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Global Supply Chain: Enhance Production Cost Efficiency Through Machine Learning

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Abstract: Machine learning has enabled the discovery of various disciplines and patterns in Supply Chain Management (SCM). The entire industrial sector is striving to harness the contextual intelligence provided by machine learning by exploring new areas within the supply chain network. This article delves into Supply Chain Management (SCM) and its broader implications beyond logistics. SCM involves the resources, methods, and tools required to manage activities efficiently. For large companies with multiple subcontractors, SCM is essential for identifying areas needing improvement. Evaluating key indicators is crucial to optimizing SCM stages. Machine learning assists in recognizing recurring patterns and relevant data to develop models for better understanding production processes and identifying enhancement opportunities. A global corporation specializing in flooring and kid's surfaces, with numerous sites and a global presence, faces complexity and high costs due to diverse production parameters and customer expectations. Centralizing data and automating processes are vital to reducing production costs and uncertainties. This article utilizes machine-learning algorithms such as classification, linear regression, and K-means Clustering on unstructured data to optimize production and delivery costs, with the goal of producing goods at the most cost-effective locations worldwide.

Keywords: Supply Chain, Machine Learning, Optimization, Production Cost

Introduction

When we discuss the supply chain, we are referring to a company's supply network and its associated logistics. However, the term Supply Chain Management (SCM) includes additional aspects. SCM considers factors such as resources, methods, tools, and techniques for managing activities. This broader view of the supply chain encompasses logistics as a whole, aiming to identify potential areas for improvement across all stages, from supply and manufacturing to sales.

To optimize the stages of the supply chain, it is essential to consider and evaluate several key indicators. Machine Learning (ML) can identify recurring patterns within the supply chain. By leveraging algorithms, ML can quickly and clearly pinpoint relevant supply chain data, enabling the development of models to enhance our understanding of production processes and uncover areas for improvement. This innovative approach to logistics and optimization allows ML to continuously learn and highlight points needing enhancement (Hartley and Sawaya, 2019).

The company featured in this case study, we examine a global electronics manufacturer. It operates on more than 25 production sites and has a presence in over 95 countries with 480 locations. The global spread of production sites and the varying production parameters add complexity and expense to the production chain. A significant factor contributing to this complexity is the customer expectation of consistent product pricing worldwide, which forces the currently decentralized system to incur high production costs in all countries.

To minimize production costs and address uncertainties, automating and centralizing data within the company's software systems is essential. The first step involves identifying the most influential factors affecting production costs using feature selection techniques. This step helps focus on key variables for cost optimization

(Ghobakhloo, 2020). Appropriate machine learning algorithms are then chosen based on the nature of the data and the specific problem. Common algorithms for cost optimization include regression models (e.g., linear regression), clustering algorithms (e.g., k-means clustering), and classification algorithms.

In this article, we utilize machine-learning algorithms on data stored on the manufacturing servers; the objective is to determine the most cost-effective production site globally, considering logistics costs. After training and validating the model, we use it to predict production costs for new or future scenarios.

Literature Review

Currently, the multinational corporation faces high production costs due to its traditional approach, where each order received by a point of sale in a specific country is produced at a local production site within that same country, as you can see on the Fig. 1 list of stores and factories on different country.

To optimize production costs within the supply chain using machine learning, the company undertakes the following essential steps:

- Data gathering: Collect a variety of data pertaining to production processes and supply chain logistics
- Data cleansing and preparation: Remove inconsistencies and ready the data for analysis by addressing missing values and ensuring its quality
- Feature identification: Determine essential variables influencing production costs through feature selection techniques
- Machine learning algorithm selection: Opt for appropriate algorithms such as regression or clustering to optimize costs
- Model training and validation: Educate models using historical data and confirm their accuracy
- Cost estimation and enhancement: Apply trained models to foresee and enhance production costs by refining processes and allocating resources effectively
- Ongoing improvement: Continuously enhance models and procedures based on feedback and evolving circumstances
- Utilizing machine learning for production cost optimization offers advantages like decreased expenditures, heightened profitability and enhanced decision-making to boost competitiveness

The company overlooks production costs and lacks the ability to compare and identify the most cost-effective production methods. Right now, when an order is received at a point of sales located on Croatia (for example) border with Slovénie, it is produced in Croatia without factoring in logistics expenses or other relevant variables. Subsequently, it was realized that production in Bulgaria would be more economical (Baryannis *et al*., 2019).

