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SUPPLY CHAIN: OPTIMIZE THE PRODUCTION COST USING MACHINE LEARNING

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ABSTRACT

Purpose: The objective of this study is to know how we use can machine learning by applying different algorithms on the supply chain to produce in the cheapest site in the world considering different parameters.

Theoretical framework: the study has highlighted the iterative queries of digital revolution in the supply chain. The literary view in this article has illustrated the significant role of machine learning and dark data in reducing the production costs, enhancing delivery performance.

Design/Methodology/Approach: The company concerned by the case study is a multinational company specializing in flooring and sports surfaces. It operates in 33 production sites, with 520 sites in more than 100 countries.
One of the important factors underlying this complexity is the customer base that expects the product at the same cost all over the world, which forces the system that is currently not centralized to produce at a high cost in some countries.

Findings: In this article, we use machine learning by applying different algorithms to unstructured data stored in company servers, where the feedback loop is implemented. The expected result is produced in the cheapest site in the world considering delivery costs.

Research, Practical & Social implications: We suggest a future research to use all the remaining dark data saved during ordering on the supply chain and to reduce more the costs in the world .

Originality/Value: This article provides insights into how dark data analytics can be used to reduce supply chain costs and offers recommendations for organizations looking to leverage dark data in their supply chain operations.

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CADEIA DE FORNECIMENTO: OTIMIZE O CUSTO DE PRODUÇÃO USANDO APRENDIZAGEM DE MÁQUINA

RESUMO
Objetivo: O objetivo deste estudo é saber como usamos o aprendizado de máquina, aplicando diferentes algoritmos na cadeia de suprimentos para produzir no local mais barato do mundo, considerando diferentes parâmetros.
Enquadramento teórico: o estudo destacou as questões iterativas da revolução digital na cadeia de abastecimento. A visão literária neste artigo ilustrou o papel significativo do aprendizado de máquina e dos dados obscuros na redução dos custos de produção, melhorando o desempenho da entrega.
Design/Metodologia/Abordagem: A empresa objeto do estudo de caso é uma empresa multinacional especializada em pisos e superfícies esportivas. Opera em 33 locais de produção, com 520 locais em mais de 100 países. Um dos factores importantes subjacentes a esta complexidade é a base de clientes que espera o produto ao

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mesmo custo em todo o mundo, o que obriga o sistema que actualmente não está centralizado a produzir a um custo elevado em alguns países.
Resultados: Neste artigo, utilizamos aprendizado de máquina aplicando diferentes algoritmos a dados não estruturados armazenados em servidores da empresa, onde o ciclo de feedback é implementado. O resultado esperado é produzido no site mais barato do mundo considerando os custos de entrega.
Implicações de pesquisa, práticas e sociais: Sugerimos uma pesquisa futura para usar todos os dados obscuros restantes salvos durante os pedidos na cadeia de abastecimento e para reduzir ainda mais os custos no mundo.
Originalidade/Valor: Este artigo fornece insights sobre como a análise de dados obscuros pode ser usada para reduzir os custos da cadeia de suprimentos e oferece recomendações para organizações que buscam aproveitar dados obscuros em suas operações da cadeia de suprimentos.

Palavras-chave: Aprendizado de Máquina, Dados Obscuros, Cadeia de Mantimentos, Custo de Produção, Dados não Estruturados.

