI model SHapely Additive exPlanations(SHAP) with Multi Criteria Decision Making method Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) to rank suppliers, as well as provide interpretability through visualizations of feature attribution. This is important because it will extend the scope of application of AI beyond C-type products in the Supplier selection process. Not only will this discount the human bias which often disrupts decision making, but it will also reduce the number of human hours spent on evaluating and selecting the best supplier.

SHAP (SHapley Additive exPlanations) represents a game theoretic approach to characterize the output of any ML model. It connects optimal credit allocation with local explanations using the classic Shapley values from game theory. The central idea behind Shapley value based explanations of ML models is to employ fair allocation output from cooperative game theory to allocate credit for a model's output f(x) among its input attributes. One of the core properties of Shapley values is they always add up the difference between the game outcome when all players are present and the game outcome when no players are present. For Machine Learning models, this means that SHAP values of all the input attributes will always add to the difference between expected/ideal model result and the current model result for the prediction being elucidated (2017).

Hwang and Yoon(1981) developed the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS). This is an approach to assess the performance of possibilities in comparison to their similarity with the best output. According to this theory, the optimum result would be one that is nearest to the positive-ideal solution and farthest from the negative-ideal solution. The positive-ideal solution is one that makes the most of the benefit criteria and minimizes the cost criteria. The negative-ideal solution maximizes the cost criteria and reduces the benefit criteria. To summarize, the positive-ideal solution comprises all best values attainable of criteria, and the negative-ideal solution comprises all the worst values attainable of criteria.

1.5 AI

Artificial intelligence (AI) is intelligence demonstrated by machines, unlike the natural intelligence displayed by humans and animals, which involves consciousness and emotionality. The distinction between the former and the latter categories is often revealed by the acronym chosen. 'Strong' AI is usually labelled as AGI (Artificial General Intelligence) while attempts to emulate 'natural' intelligence have been called ABI (Artificial Biological Intelligence). Leading AI textbooks define the field as the study of "intelligent agents": any device that perceives its environment and takes actions that maximize its chance of successfully achieving its goals. Colloquially, the term "artificial intelligence" is often used to describe machines (or computers) that mimic "cognitive" functions that humans associate with the human mind, such as "learning" and "problem solving".

The traditional problems (or goals) of AI research include reasoning, knowledge representation, planning, learning, natural language processing, perception and the ability to move and manipulate objects. General intelligence is among the field's long-term goals. Approaches include statistical methods, computational intelligence, and traditional symbolic AI. Many tools are used in AI, including versions of search and mathematical optimization, artificial neural networks, and methods based on statistics, probability and economics. The AI field draws upon computer science, information engineering, mathematics, psychology, linguistics, philosophy, and many other fields.

In the twenty-first century, AI techniques have experienced a resurgence following concurrent advances in computer power, large amounts of data, and theoretical understanding; and AI techniques have become an essential part of the technology industry, helping to solve many challenging problems in computer science, software engineering and operations research.

CHAPTER 2

LITERATURE SURVEY

Literature in the area of supplier selection has primarily been focused on four primary approaches: Mathematical, Statistical modelling, Multi criteria Decision making(MCDM) methods and Artificial intelligence. Table 2.1 consists of the taxonomy of popular approaches that have been deployed for supplier selection and evaluation process.

CATEGORY	**APPROACH**	**PROPOSED BY**
MATHEMATICS	Analytic Hierarchy Process (AHP)	Hou and Su (2007)
	Analytic Network Process (ANP)	Gencer and Gürpinar (2007)
	Linear Programming (LP)	Talluri and Narasimhan (2007)
	Multi-Objective Programming (MOP)	Wadhwa and Ravindran (2007)
	Total Cost Ownership (TCO)	Ellram(1995)
	Goal Programming (GP)	Karpak et al. (2001)
	Data Envelopment Analysis (DEA)	Wu et al. (2003)
STATISTICAL MODEL	Cluster Analysis	Hinkle et al.(1969)
	Multiple Regression	Ho (2012)

	Conjoint Analysis	Mummalaneni et al. (1996)
	Principal Component Analysis(PCA)	Petroni(2000)
MULTI CRITERIA DECISION MAKING(MCDM) METHODS	Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS)	Yoong and Hwang (1981)
	VIKOR	Opricovic (1980)
	ELECTRE	Roy (1991)
	MAUT	Min (1994)
	Smart multi-attribute rating technique (SMART)	Seydel (2005)
ARTIFICIAL INTELLIGENCE	Fuzzy Set Theory(FST)	Zadeh (1978)
	Neural Networks(NN)	Jinlong and Zhicheng (1997)
	Genetic Algorithm(GA)	Ding et al. (2005)
	Case-based Reasoning(CBR)	Choy et al. (2005)
	Expert Systems(ES)	Vokurka et al. (1996)

Table 2.1 List on taxonomy of popular approaches

Ghorabaee (2016) presented that Fuzzy MCDM methods are efficient tools to deal with the uncertain decision-making problems. These methods can be used in the decision-making software to make some efficient support systems.The result of the sensitivity analysis shows the stability of the fuzzy EDAS method in solving multi-criteria decision-making problems. In a case study published by Mehmood

(2017), TOPSIS was found to be one of the most efficient MCDM methods for evaluating suppliers where virtually any number of characteristics could be incorporated in the decision making process. Shyur and Shih(2006) present an effective model using both ANP and modified TOPSIS, to accommodate the criteria with interdependencies in supplier selection problem. Junior et al. (2014) presented a comparing study between the fuzzy AHP and the fuzzy TOPSIS methods to solve the problem of supplier selection. Wood (2016) applied fuzzy and intuitionistic fuzzy TOPSIS with flexible entropy weighting to evaluate and select suppliers considering criteria relevant to an oil and gas facilities development project. Aouadni et al. (2017) developed the cardinal data TOPSIS method (TOPSIS-CD method) and the meaningful mixed data TOPSIS method (TOPSIS-MMD method) which suggest novel reference points and extend the TOPSIS method to mixed data. These two extended methods applied to a multi-attribute supplier selection problem. Aouadni et al. (2017) developed the cardinal data TOPSIS method (TOPSIS-CD method) and the meaningful mixed data TOPSIS method (TOPSIS-MMD method) which suggest novel reference points and extend the TOPSIS method to mixed data.

In 1966, Dickson assessed a set of 23 different criteria that 273 purchasing agents considered in their selection process. He concluded that quality, delivery and performance history were the three common criteria. Guneri et al. (2009) summarized the attributes that have cropped up in various studies since 1966. Price, quality, delivery, reputation and position in an industry, after-sales service, geographical location and impression were the most important criteria. Ho (2010) reviewed the supplier selection studies and concluded that quality, delivery, price/cost, manufacturing capability, service, management, technology, research and development, finance, flexibility, reputation, relationship, risk and safety and environment were the most popular traditional criteria for supplier selection.

Samut (2019) proposed a model that engineering managers can use to select suppliers efficiently using qualitative and quantitative criteria simultaneously and emphasized on the importance of qualitative measures in the decision making process.