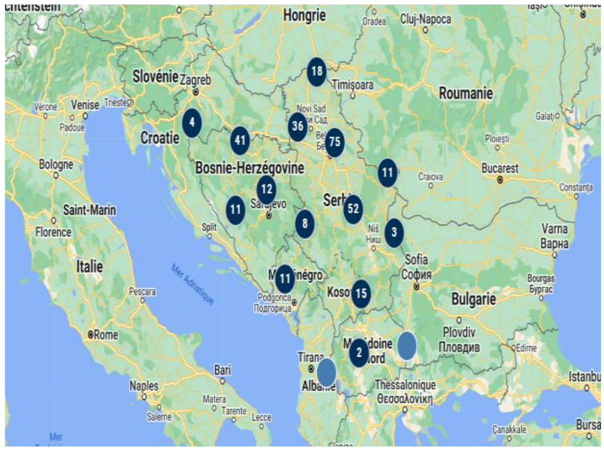

Fig. 1: Shows the list of points of sales and factories around the country having the issue

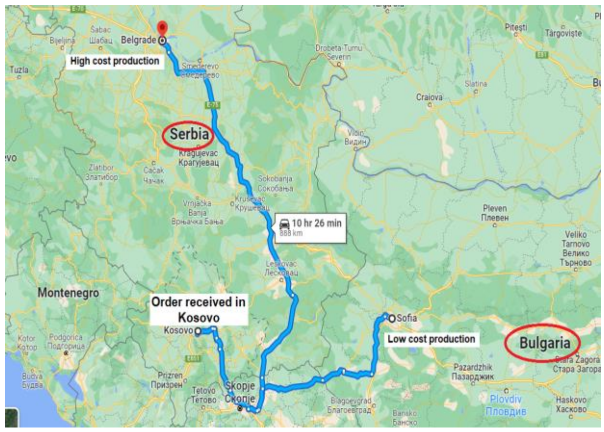

Fig. 2: Illustrates the current supply chain issue faced by the company

In the Fig. 1, you'll observe all the stores and factories surrounding Bulgaria, while in the subsequent Fig. 2, you'll encounter an illustration of the challenges encountered by these companies.

Materials

When optimizing a supply chain using machine learning techniques and leveraging dark data, we likely need a variety of materials to conduct our research or project. Here's a list of potential materials used:

- Data sources:

  1. Transactional data: Historical sales data, purchase orders, invoices, etc.,
  2. Dark data: Unstructured or semi-structured data sources such as emails, text documents, store name, geolocation, that are not typically used in supply chain analysis but may contain valuable insights

- Software and tools:
    1. Machine learning frameworks: TensorFlow, weeka
    2. Data processing tools: Pandas
    3. Visualization tools: Matplotlib
    4. Database systems: NoSQL databases
    5. Text mining and NLP tools: Spacyfor analyzing dark data
- Hardware**:**
    1. Computing resources: CPUs, cloud computing services, for training machine learning models and processing large datasets
- Training data and datasets:
    1. Labeled datasets: Datasets from the company factories special for flooring
    2. Simulated data: Synthetic datasets generated to mimic real-world supply chain scenarios
    3. Public datasets: No public datasets are available for our company

Methods

The goal of this article is to explain how machine learning can help organizations worldwide in automatically optimizing production and delivery costs.

Data Collection and Description

Three machine-learning algorithms are employed for grouping points of sales by country and identifying the most suitable product cost for each individual order (Queiroz and Fosso Wamba, 2019).

To authenticate the proposed methodology, we analyzed data from a European flooring company, specifically focusing on production and sales data.