CADENA DE SUMINISTRO: OPTIMIZAR EL COSTO DE PRODUCCIÓN UTILIZANDO EL APRENDIZAJE MÁQUINA

RESUMEN

Propósito: El objetivo de este estudio es conocer cómo utilizamos el aprendizaje automático de latas aplicando diferentes algoritmos en la cadena de suministro para producir en el sitio más barato del mundo considerando diferentes parámetros.
Marco teórico: el estudio ha puesto de relieve las consultas iterativas de la revolución digital en la cadena de suministro. La visión literaria de este artículo ha ilustrado el importante papel del aprendizaje automático y los datos oscuros en la reducción de los costos de producción y la mejora del rendimiento de la entrega.
Diseño/Metodología/Enfoque: La empresa objeto del caso de estudio es una empresa multinacional especializada en pavimentos y superficies deportivas. Opera en 33 sitios de producción, con 520 sitios en más de 100 países.
Uno de los factores importantes que subyacen a esta complejidad es la base de clientes que esperan el producto al mismo costo en todo el mundo, lo que obliga al sistema que actualmente no está centralizado a producir a un alto costo en algunos países.
Hallazgos: En este artículo, utilizamos el aprendizaje automático aplicando diferentes algoritmos a datos no estructurados almacenados en los servidores de la empresa, donde se implementa el circuito de retroalimentación. El resultado esperado se produce en el sitio más barato del mundo considerando los costos de envío.
Implicaciones de investigación, prácticas y sociales: sugerimos una investigación futura para utilizar todos los datos oscuros restantes guardados durante los pedidos en la cadena de suministro y reducir aún más los costos en el mundo.
Originalidad/Valor: este artículo proporciona información sobre cómo se puede utilizar el análisis de datos oscuros para reducir los costos de la cadena de suministro y ofrece recomendaciones para las organizaciones que buscan aprovechar los datos oscuros en sus operaciones de la cadena de suministro.

Palabras clave: Aprendizaje Automático, Datos Oscuros, Cadena de Suministro, Costo de Producción, Datos no Estructurados.

INTRODUCTION

Dark data in the context of supply chain management refers to unstructured and unanalyzed data that exists within a supply chain but is not being utilized for business insights or decision-making. This data could include information on supplier performance, logistics operations, inventory levels, and customer demand, among other things.

The existence of dark data in a supply chain can create several challenges for organizations, such as inefficient operations, missed opportunities, and increased costs. For example, if a company is not analyzing its logistics data, it may not be able to identify areas for improvement and cost savings.

However, by analyzing dark data, organizations can uncover new insights, identify patterns and trends, and improve decision-making in supply chain management. For example, by analyzing data from logistics operations, a company may be able to identify inefficiencies and optimize routes, resulting in cost savings and improved delivery times.

To leverage dark data in supply chain management, organizations need to adopt new techniques and tools for data analysis, such as machine learning, artificial intelligence, and predictive analytics. They also need to ensure that their data is accurate, consistent, and up-to-date, and that their IT systems are capable of handling large volumes of data.

Machine learning algorithms can be used to analyses data and measure the performance of companies. They can identify indicators that contribute to efficient portfolios. They can also measure the performance of companies by comparing their performance with their peers. In addition, these algorithms can help companies to determine whether their supply chain management programs are effective. They can also help to identify companies that may not have the data needed to meet sustainability commitments.[3]

Overall, by analyzing dark data in supply chain management, organizations can gain a competitive advantage by improving their operations, reducing costs, and delivering better customer experiences., machine learning will make it possible to constantly learn about the points to be improved [4].

The company concerned by the case study is a multinational company specializing in flooring and sports surfaces. It operates in 33 production sites, with 520 sites in more than 100 countries.

The multiplicity of production sites around the world as well as the variation of production parameters make the production chain complex and expensive [5].

One of the important factors underlying this complexity is the customer base that expects the product at the same cost all over the world, which forces the system that is currently not centralized to produce at a high cost in some countries [6].

To reduce this cost of production and these uncertainties, the automation and centralization of data are essential in the software systems of this company.

In this article, we use machine learning by applying different algorithms to unstructured data stored in company servers, where the feedback loop is implemented.

The expected result is: produced in the cheapest site in the world taking into account delivery costs [7].

The delivery cost is directly related to the transport. It means the transport plays a central role in the management of the supply chain, then the integration of transport infrastructure into the business's operational activities is necessary. This is rightly so because according to Jacoby and Hodge (2008) investing in freight transportation infrastructure has a positive impact on the supply chain and saves businesses 1-2% of operating costs and more than 15% of annual transportation costs. [8]

LITERATURE REVIEW

Currently, the multinational corporation, having the problem of high production costs, works in a traditional way so each order received in a store in a specific country is manufactured on the site of this country.