Furthermore, Lundberg (2017) proposed a unified approach to interpreting models by developing SHAP, which is a model agnostic feature attribution framework that is based upon 6 existing methods. In a literature review published in 2019 by Mueller (2019),It was concluded that the tasks involving human-AI interactivity and co-adaptation, such as bug or oddity detection, seem to hold the promise for XAI evaluation since they conform to the notions of explanation as exploration and explanation as a co-adaptive dialog process. Also, tasks that involve predicting the AI's determinations, combined with post-experimental interviews, hold promise for the study of mental models in the XAI context.

CHAPTER 3

SYSTEM DESIGN

3.1 GENERAL

The system design aims at fulfilling the requirements at its fullest. The design of this system is simple and easy to understand so that any further development would not require special efforts in understanding the design. The system maintains a centralized database where all the supplier data is stored. Based on the data growth and number of users the data can be replicated. The system has a function which is responsible for fetching the user data and updating results to users but no changes are made whatsoever to the actual data stored. There is only one interface- admin module since there will be no interaction of the suppliers with the system.

3.2 ARCHITECTURE DIAGRAM

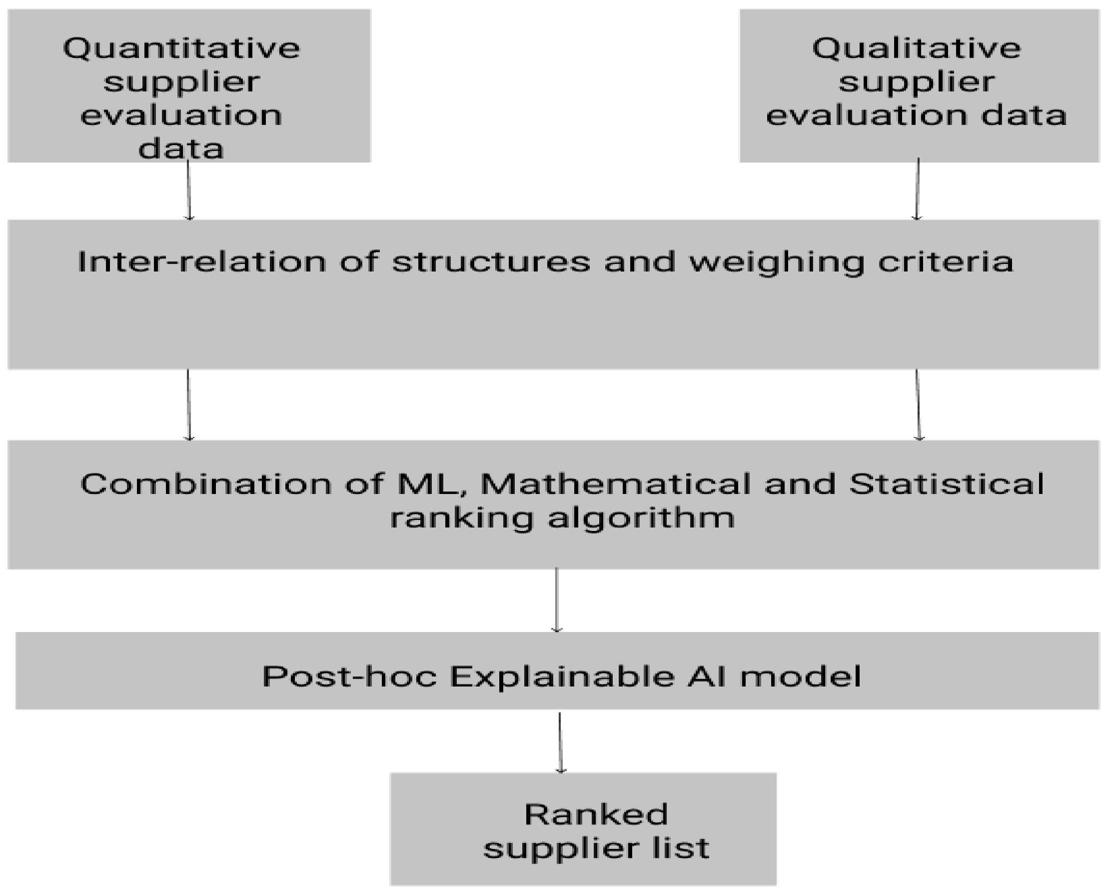

Figure 3.1 Architecture Diagram

3.3 DEVELOPMENT ENVIRONMENT

3.3.1 HARDWARE ENVIRONMENT

The hardware requirements may serve as the basis for a contract for the implementation of the system and should therefore be a complete and consistent specification of the whole system. They are used by software engineers as the starting point for the system design. It shows what the systems do and not how it should be implemented.

- Hard disk : Minimum 120 GB
- Ram : 4GB
- Processor : Pentium iv and above (or) equivalent
- Processor speed : Minimum 500 MHZ

3.3.2 SOFTWARE ENVIRONMENT

The software requirements are the specification of the system. It should include both a definition and a specification of requirements. It is a set of what the system should do rather than how it should do it. The software requirements provide a basis for creating the software requirements specification. It is useful in estimating cost, planning team activities, performing tasks and tracking the team's and tracking the team's progress throughout the development activity.

- Operating system : Windows 7 and above
- Languages : Python 3.3
- DataSet : Comma Separated Excel file(CSV)
- IDE : Google Collaboratory / Jupyter

3.4 DESIGN OF THE ENTIRE SYSTEM

3.4.1 USE CASE DIAGRAM

In this use case there is one user, namely client. The client shares their requests and the data for processing and analysing, this data undergoes data cleaning,where the data is sorted and the output is fed to the ML model, the output from this model gives us a ranking list of the products in a descending order, this ranking is also given in the form of a graph which compares the data , using the produced output the client can now decide the product that he wants to buy or proceed with.