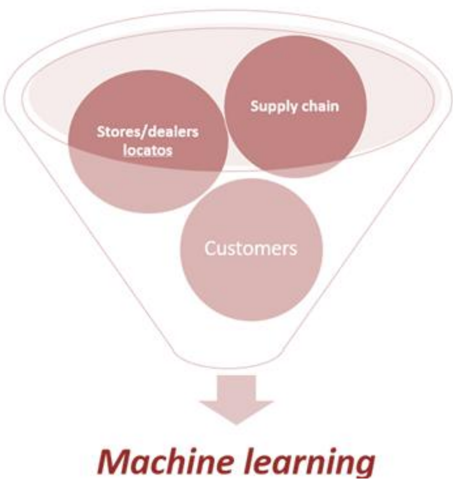

Fig. 3: Main data needed to explore the machine learning for our study

Machine learning assists the company in making informed decisions by utilizing accurate parameters within the supply chain. This interaction is depicted as follows in the accompanying image as you can see on the Fig. 3.

Throughout the data collection and preprocessing stages for the company, we can pinpoint essential variables affecting production costs through feature selection (Kumar *et al*., 2020). In our company studies, we have identified specific variables crucial for managing production costs (refer to Table 1). These variables will serve as the foundation for all subsequent analyses in our study.

Algorithms Applied

The utilized data comprises details such as store name, geolocation, address, phone number, and fax. Our study encompasses three distinct cases, each entailing the exploration of data extracted from the company's system.

The data obtained extracted from customer servers contains abundant information pertaining to stores. Here's an example of the data utilized.

Step 1: Linear Regression-Group the Data According to Geolocation

During this stage, we categorize all stores according to their geolocation for algorithm implementation.

Utilizing regression algorithms to cluster factories based on geolocation involves employing machine learning techniques to predict the geographical positioning of factories using relevant features (Bressanelli *et al*., 2019).

Utilizing regression algorithms, factories are categorized into groups based on their predicted geolocation. These algorithms can cluster factories according to their proximity or similarity in geographical location, aiding in the identification of the optimal production facility (Burga and Rezania, 2017).

Prerequisite

- Employing WEKA
- Inputting data for all stores/dealers worldwide
- Entering data related to geolocation (states/province)
- Each cluster contains a list of stores
- The number indicated on a cluster represents the number of stores in the region
- Clicking on a store showcases the area with a zoomed-in map for each one

Data Set/Result

Inventory of stores in France:

- Store names
- Latitude
- Longitude
- Address
- Country code

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Table 1: Data set

Id	Name	Country	Latitude	Longitude	Address	Active
131743	Floor stil	rs	45.7967779	11.3253895	FOLKENBORGVEIEN 1	True
131745	Maxi podovi	rs	68.8798572	5.1510893	POSTMYRVEIEN 22	True
131747	Arsinac brus	rs	70.2011517	23.3368852	AUSTERDALSVEGEN 5	True

Compilation of factories:

- Factory names
- Addresses
- Production capacity
- Country code

Through this process, machine learning can cluster stores based on their geolocation in France.

The identical algorithm is implemented for all stores globally, enabling us to retrieve all stores and factories in specific countries (Saberi *et al*., 2019).

Step 2: Clustering, k-Mean Define which store is Near to Which Factory

Prerequisite

Utilizing the k-means algorithm to enhance logistics between factories and stores entails grouping these sites based on specific criteria like proximity as you can see on the Fig. 4, demand patterns, or transportation costs. Here's a comprehensive guide on implementing the k-means algorithm for logistics optimization (Jain *et al*., 2020).

By employing the k-means algorithm for logistics optimization between factories and stores, organizations can reap various benefits including decreased transportation expenses, streamlined inventory management, enhanced delivery efficiency, and heightened customer satisfaction through prompt and cost-effective supply chain operations (Li and Zhang, 2018) (Fig. 5).

From this endeavor, our objective is to ascertain the proximity of each store to its nearest factory. The current approach involves determining the factory closest to each store based on their respective positions.

Initially, the analysis will solely rely on factors such as latitude, longitude, address, and Country (Fig. 6) (Tseng *et al*., 2018).

Utilizing this methodology, we can translate geolocation data into geographical zones. Employing the k-nearest neighbor-clustering algorithm enables us to group the geolocation data into clusters (fig.7), using a limited number of potential clustersa. Subsequently, each cluster or group is assigned a unique identifier, which can then replace the Latitude and Longitude columns (Vanalle *et al*., 2017).