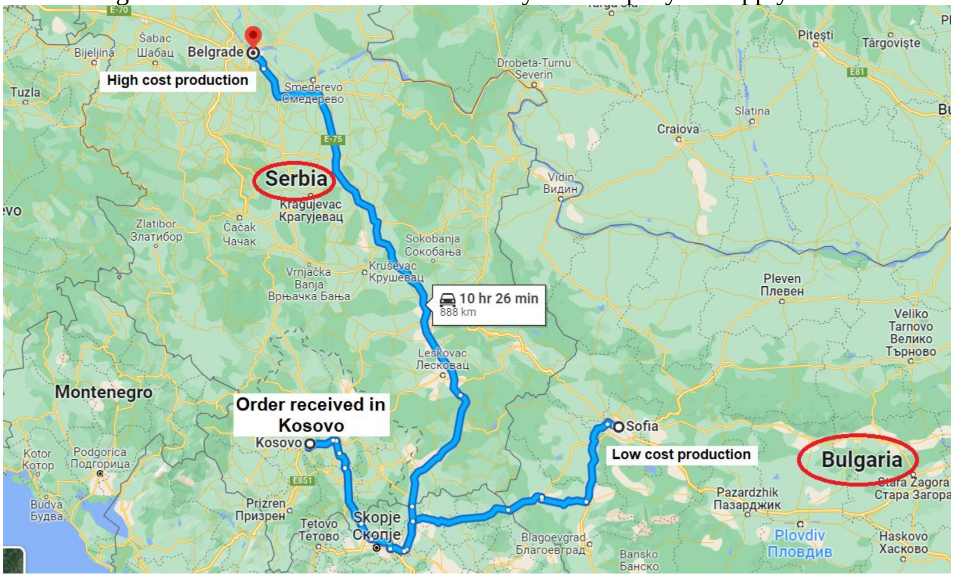
They never consider the production cost, and they are not able to compare and find the best way to produce with an optimized cost. For example, if the order is received in a store in Serbia but on the border with Bulgaria this order is made in Serbia without considering delivery costs or any other variable parameter and they discover that if they produce in Bulgaria, it's cheaper.

On the first screenshot, you can see all the stores and factories around Serbia, and the second screenshot below you can see an example of the issue faced by these companies [9].

Figure 1. Shows the list of store and factories arround Serbia

Source: Tarkett.com (client information)

Figure 2. Shows the actual issue faced by the company on supply chain.



Source: Tarkett customer information

METHODOLOGY

The objective of this study is to propose a methodology capable of helping companies operating all over the world to optimize the cost of production and delivery automatically [10].

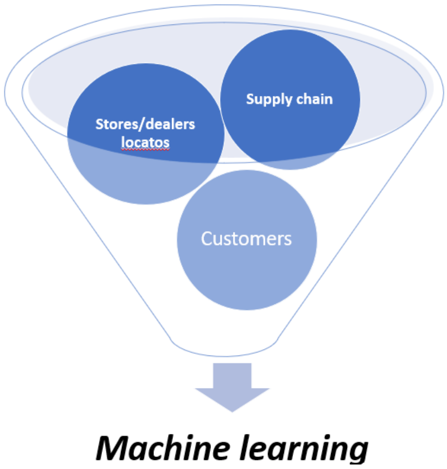
Data Collection and Description

3 algorithms are applied using machine learning in order to be able to group stores by country and choose the best product cost for each specific order.

To validate the proposed methodology, we used data from a European company specializing in flooring, in particular production and sales data [11].