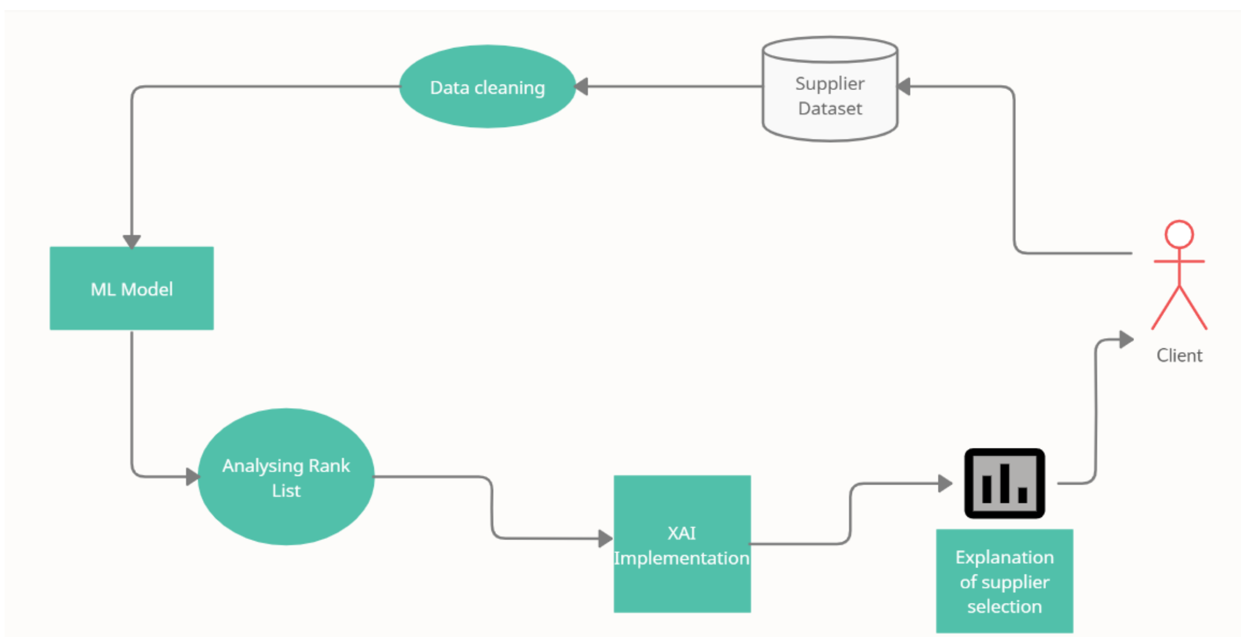

Figure 3.2 Use Case Diagram of supplier selection using XAI

3.4.2 SEQUENCE DIAGRAM

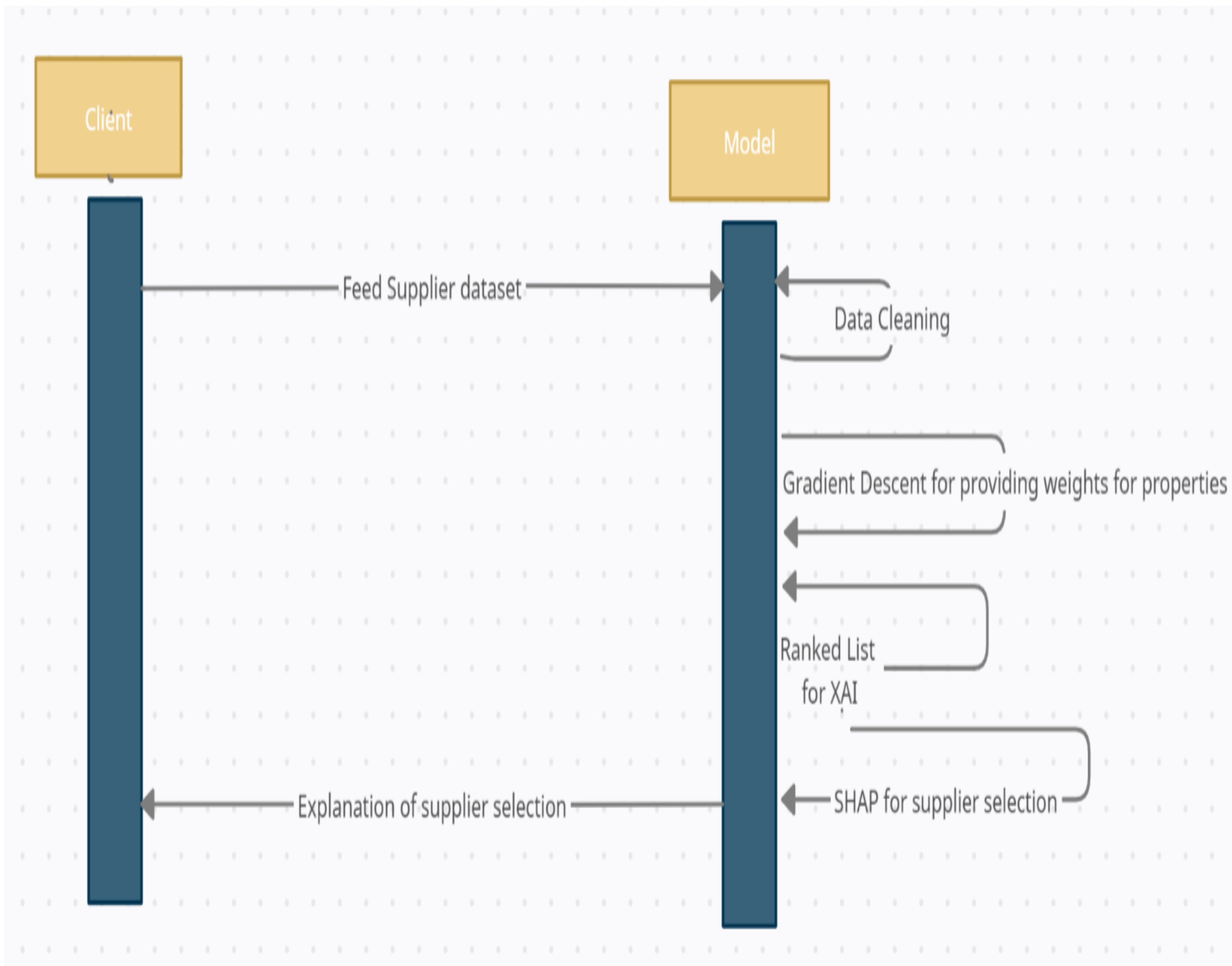

Figure 3.3 Sequence Diagram of the supplier selection using XAI

3.4.3 ACTIVITY DIAGRAM

Once the client feeds a dataset of suppliers , the fed data is cleaned if it has any null values or discrepancies, it is trained and tested using the TOPSIS model , the output from this model gives a ranked list of suppliers. The ranked list is then fed as input to SHAP algorithm that provides explanation of the supplier selection.