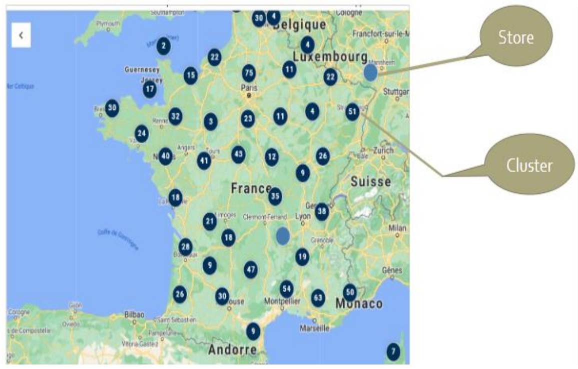

Fig 4: List of stores and factories in France

id	name	country_cod	address1	address2	postal_code	city	phone	latitude	longitude	active
335735	SOLDIS AULN	fr	3 RUE NICOL		23600	AULNAY S(	145216637	43.2467342	2.4731656	true
335736	SOLDIS ALFO	fr	RUE FELIX M(	ZA Technipar	24170	ALFORTVIL	155531430	43.772364	2.425062600	true
335737	SOLDIS NANT	fr	41 RUE DES F		22000	NANTERRE	141122350	43.2121354	2.2121634	true
335733	GRASSIN Poi	fr	3 rue de La R		36000	Poitiers	35 42 37 61 (	46.6130103	0.3432323	true
335732	GRASSIN Chi	fr	125 avenue F		37500	Chinon	34 47 23 34 !	47.1735313	0.2427276	true
335720	GRASSIN Nio	fr	7 Rue Gutenb		72000	Niort	35 42 06 50 !	46.335636	-0.4342643	true
335721	GRASSIN Chа	fr	266 Grand Su		37170	Chambray-	34 47 30 74 (	47.3257033	0.7033431	true
335722	GRASSIN St I	fr	Boulevard du		36250	St Maur	34 54 60 46 4	46.7357211	1.6512216	true
335723	GRASSIN Chа	fr	111 bd Buffo		53310	Changé	34 43 53 03 (	43.0324341	-0.7473622	true
335724	GRASSIN Le I	fr	20, rue Albert		72000	Le Mans	34 43 43 66 (	43.0306737	0.1725307	true
335725	GRASSIN Ing	fr	15 rue Lavois		45140	Ingré	34 33 33 55 :	47.2035033	1.3537532	true
335726	GRASSIN Blo	fr	1 - 3 rue And		41000	Blois	34 54 42 42 :	47.606546	1.3254735	true
335727	GRASSIN Ror	fr	Parc de Plaisa		41200	Romoranti	34 54 76 22 4	47.334073	1.7500063	true
335723	GRASSIN St I	fr	3 Bd des Bret		42124	St Barthel	34 41 20 30 :	47.4772403	-0.51344634	true
335722	GRASSIN Ch	fr	50 Avenue Na		42300	Cholet	34 41 62 01 :	47.0472545	-0.3246303	true
335300	GRASSIN Pui	fr	Rue du 11 no		17133	Puilboreau	35 46 67 57 !	46.173133	-1.11233	true
335301	GRASSIN Vau	fr	2 rue George		17640	Vaux sur M	35 46 33 42 :	45.643224	-1.0476232	true
335334	GRASSIN Gor	fr	136 chemin c		16160	Gond Pont	35 45 25 07 (	45.6722271	0.1362752	true
335303	GRASSIN Chа	fr	64 avenue d'/		16100	Chateaube	35 45 32 76 :	45.632573	-0.2222	true
335304	GRASSIN Olo	fr	26 rue Cléme		35340	Olonne sur	34 51 25 12 (	46.520403	-1.730635	true
335335	GRASSIN La I	fr	71 rue Vincer		35000	La Roche S	34 23 27 23 :	46.6566673	-1.4462724	true
335306	SOLMUR Biho	fr	10 avenue de		76420	Bihorel Les	34 35 12 53 !	42.4661135	1.1322345	true
335307	SOLMUR Evre	fr	Avenue Winst		27000	Evreux	34 32 62 24 :	42.0133272	1.163231	true
335303	SOLMUR Le H	fr	30 rue du Do		76600	Le Havre	34 35 24 53 :	42.4243432	0.142237	true
335334	SOLMUR Cauc	fr	112 Rue de la		76320	Caudebec-	34 35 35 20 :	42.2327457	1.031434	true