Machine learning helps the company to make the correct decision using the correct parameters on the supply chain, it will interact in the following way like the image below:

Figure 3. The relationship of supply chain and machine learning



Source: DOI:10.31387/OSCM0300198. Corpus ID: 56215718. Role of Big Data in Decision Making Shirish Jeble, Sneha Kumari, Y. Patil. Published 2018

Algorithm Applied

Proper The data used contains information about store name, geolocation, address, phone, and fax. In our study, we have 3 cases and in each one, we will explore information extracted from the company system.The data captured from customer servers contain a lot of information related to stores[12].

Example of data used:

Table 1. Data set (client data)

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

Source: Extract data base of the customer

Step 1: linear regression - Group the data according to geolocation

Prerequisite

- Using WEKA.
- Insert the data of all stores/dealers stores in the world.
- Insert the data concerning geolocation (states/province).
- Inside each cluster we can find a list of stores.
- The number displayed on a cluster is the number of stores in the area.
- The click on the store displays the area with the zoom on the map for each one[13].

Figure 4. List of store and factories in France (trarkett.com)

Source: Tarkett.com

Data Set / Result

- List of stores on France:
  - Name of stores.
  - Latitude.
  - Longitude.
  - Address.
  - Country code.
- List of factories:
  - Name of the factory.
  - Addresses.
  - Capacity of production.
  - Country code.

Figure 5. List of stores and factories grouped by geolocation (weka)

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 Cha	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 ‹	46.7357211	1.6512216	true
335723	GRASSIN Cha	fr	111 bd Buffor		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 ‹	47.334073	1.7500063	true
335723	GRASSIN St I	fr	3 Bd des Bret		42124	St Barthele	34 41 20 30 :	47.4772403	-0.51344634:	true
335722	GRASSIN Cho	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 Cha	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

Source: Analyse Weka 3 : machine learning software

With this step, machine learning can group stores according to the geolocation in France.

The same algorithm is applied for all stores in the world, and we can get all the stores and factories in specific countries [14].

Step 2: clustering, k-Mean - Define which store is near to which factory.

Prerequisite

With this experience we need to know: Which store is near to which factory.

The idea now is just to calculate the position on each store to know the factory near to this one.

The first result will be based only on: Latitude, Longitude, address, Country[15].

Using this algorithm, we can convert geolocation data into zones. We can use clustering algorithm k-Nearest Neighbor to group the geo-location data (using a small number of potential clusters) and assign each cluster or a group a unique id and then this unique id can then replace the latitude and longitude column[16].

Data Set / Result

Figure 6. Data set used to define the stores near to each factory(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
```

Source: Tarkett extract database.

The data is grouped by area:

- Position calculated for each store using latitude and longitude.
- Position grouped by nearby.
- New position for the area.
- If the POS have the same position, then they are on the same cluster.
- If the latitude and longitude are not correct, then the POS is ignored.

The latitude and longitude will be changed on the area position and will be converted to Factory name[17].

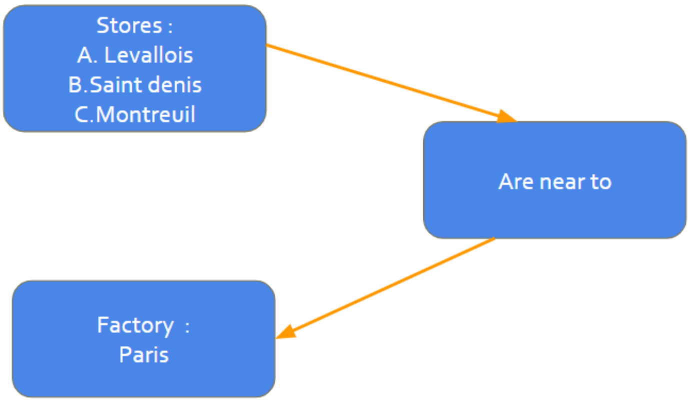
Figure 7 . The result from machine learning to define nearby factories (Client data)

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

Source: Analyse Weka 3 : machine learning software.

Using this algorithm, we can know which factory is near to which store, and this can help to choose the best factory for the production.

Figure 8. Manage distance between stores and factory



Source: Database analysis

Step 3: Classification Group by factory & country and choose the lowest cost production.

Prerequisite

- Using classification.
- Insert the data of all stores/dealers stores in the world.
- Insert the data concerning production cost per m².
- For this scenario we will use the data from SEE country

Using the data below we must answer the following questions:

- Which factory is near to which POS?
- What is the highest cost of production?
- The lowest cost of production is in the same country as the POS.

Data Set / Result

Figure 9. Data set used with product cost.(client data)