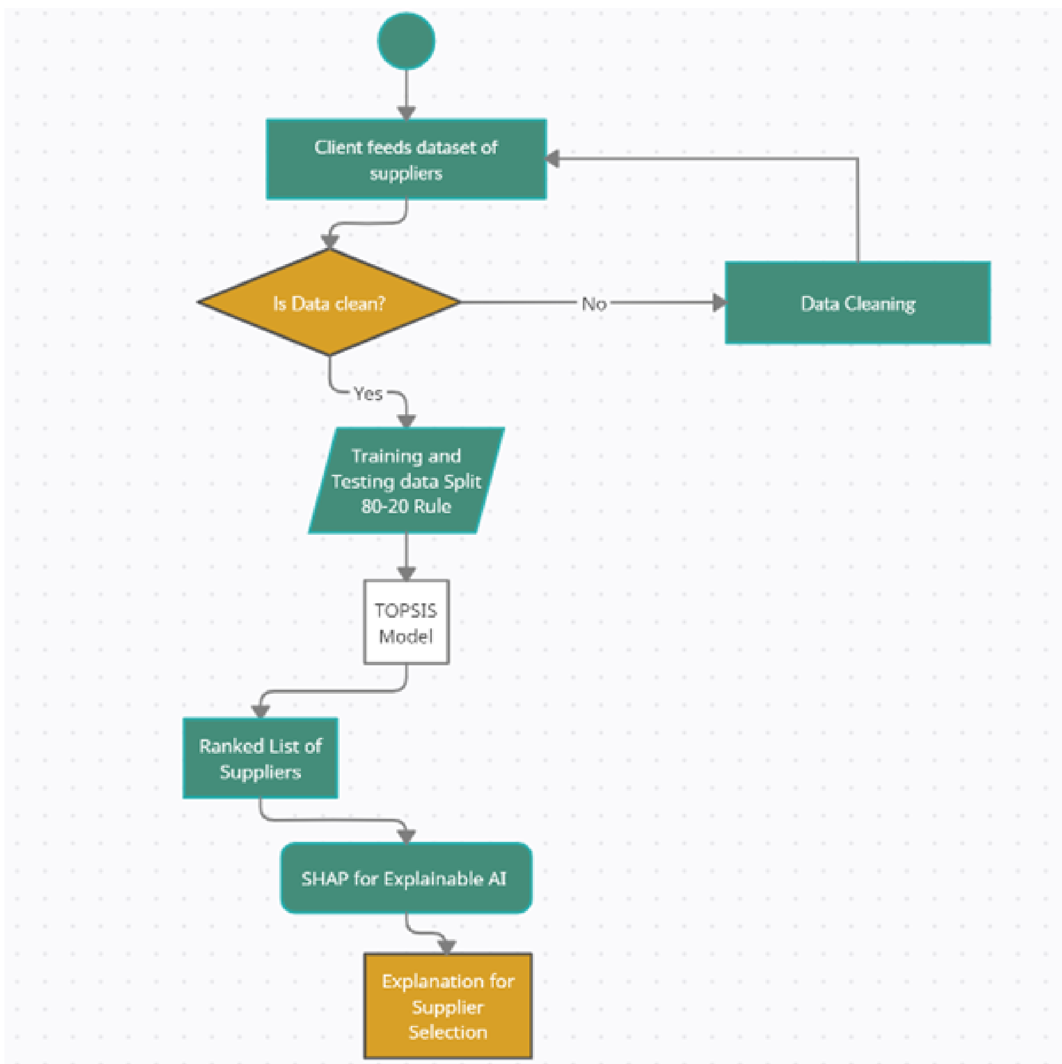

Figure 3.4 Activity Diagram for Supplier Selection

CHAPTER 4

PROJECT DESCRIPTION

4.1 GENERAL

The qualitative and quantitative evaluation criteria contain 8 parameters each which would be used for supplier evaluation. These records are then pre-processed and assigned weights through various DL algorithms. The data would then be passed onto the combination of AI, statistical and mathematical algorithms to generate a ranked list. Further, this list would be evaluated by an post-hoc XAI algorithm to see which features attribute the most to a particular ranking of a supplier.

4.2 METHODOLOGIES

4.2.1 MODULES

- Quantitative supplier evaluation data
- Qualitative supplier evaluation data
- Inter relation of structures and weighting criteria
- Ranking algorithm
- Explainable AI model
- Ranked list

QUANTITATIVE SUPPLIER EVALUATION DATA

The classification of the supplier’s data based on a quantitative approach for supplier selection contained three main categories: mathematical programming models, linear weighting models, and statistical / probabilistic approaches. Generally, linear weighting models are based on a situation where a weight is assigned to each criterion (typically subjectively determined) to reach a total score for each supplier by summing up his performance on the criteria multiplied by these weights .

To be more detailed, literature reviews point out that the main single and combined approaches used to solve this are mathematics methods and artificial intelligence approaches, especially including Analytic Hierarchy Process, Linear Programming, Multi-Objective Programming, Total Cost Ownership, Goal Programming, Data Envelopment Analysis, Simulation, Heuristics , Statistical , Cluster Analysis , Multiple Regression , Discriminant Analysis, Conjoint Analysis, Principal Component Analysis , Neural Networks , Software Agent , Case-Based Reasoning , Expert System , and Fuzzy Set Theory as well as combinations of selected pairs.

For example, fuzzy set theory has been integrated with multiple criteria techniques, as TOPSIS in our case . These methods range from classic mathematical approaches and artificial intelligence solutions to more sophisticated semantic-matching-based ones using ontologies .

QUALITATIVE SUPPLIER EVALUATION DATA

The supplier data's properties are based on the quality affecting criterion where mainly Suppliers play a key role in supply chain management which involves evaluation for supplier selection problems based on the quality aspects, as well as other multifaceted issues that organizations should consider. Supplier selection problem is one of the most important competitive challenges used by modern enterprises, although one problem is which criteria should be considered during the selection problem, the second one is which method should be used.

Nowadays, companies have to enhance the effectiveness of their sustainable supply chain management activities to survive in the global marketplace. In searching supplier selection methods various techniques are used to evaluate and to select suppliers. Supplier selection process is a complex and multi-dimensional problem because there may be conflicts among qualitative, quantitative criteria and also sustainable criteria. In this regard, numerous organizations have been invested in combined supplier development programs to enhance their sustainable performance with respect to the supply chain.

The process of selecting appropriate suppliers starts from performing sustainable supplier evaluation, which is crucial to the performance of supply chain operations. However, methodological approaches are needed for further evaluation. Undoubtedly, a systematic approach for managing the qualitative properties related to suppliers is required as it can help to build the closeness and long-term relationship between clients and suppliers.

INTER RELATION OF STRUCTURES & WEIGHING CRITERIA

As already discussed in the above literature review that there exists a number of criteria for supplier selection and that they also vary from product to product and organisation to organisation therefore the next step is the selection of supplier selection criteria. Since the data was to be collected from the automobile organisation, therefore the most dominant criteria in the particular sector are selected for supplier selection and are: quality, delay time, unit cost, quantity, and service. The above selected criteria are in accordance with the discussion held with the executives of the automobile sector.

The next step is the selection of the methodology for supplier selection. Among the existing methodologies, TOPSIS and ANN are integrated together for the MCDM problem. The reason for using the ANN model to solve supplier selection problem are: ANN permits solutions to problems where multiple constraints must be satisfied simultaneously, weights in the ANN can be modified with any EAs/other techniques very easily, ANN possess the capability to generalise, can predict new outcomes on past trends, ANN can be easily integrated with other methods, ANN exhibit mapping capabilities.

The reason for using TOPSIS in supplier selection process are: TOPSIS can solve multi-dimensional, non-differential, non-continuous, and even non-parametric problems, TOPSIS searches from one population of solutions to another, rather than from individual to individual, TOPSIS solves problems with multiple solutions, TOPSIS only uses objective function information to guide themselves through solution space and not derivatives, TOPSIS are easily transferred to existing simulations and models, TOPSIS can easily solve the problem if number of parameters are very large.

RANKING ALGORITHM

Ranking is a central part of many information retrieval problems, such as document retrieval, collaborative filtering, sentiment analysis, and online advertising. A possible architecture of a machine-learned search engine is shown in the accompanying figure. Training data consists of queries and documents matching them together with the relevance degree of each match. It may be prepared manually by human *assessors* (or *raters*, as Google calls them), who check results for some queries and determine relevance of each result. It is not feasible to check the relevance of all documents, and so typically a technique called pooling is used — only the top few documents, retrieved by some existing ranking models are checked. Training data is used by a learning algorithm to produce a ranking model which computes the relevance of documents for actual queries.

EXPLAINABLE AI MODEL

AI and related technologies and methods will be used in the near future to do better forecasting and to better understand users and customers.This will have a significant impact on the optimization of the forecast on a strategic/tactical level and may be also used to determine new customer demand. In the future, AI may be used also in Sustainability 2020, higher-level processes to detect fraud, prevent cybersecurity threats, and generally optimize higher-level processes. Possibilities of the future use of AI can also be in project management tasks, reducing the failure rate of projects thanks to predictive analysis and to more accurate project management.