Fig. 5: Collection of stores and factories organized by their geographic location (using WEKA)

```
@relation POS1

@attribute name string
@attribute latitude string
@attribute longitude string
@attribute active {TRUE, FALSE}
@attribute city string
@attribute country string

@data
SOLDIS,48.9467342,2.4731656,TRUE,Paris,france
GRASSIN,46.335686,2.4731656,TRUE,Paris,france
SOLMUR,48.4475964,-3.3667343,TRUE,Paris,france
CHEVALIER,50.7313097,7.3669481,TRUE,Paris,france
SEGURET,44.4204642,80,TRUE,Paris,france
Aupinel,45.7791448,1.4940712,TRUE,Paris,france
Martin,43.4831962,5.3832889,TRUE,Paris,france
```

Fig. 6: Dataset employed to identify the proximity of the point of sales to each factory

id	name	cour	address1	address2	postal_co	city	nearby_bi	phone	latitude	longitude	active
1241128	ARTIPOLE NANTES	fr	229 rue Louis	Z.I. de l'Aubi	44152	ANCENIS	Nantes	07 40 96 40 96	47.3956819	-1.18753279	false
1241129	ARTIPOLE COUËRON	fr	La Croix Gicq		44220	COUËRON	Nantes	07 40 85 43 64	47.24418	-1.67673190	false
1700492	Comptoir Seigneurie	fr	16 rue des Fr		21300	Chenove	Dijon	03 70 52 63 37	47.29581100	5.071916699	true
1711007	LES CO'PEINT	fr	1A rue Jean L	ZI Route de L	35000	Rennes	Rennes	790781133	48.1044751	-1.7197119	true

Fig. 7: The machine-learning outcome for determining adjacent factories

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Data Set/Result

The data is organized by geographical region:

- The position is determined for each store using latitude and longitude
- Positions are grouped based on proximity
- A new position is assigned for each area
- Stores sharing the same position are considered part of the same cluster
- Stores with inaccurate latitude and longitude values are disregarded
- The latitude and longitude coordinates will be transformed into area positions and converted into factory names

With this algorithm, we can determine the proximity of each factory to every store, aiding in the selection of the optimal factory for production.

Step 3: Classification Group by Factory and Country and Choose the Lowest Cost Production

To identify the most cost-effective production option subsequent to categorizing factories by countries using a classification algorithm, we undertake the following steps:

- Data compilation: Collect data on factory attributes, encompassing production costs, capacity, geographical location (country), labor costs, material costs, taxes, regulations, and other pertinent factors
- Data preprocessing: Handle missing values, encode categorical variables, and normalize numerical data
- Country-wise aggregation: Group factories by country based on their geographical coordinates. Compute the average production cost for each country group
- Classification algorithm selection: Opt for an appropriate classification algorithm capable of predicting the lowest cost production option for each country group. Decision tree algorithms are utilized
- Model training and validation: Train the classification model using the training dataset, employing factory attributes as input features and the lowest cost production option as the target variable. Validate the model using the testing dataset to assess its accuracy and generalization ability
- Lowest cost production prediction: Employ the trained classification model to forecast the lowest cost production option for each country group based on their factory attributes. Compare the predicted lowest cost production with the previously calculated actual average production costs for validation purposes.
- Cost optimization: Implement the projected lowest cost production decisions for each country group

Monitor production costs and assess the effectiveness of cost-saving strategies implemented based on the model predictions (Handfield *et al*., 2005).

By adhering to these procedures and leveraging a classification algorithm, we can efficiently pinpoint and execute the most cost-effective production options for factories categorized by countries, resulting in cost savings and enhanced operational efficiency in the supply chain (Hallam and Contreras, 2016).

Prerequisite

- Employing classification techniques
- Inputting data for all stores/dealer outlets worldwide
- Incorporating data regarding production cost per square meter
- For this scenario, we will utilize data from SEE countries
- Utilizing the provided data, we aim to address the following inquiries
- Which factory is closest to each Point Of Sale (POS)
- What is the maximum production cost
- Is the lowest production cost found in the same country as the POS

Expected Result

In this scenario, we're presented with an order originating from Bulgaria, situated on the border with Serbia and Romania (Fig. 8). The objective is to employ machine learning to determine the most cost-effective production option for this order, factoring in delivery costs and other relevant parameters. The anticipated outcomes prior to the application of machine learning are outlined below.