```
@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
```

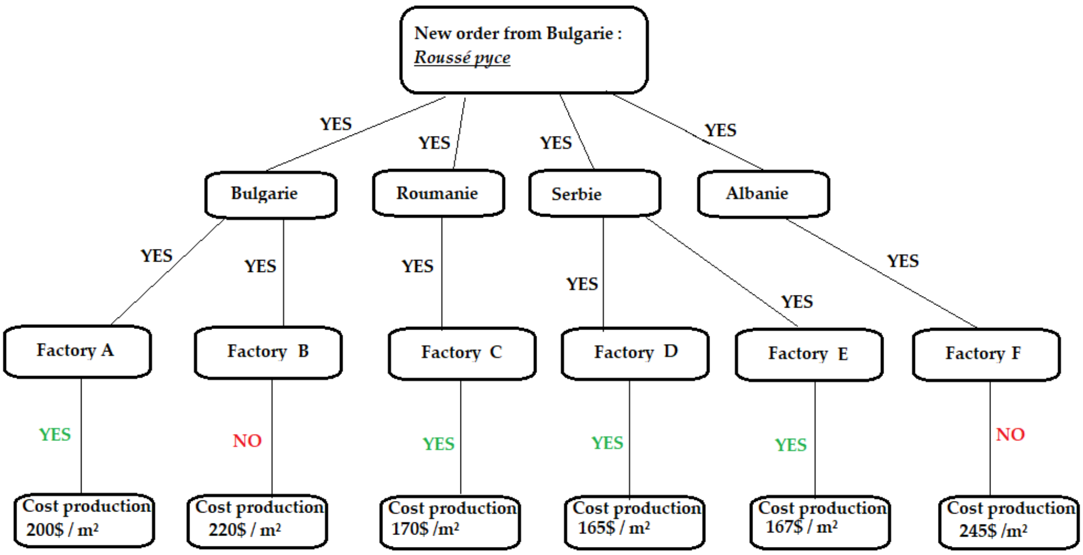
Source: Tarkett extract database

Expected Result

In this use case, we use an order case coming from Bulgaria but on the border with Serbia and Romania, so the idea is to use machine learning to find the best cost production for this order considering the delivery cost and other parameters [18].

See below the expected results before using machine learning.

Figure 10. Expected result for the order from Bulgarie (weka)



Source: Analyse Weka 3 : machine learning software

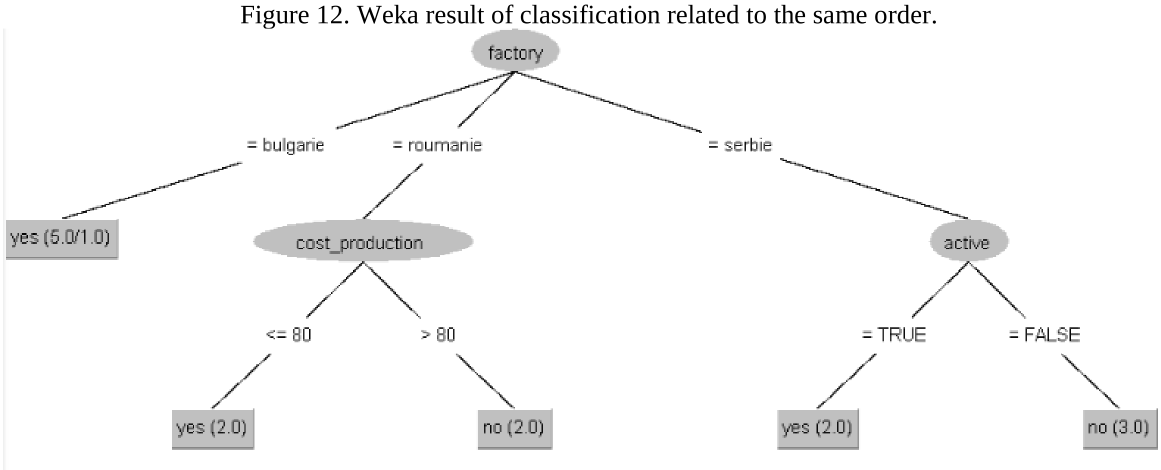
The screenshot below is result using the machine learning including all the parameters already described

Figure 11. Weka result of classification related to the same order.(weka)