In addition, if AI algorithms can win chess games, they will also be able to be used in the generation of corporate strategies. and in a further step a bidirectional information flow between both models to control the physical system through a so-called digital twin. determining data patterns and therefore automating workflows and processes for more immediate and more qualitative control of logistics systems.As AI methods depend a lot on the availability of a large amount of data, the field of predictive maintenance is a highly important research direction due to new generations of logistics systems equipped with sensors and providing large amounts of data that can be used for data analytics.

Seeing this development, we consider predictive maintenance as one of the more consolidated fields of research for AI in logistics, although we are conscious of the fact that there is still a huge need for investigation especially for applied research and case study research.It will become important to develop solutions using an approach based on so-called Explainable AI and thus a hybrid way where the human is still able to understand the result through explainable interfaces.

RANKED LIST

The output of this Model provides a Ranked List based on a score that is generated by the gradient descent algorithm ,that gives each property input with corresponding weights based on their impact in the selection process. The list of suppliers along with the score , which is calculated based on those properties values , give us a ranked list after sorting them in an descending order. This list is an input to the Explainable AI Adhoc which inturn provides us with information about each and every supplier and the reason for their position in the ranked list.

4.2.2 ALGORITHMS

- Gradient Descent
- TOPSIS
- SHAP

GRADIENT DESCENT

Gradient descent is a first-order iterative optimization algorithm for finding a local minimum of a differentiable function. The idea is to take repeated steps in the opposite direction of the gradient (or approximate gradient) of the function at the current point, because this is the direction of steepest descent. Conversely, stepping in the direction of the gradient will lead to a local maximum of that function; the procedure is then known as gradient ascent.

Gradient descent works in spaces of any number of dimensions, even in infinite-dimensional ones. In the latter case, the search space is typically a function space, and one calculates the Fréchet derivative of the functional to be minimized to determine the descent direction. That gradient descent works in any number of dimensions (finite number at least) can be seen as a consequence of the Cauchy-Schwarz inequality. That article proves that the magnitude of the inner (dot) product of two vectors of any dimension is maximized when they are collinear. In the case of gradient descent, that would be when the vector of independent variable adjustments is proportional to the gradient vector of partial derivatives. The gradient descent can take many iterations to compute a local minimum with a required accuracy, if the curvature in different directions is very different for the given function. For such functions, preconditioning, which changes the geometry of the space to shape the function level sets like concentric circles, cures the slow convergence. Constructing and applying preconditioning can be computationally expensive, however.

In this project, we utilized gradient descent to predict the weights of the attributes before applying TOPSIS on it. This was done bearing in mind that there was a linear relationship observed between the dependent variable and the independent variables. Through the process of hyperparameter tuning, the learning rate and the number of iterations were fixed.

TOPSIS

The Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) is a multi-criteria decision analysis method, which was originally developed by Ching-Lai Hwang and Yoon in 1981 with further developments by Yoon in 1987, and Hwang, Lai and Liu in 1993. TOPSIS is based on the concept that the chosen alternative should have the shortest geometric distance from the positive ideal solution (PIS) and the longest geometric distance from the negative ideal solution (NIS).

It is a method of compensatory aggregation that compares a set of alternatives by identifying weights for each criterion, normalising scores for each criterion and calculating the geometric distance between each alternative and the ideal alternative, which is the best score in each criterion. An assumption of TOPSIS is that the criteria are monotonically increasing or decreasing. Normalisation is usually required as the parameters or criteria are often of incongruous dimensions in multi-criteria problems. Compensatory methods such as TOPSIS allow trade-offs between criteria, where a poor result in one criterion can be negated by a good result in another criterion. This provides a more realistic form of modelling than non-compensatory methods, which include or exclude alternative solutions based on hard cut-offs. An example of application on nuclear power plants is provided in.

In this project, we used the weights obtained from Gradient Descent are used as coefficients for every column. The Euclidean Distance of every instance is calculated from the best and worst possible cases and the average of this is used to calculate the score which then further generates the ranked list.

SHAP

SHAP (SHapley Additive exPlanations) is a game theoretic approach to explain the output of any machine learning model. It connects optimal credit allocation with local explanations using the classic Shapley values from game theory and their related extensions. For the purpose of this project, SHAP is used to visualize the results obtained from TOPSIS.

The central idea behind Shapley value based explanations of ML models is to employ fair allocation output from cooperative game theory to allocate credit for a model's output f(x) among its input attributes. One of the core properties of Shapley values is they always add up the difference between the game outcome when all players are present and the game outcome when no players are present.

For Machine Learning models, this means that SHAP values of all the input attributes will always add to the difference between expected/ideal model result and the current model result for the prediction being elucidated (2017).

4.2.3 PYTHON LIBRARIES

- Pandas
- Numpy
- Scikit learn

PANDAS

Pandas is a Python package that provides fast, flexible, and expressive data structures designed to make working with structured (tabular, multidimensional, potentially heterogeneous) and time series data both easy and intuitive. It aims to be the fundamental high-level building block for doing practical, real world data analysis in Python. Additionally, it has the broader goal of becoming the most powerful and flexible open source data analysis / manipulation tool available in any language. It is already well on its way toward this goal.

Here are a few of the things that pandas does well:

- Easy handling of missing data (represented as NaN) in floating point as well as non-floating point data

- Size mutability: columns can be inserted and deleted from DataFrame and higher dimensional objects
- Automatic and explicit data alignment: objects can be explicitly aligned to a set of labels, or the user can simply ignore the labels and let Series, DataFrame, etc. automatically align the data for you in computations
- Powerful, flexible group by functionality to perform split-apply-combine operations on data sets, for both aggregating and transforming data
- Make it easy to convert ragged, differently-indexed data in other Python and NumPy data structures into DataFrame objects
- Intelligent label-based slicing, fancy indexing, and subsetting of large data sets
- Intuitive merging and joining data sets
- Flexible reshaping and pivoting of data sets
- Hierarchical labeling of axes (possible to have multiple labels per tick)
- Robust IO tools for loading data from flat files (CSV and delimited), Excel files, databases, and saving / loading data from the ultrafast HDF5 format
- Time series-specific functionality: date range generation and frequency conversion, moving window statistics, date shifting and lagging.

NUMPY

NumPy is a library for the Python programming language, adding support for large, multi-dimensional arrays and matrices, along with a large collection of high-level mathematical functions to operate on these arrays.

It provides:

- a powerful N-dimensional array object
- sophisticated (broadcasting) functions
- tools for integrating C/C++ and Fortran code
- useful linear algebra, Fourier transform, and random number capabilities

Besides its obvious scientific uses, NumPy can also be used as an efficient multi-dimensional container of generic data. Arbitrary data-types can be defined. This allows NumPy to seamlessly and speedily integrate with a wide variety of databases.

SCIKIT LEARN

Scikit-learn (Sklearn) is the most useful and robust library for machine learning in Python. It provides a selection of efficient tools for machine learning and statistical modeling including classification, regression, clustering and dimensionality reduction via a consistent interface in Python. This library, which is largely written in Python, is built upon NumPy, SciPy and Matplotlib.