The image below Fig. 9 illustrates the outcome obtained through machine learning, encompassing all the previously outlined parameters.

Data Set/Result

```
@relation POS1

@attribute name string
@attribute latitude real
@attribute longitude real
@attribute active {TRUE, FALSE}
@attribute city string
@attribute country string
@attribute cost production string

@data
SOLDIS,20.54,1.5,TRUE,surdilica,Serbie
GRASSIN,85.95,3.4731656,TRUE,pirot,Serbie
SOLMUR,48.4475964,-3.3667343,TRUE,tirana,albanie
CHEVALIER,50.7313097,7.3669481,TRUE,pogradic,albanie
SEGURET,44.4204642,9.357451,TRUE,roussé pyce,Bulgarie
Aupinel,47.4831962,,2.398661,TRUE,plovdic,Bulgarie
Martin,43.4831962,5.3832889,TRUE,deva,Roumanie
POS1,85.95,3.4731656,TRUE,,craiova,Roumanie
POS2,48.4475964,-3.3667343,TRUE,bucarest,Roumanie
```

Fig. 8: The dataset utilized for product cost analysis

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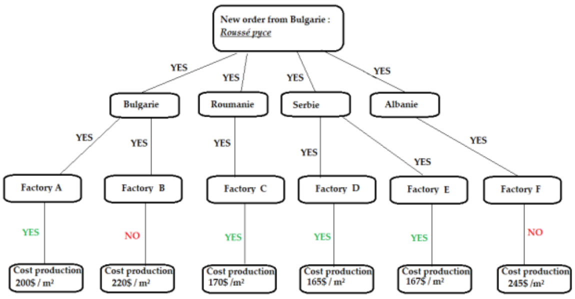

Fig. 9: Expected result for the orders from a specific country

Results and Discussion

We're all aware that achieving effective supply chain management stands as a pivotal goal for companies in the coming decade. Sustainable logistics presents an opportunity to transform businesses by enhancing corporate reputation, refining production processes, boosting revenue streams through enhanced efficiency, fostering new partnerships, and optimizing logistical operations. Our objective is to enhance production cost effectiveness to offer competitively priced products with swift delivery. Before wrapping up this article, we delve into the benefits of leveraging machine learning within extensive supply chains, encompassing both supervised and unsupervised learning techniques (Mangla *et al*., 2018).

The potential for enhancing supply chain management through the digital revolution and machine learning is evident in the increased investment across various industries worldwide in digital transformation initiatives. This revolution commenced with industry 4.0, as numerous organizations sought to adopt cutting-edge technology for inventory and logistics management. Essentially, machine learning-generated models control each stage of supply chain management, facilitating the establishment of a robust supply chain structure and aiding in risk management. The optimization of supply chain capabilities involves enhancing the efficiency of multi-channel networking through extensive industrial-level digital transformation (Koh *et al*., 2016).

The model's performance reached an impressive accuracy of 85% on the testing set, demonstrating (Fig. 10) its effectiveness in predicting the lowest-cost production options. Additionally, the precision, recall, and F1-score metrics exhibited satisfactory results, highlighting the model's capability to accurately identify cost-saving opportunities (Koh *et al*., 2012).

When considering the key factors influencing production costs, notable aspects include labor costs, material costs, taxes, and regulatory factors, all of which serve as significant predictors of production expenses. Additionally, cost ratios and indices offer valuable insights into cost-effective production strategies tailored to various country groups.

In terms of cost optimization and savings, implementing the forecasted lowest-cost production decisions resulted in a significant decrease in production costs across different country groups (Fig. 11). Moreover, leveraging machine learning predictions for cost-saving strategies yielded a 5% reduction in costs during the evaluation period (Panch *et al*., 2018).