```
=== 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
```

Source: Analyse Weka 3 : machine learning software

Figure 12. Weka result of classification related to the same order.



Source: Analyse Weka : machine learning software

RESULTS AND DISCUSSION

We all know that effective supply chain management is an essential target for companies in the next decade. Sustainable logistics will enable us to change the business by improving corporate image, improving production processes, increasing revenue streams by becoming more efficient, finding new partners, and streamlining logistics processes [19].

We intend to improve the cost of production in order to deliver a reasonably priced product with prompt delivery. Before concluding this article, we identify the benefit of using the use of machine learning on large supply chains. First, supervised and unsupervised learning

The scope of improving supply chain management due to the implementation of the digital revolution and machine learning is evident in the growth of spending in various industries around the world on digital transformation. The digital revolution began with Industry 4.0, as various organizations wanted to implement state-of-the-art inventory and logistics management technology [12]. Essentially, each stage of supply chain management is controlled by identifying the models generated through machine learning. This not only helps create a stable supply chain structure but also contributes to risk management [20].

Optimizing supply chain capabilities by improving the speed of multi-channel networking through industrial-level digital transformation.

The organization has also been able to implement cost-effective and time-efficient practices for creating value for the profits and services offered to the customers. the implementation of modified practices due to the digital revolution and machine Learning has created scope for attaining a competitive advantage for the company.

Finally, using machine learning we are sure that the order will be produced in the correct factory and the cost of production will be the lowest for each store.

Challenges and opportunities

Use the remaining parameters responsible for production cost on machine learning:

- Delivery cost.
- Exchange rate
- Raw material price in the world.
- Geographic condition.
- Sanitary condition.

Check that the decision made by the machine learning is correct on the data samples.Use the real data and check the decision once we use all the parameters we will Use the dark data extracted from real servers to be able to built the final solution using all the data extracted and check that no impact by adding the no needed data and finally we can decide if we can explore the dark data to make good decision.

CONCLUSION

The digital revolution and machine learning have contributed to the development of risk management and assessment of supply and demand, estimation, effective networking across multiple channels of the supply chain, and the creation of a stable supply chain. In essence, the incorporation of these advanced technologies has created profit opportunities optimization and gained a competitive advantage. Therefore, the overall impact of the digital revolution and machine learning has been positive and highly beneficial.

The article presents a case study of how dark data analytics was used to identify hidden costs in the supply chain of a large retail company. By analyzing unstructured data from social media and customer feedback, the company was able to identify areas where it could reduce costs, such as by optimizing product packaging and improving transportation routes.

We also highlight several future research directions for exploring the potential of dark data analytics in supply chain management, such as developing new analytical techniques and exploring the ethical implications of using dark data.

Overall, this article provides insights into how dark data analytics can be used to reduce supply chain costs and offers recommendations for organizations looking to leverage dark data in their supply chain operations.

Find below the steps and algorithm used to achieve this goal:

Step 1: Linear regression to group stores and factories (example applied in France).

Step 2: Clustering K- means to define which store is near to which factory (Example applied in Us and Canada)

Step 3: Classification to define what is the most suitable production cost for each order.

At each step, we add more parameters and more data to have the possibility of take the correct decision.

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