Rather than focusing on loading, manipulating and summarising data, Scikit-learn library is focused on modeling the data. Some of the most popular groups of models provided by Sklearn are as follows −

- **Supervised Learning algorithms** − Almost all the popular supervised learning algorithms, like Linear Regression, Support Vector Machine (SVM), Decision Tree etc., are the part of scikit-learn.

- **Unsupervised Learning algorithms** − On the other hand, it also has all the popular unsupervised learning algorithms from clustering, factor analysis, PCA (Principal Component Analysis) to unsupervised neural networks.
- **Clustering** − This model is used for grouping unlabeled data.
- **Cross Validation** − It is used to check the accuracy of supervised models on unseen data.
- **Dimensionality Reduction** − It is used for reducing the number of attributes in data which can be further used for summarisation, visualisation and feature selection.
- **Ensemble methods** − As the name suggests, it is used for combining the predictions of multiple supervised models.
- **Feature extraction** − It is used to extract the features from data to define the attributes in image and text data.
- **Feature selection** − It is used to identify useful attributes to create supervised models.
- **Open Source** − It is an open source library and also commercially usable under BSD license.

CHAPTER 5

PROJECT IMPLEMENTATION

DATASET GATHERING

The data is the backbone of this project. Here data was collected from real world clients who indulge in supplier selection as their profession. These industrial experts have acted as our core data providers and given data based on various criterias that they look for while they do supplier selection. Supplier selection is a long process that involves qualitative and quantitative data collection. Here Qualitative refers to properties that describe the quality of the supplier and the quality of goods or services, a few would be supplier relation, flexibility, Tech capability, etc. On the other hand quantitative properties refer to the mathematical constraints of the project like price , logistics cost, warranty period. These data in turn play an important role in the score production of each supplier. The major factors that were considered for ranking suppliers are listed below.

QUANTITATIVE FACTORS	QUALITATIVE FACTORS
Price	Supplier relation
Logistics cost	Quality of service
Percentage of defective items	Quality of product
Warranty	Flexibility
Delivery compliance	Tech Capability
Lead time	Political stability
Production capability	Market reputation
Annual cost reduction	Customer response

Table 5.1 Factors considered for ranking suppliers

Name	price	logistics_cost	no_of_def_items	warranty	delivery_compliance	lead_time
A	5	5	4	5	5	5
B	4	5	5	4	5	5
C	5	5	4	4	4	4
D	4	4	4	5	5	5
E	5	5	3	4	4	4
F	4	4	3	3	4	3
G	3	3	4	4	3	4
H	4	3	3	3	3	3

Figure 5.1 Sample Input data-1

K	2	2	2	2	2
L	2	2	2	1	1
M	2	3	3	2	2
N	1	2	1	2	1
O	1	1	1	1	1
P	2	5	5	3	2
Q	3	4	4	4	5
R	4	2	3	4	5
S	1	5	5	4	5
T	3	1	5	4	4
U	3	1	4	5	5

Figure 5.2 Sample Input data-2

DATA PROCESSING FOR DATA CLEANING

On a predictive modeling project, machine learning algorithms learn a mapping from input variables to a target variable. We cannot fit and evaluate machine learning algorithms on raw data, instead, we must transform the data to meet the requirements of individual machine learning algorithms. More than that, we must choose a representation for the data that best exposes the unknown underlying structure of the prediction problem to the learning algorithms in order to get the best performance given our available resources on a predictive modeling project.

Given that we have standard implementations of highly parameterized machine learning algorithms in open source libraries, fitting models has become routine. In this project we look for a dataset with null values for qualitative and zero as values for quantitative, and use an average method to overcome the quantitative missing values. For Qualitative missing values we removed the data field as a whole, as the algorithm does not function in a desired manner with such null values as input. Hence data cleaning plays a vital role in the model's functioning.

ATTRIBUTE	GUIDELINE
Supplier relation	Number of value-adding services that company encourages, higher the better
Flexibility	Number of type of products that company can make with little changeover, higher the number the better
Quality of service	Responsiveness, quicker the better
Quality of product	How closely the product matches the description, lower the error the better
Tech Capability	Number of products company can produce, higher the better
Political stability	Physical distance between the company and your organisation. Closer the better
Market reputation	Higher the sales revenue, higher the rating
Customer response	Overall customer satisfaction, Higher the better
Price	Closer to desired price, higher the score
Logistics cost	Lower the cost, higher the score
Percentage of defective items	Lower the percentage, higher the score
Warranty	Longer the warranty, higher the score
Delivery Compliance	Closer to promised date, higher the score
Lead time	Closer to desired date, higher the score
Production capability	Higher the total production quantity, higher the score
Annual cost reduction	Higher the reduction, higher the score

Table 5.2 Guidelines for scoring suppliers

ATTRIBUTE	SOLUTION
Warranty	Warranty is applicable for OEM Parts (where design is owned by supplier). For Built to Print parts, there is no part warranty however standard Material warranty applies which is included in Quality. For Built to print, use 3
Production capability	Trading companies do not manufacture anything. Use value 3
Flexibility	Trading companies do not manufacture anything. Use value 3

Table 5.3 Dealing with missing values in data

IMPLEMENTATION OF ALGORITHM

The dataset involving the supplier's quantitative and qualitative data are first split into Training data and Testing data. This data is then fed to a gradient descent model ,which in turn adds weights to the properties based on their impact to the final score which is the target. This model is trained accordingly along with the TOPSIS algorithm to get a Ranked list as output. This output is a list of suppliers which are ranked based on their score provided by the client with respect to the properties and the weightage of those properties.

Now this ranked list along with the weighted inputs are sent to the XAI post hoc part, developed from the SHAP algorithm which provides the explanation for the ranking of the suppliers as the output. Now given this the model is tested based on new dataset and checked if the score is attained, Our models accuracy is subjective and depends on the industrial agent, which the industrial agents verified and further after the ranked list was fed to the SHAP algorithm , it provides us with an explanation to the suppliers ranking based on the weightage of the quantitative and qualitative properties.

Further the model provides a visual representation of the explanation in the form of a graph which is readable and understandable to the client, using which a supplier can easily be chosen as the model provides not only the ranked list but also supports its decision by providing an explanation for that ranking.