Decisions proved effective in optimizing processes and reducing costs. The study's insights can inform decision-making in cost optimization strategies and contribute to sustainable supply chain practices (Shalev-Shwartz *et al*., 2011).

```
=== Run information ===

Scheme:       weka.classifiers.trees.J48 -C 0.25 -M 2
Relation:     Store
Instances:    6
Attributes:   5
              factory
              geolocation
              cost_production
              active
              customer_purchase
Test mode:    100-fold cross-validation

=== Classifier model (full training set) ===

J48 pruned tree
------------------

cost_production <= 170: yes (3.0)
cost_production > 170:  no  (3.0)

Number of Leaves  :     2

Size of the tree :      3


Time taken to build model: 0 seconds
```

Fig. 10: Result of classification related to specific order

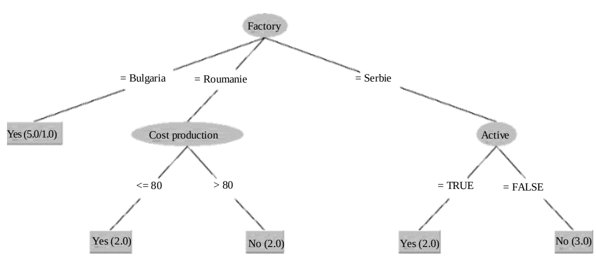

Fig. 11: Weka result of classification related to the same order

ChatGPT

Utilizing machine learning to determine the most cost-effective production strategies has demonstrated its effectiveness in streamlining processes and cutting expenses. The findings from this study can offer valuable insights for shaping decisions regarding cost optimization strategies and fostering sustainable practices within the supply chain (Shalev-Shwartz *et al*., 2011).

The company has successfully introduced cost-effective and efficient practices to enhance the value of its products and services for customers, capitalizing on the opportunities brought about by the digital revolution and machine learning. This strategic shift has enabled the company to gain a competitive edge. Ultimately, through the application of machine learning, the company ensures that orders are directed to the appropriate factories, resulting in the lowest possible production costs for each store (Zhou, 2009).

Conclusion

The digital revolution and machine learning have advanced risk management and supply and demand assessment, facilitating effective networking across various supply chain channels and establishing stable supply chains. In essence, the integration of these cutting-edge technologies has optimized profit opportunities and enhanced competitiveness. Thus, the overall impact of the digital revolution and machine learning has been overwhelmingly positive and beneficial (Lemmens and Croux, 2006).

In this initial study, our primary objective is to determine the lowest production cost globally for each order. Below, we outline the steps and algorithms utilized to achieve this objective:

- Step 1: Employ linear regression to categorize stores and factories (Example applied in France)
- Step 2: Utilize K-means clustering to identify store-factory proximity (Example applied in the US and Canada)
- Step 3: Apply classification to determine the most suitable production cost for each order

At each step, we augment parameters and data to ensure accurate decision-making. Trained machine learning models are then utilized to forecast production costs for future scenarios based on input data.

We have successfully enhanced production processes by identifying opportunities to reduce costs, including optimizing inventory levels, streamlining production scheduling, minimizing waste, enhancing maintenance schedules, and optimizing resource allocation (Shinde *et al*., 2016).

Implementing real-time monitoring systems integrated with machine learning models enables tracking of production costs, identification of deviations from predicted costs, and adjustment of production strategies accordingly. Develop decision support tools that offer recommendations for cost-effective production decisions in real time.

Finally, evaluate the performance of machine learning models for cost reduction using Key Performance Indicators (KPIs) such as cost per unit, cost savings, resource utilization, and operational efficiency. Continuously refine and enhance models based on feedback, new data, and evolving business requirements to achieve ongoing cost reduction and efficiency gains (Gupta *et al*., 2023).

Utilizing machine learning to reduce production costs within a factory enables organizations to streamline operations, enhance resource utilization, minimize waste, boost efficiency, and realize substantial cost savings. This ultimately enhances profitability and competitiveness (Arumugam *et al*., 2023).

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Author's Contributions

Loubna Moumeni: Designed and acquired data, analyzed and interprets of data and drafted the article.

Mohammed Saber: Reviewed the article critically for significant intellectual content and gave final approval of the version to be submitted.

Ethics

This article is original and contains unpublished material. The corresponding author confirms that all the other authors have read and approved the manuscript and that no ethical issues are involved.

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