CHAPTER 6

RESULT

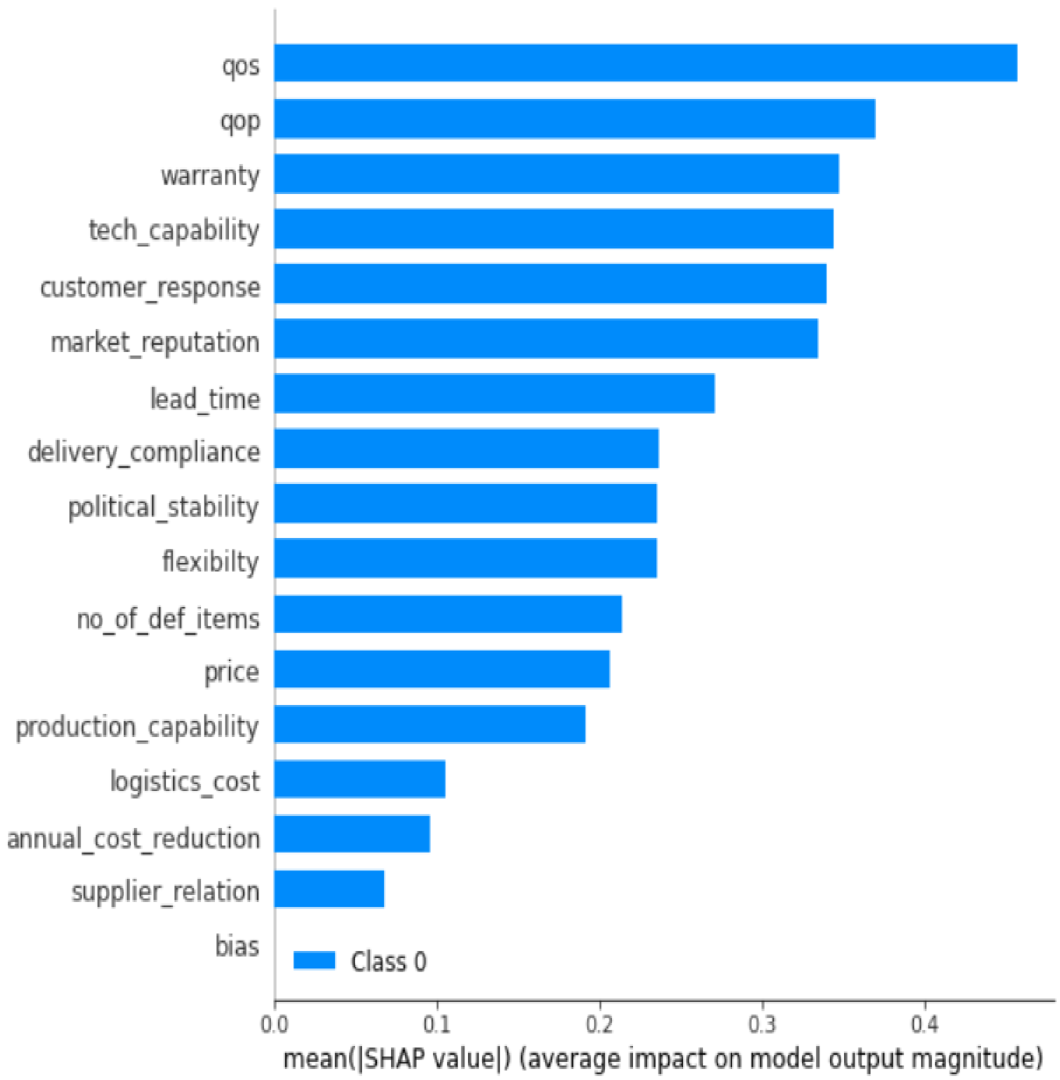

Figure 6.1 Bar plot showing feature attribution for test set

	Name	score
3	D	0.844351
0	A	0.835616
1	B	0.834378
2	C	0.769826
31	AF	0.756174
16	Q	0.726324
4	E	0.724523
17	R	0.689920
19	T	0.661813
20	U	0.632099
6	G	0.618718
15	P	0.613617
21	V	0.609659
18	S	0.606534
5	F	0.604608
22	W	0.576300
7	H	0.561598
24	Y	0.548680
25	Z	0.523641
8	I	0.500722
23	X	0.500282
9	J	0.479162

Figure 6.2 Ranked list of suppliers with their score for test set

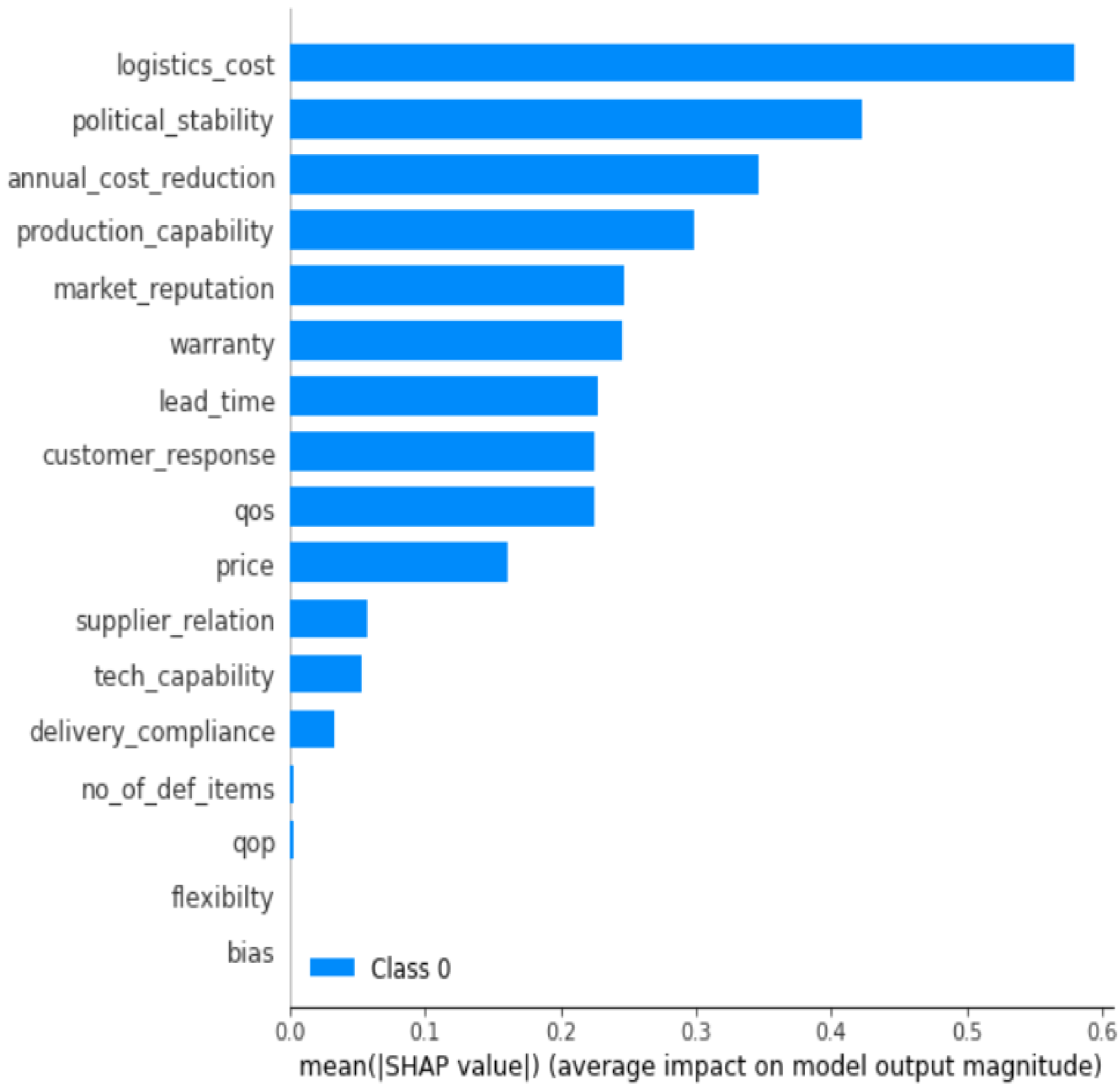

Figure 6.3 Bar plot showing feature attribution for train set

	Name	score
9	SPM	0.869438
15	Al Ren Electro	0.838696
4	Connex	0.826526
14	Dynavative	0.807581
13	Excel Industry	0.798039
3	Wurth	0.777024
1	Cestaro	0.726771
6	Esma	0.704140
5	Dynamic	0.703381
22	ADT	0.696523
10	Zanetti	0.677507
11	ZF	0.672459
2	Componenta	0.667593
12	Horstman	0.653077
17	HEMA	0.631266
19	Lamco	0.626035
16	Automech	0.618247
7	Fujin	0.610883
0	AVT	0.595532
8	Hanacke	0.587484
18	Koni	0.576438
23	Blue Shift	0.539265
20	Pailton	0.537972

Figure 6.4 Ranked list of suppliers with their score train set

CHAPTER 7

CONCLUSION AND FUTURE ENHANCEMENT

CONCLUSION

A combination of mathematical, statistical and AI approaches are employed to gauge the performance and suitability of a supplier based on objective and subjective attributes. Subsequently, a post-hoc Explainable AI structure is developed to help detect and resolve bias, drift and other gaps in the data while simultaneously growing end-user trust by improving transparency with human-interpretable explanations. The supplier selection problem has gained more attention emphasizing the role of the efficient discovery and selection of capable suppliers. To each selected model, a number of examples of research papers were investigated. Based on that, the approach synthesized the analysed methods and related outcomes were proposed.

FUTURE ENHANCEMENT

Through the phenomenon of sustainable development, sustainable practices and increased awareness of environmental, economic and social issues have direct influence on building a long-term supply chain collaboration. Selecting the optimum supplier is crucial for sustainable supply chain management, which is a challenging multi-dimensional problem. A limitation of this project is that it does not provide insights on individual supplier performance. In the future, this can be implemented.

APPENDIX

SOURCE CODE

```
import numpy as np

import pandas as pd

import matplotlib.pyplot as plt

import warnings

import os

import sys

import sklearn

from sklearn import linear_model

import shap

for dirname, _, filenames in os.walk('/kaggle/input'):

    for filename in filenames:

        print(os.path.join(dirname, filename))


def computeCost(X,y,theta):

    tobesummed = np.power(((X @ theta.T)-y),2)
```

```
    return np.sum(tobesummed)/(2 * len(X))


def gradientDescent(X,y,theta,iters,alpha):
    cost = np.zeros(iters)
    for i in range(iters):
        theta = theta - (alpha/len(X)) * np.sum(X * (X @ theta.T - y), axis=0)
        cost[i] = computeCost(X, y, theta)
    return theta,cost


def floater(a):  # .astype() can be used but is not reliable
    b = []
    for i in a:
        try:
            ix = []
            for j in i:
                ix.append(float(j))
        except:
            ix = float(i)
            pass
```

```
        b.append(ix)
    b = np.array(b)
 return b


def normalize(matrix, r, n, m):
    for j in range(m):
        sq = np.sqrt(sum(matrix[:, j]**2))
        for i in range(n):
            r[i, j] = matrix[i, j]/sq
    return r


def weight_product(matrix, weight):
    prod = matrix*weight
    return prod


def calc_ideal_best_worst(sign, matrix, n, m):
    ideal_worst = []
    ideal_best = []
    for i in range(m):
```

```
        if sign[i]>0:
            ideal_worst.append(min(matrix[:, i]))
            ideal_best.append(max(matrix[:, i]))
        else:
            ideal_worst.append(max(matrix[:, i]))
            ideal_best.append(min(matrix[:, i]))
    return (ideal_worst, ideal_best)


def euclidean_distance(matrix, ideal_worst, ideal_best, n, m):
    diw = (matrix - ideal_worst)**2
    dib = (matrix - ideal_best)**2
    dw = []
    db = []
    for i in range(n):
        dw.append(sum(diw[i, :])**0.5)
        db.append(sum(dib[i, :])**0.5)
    dw = np.array(dw)
    db = np.array(db)
    return (dw, db)
```

```
def performance_score(distance_best, distance_worst, n, m):
    score = []
    score = distance_worst/(distance_best + distance_worst)
    return score


def topsis(a, w, sign):
    a = floater(a)
    n = len(a)
    m = len(a[0])
    r = np.empty((n, m), np.float64)
    r = normalize(a, r, n, m)
    t = weight_product(r, w)
    (ideal_worst, ideal_best) = calc_ideal_best_worst(sign, t, n, m)
    (distance_worst, distance_best) = euclidean_distance(
        t, ideal_worst, ideal_best, n, m)
    score = performance_score(distance_best, distance_worst, n, m)
    column_name=['score']
    return pd.DataFrame(data=score,columns=column_name)
```

```
def rank(url):
    train=pd.read_csv(url)
    X=train.iloc[:,1:17]
    Name=train.iloc[:,0:1]
    X=X.astype(float)
    columns=X.columns
    columns=columns.insert(0,'bias')
    y=train.iloc[:,-1:].values
    y=y.astype(float)
    ones = np.ones([X.shape[0],1])
    X = np.concatenate((ones,X),axis=1)
    theta = np.zeros([1,17])
    alpha = 0.01
    iters = 200
    w,cost = gradientDescent(X,y,theta,iters,alpha)
    finalCost = computeCost(X,y,w)
    score=topsis(X,w,y)
    data = [Name["Name"], score["score"]]
```

```
    headers = ["Name", "score"]

    score_card= pd.concat(data, axis=1, keys=headers)

    result=score_card.sort_values(by='score',ascending=False)

    X_train_summary = shap.kmeans(X, 10)

    lin_regr = linear_model.LinearRegression()

    lin_regr.fit(X, y)

    ex = shap.KernelExplainer(lin_regr.predict, X)

    shap_values = ex.shap_values(X)

    shap.summary_plot(shap_values, features=X, feature_names=columns)

    return result
```

main():

```
        url='../input/final-data/Test.csv'

        rank(url)
```

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ARMSTRONG
ENGINEERING

24-Mar-2021

TO WHOMSOEVER IT MAY CONCERN

I, Manish Agarwal, acted as the industry expert for the project “Supplier selection using XAI” undertaken by Ms. Ritu Bansal, Ms. Rhea Sudesh and Ms. Roshika under the guidance of Mr. P.V. Rajaraman for the partial fulfillment of their degree “Bachelor of Engineering in Computer Science and Engineering” at Rajalakshmi Engineering College(Batch 2017-2021).

I work as Procurement Head at Armstrong Engineering FZCO. I was approached by Ms. Ritu Bansal in Winter 2020 regarding this project. After a short presentation made by her team, I agreed to act as their external consultant for this project. Additionally, I consented to providing them with necessary data sets needed to begin their project. Throughout the duration of this project, Ms. Ritu Bansal and her team were in constant contact with me and regularly had their progress validated in terms of industry applicability.

Supplier selection is a problem which requires human validation. Nearing the completion of their project, the team ran through their results with me and I am confident that the outcomes presented fulfilled the objectives set at the beginning of the project. Implementation of Explainable AI was done seamlessly and it greatly enhanced the interpretability of the ranked supplier list, which I also validated.

In conclusion, I strongly believe that the team was able to reach their goal and I wish them luck for all their future endeavors.

Kind Regards,

Manish Agarwal

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