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SUPPLY CHAIN LOGISTICS MANAGEMENT: AN INTEGRATION OF AUTOMATED MACHINE LEARNING

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Abstract

Backorder is a scenario in inventory management that occurs when a client orders an item that is not presently in stock and has a delayed delivery date, leading to high demand for companies and ultimately resulting in the loss of clientele. The potential to forecast backorders using AI techniques will certainly reduce a company's resource losses. This paper addresses the issues of dealing with backorders based on an automated backorder forecasting system to deal with product backorder problems. We used LightAutoML (LAMA) to predict backorders effectively. We have compared our model with existing systems to provide evidence and support our thesis.

Keywords: Automated Machine Learning, Backorder, Forecasting model, Imbalanced dataset, LightAutoML

Introduction

Backorder: Companies at specific points of the year receive more than the predicted number of orders for which the demand cannot be met. Backorders are orders for items that a company cannot fulfil due to a supply shortage. It might be a product in production or an item that has not yet started. For instance, it might represent orders that are half completed and waiting for a component to arrive in an assemble-to-order environment. Primary causes of backorder can be linked to unusual demands, lack of inventory, low safety, and suppliers/manufacturers issues. Additional factors influencing buyer behaviour include inventory management issues, labour shortages, weather and pandemic-related uncertainties, cyber security risks, and capacity limits contributing to supply chain unpredictability.

Artificial Intelligence: Artificial Intelligence (AI) is the ability of a computer to mimic human behavior. As AI progresses from customer segments to organizations, then to the industrial sector and logistics, it presents enormous opportunities [1].

Supply Chain: A supply chain is a system that unites a company's suppliers to produce and distribute a product or service [2]. The primary purpose of the supply chain is to meet demands efficiently, increase customer value, improve responsiveness, enable financial success by minimizing risks, and create a strong network. Most supply chain risks are based on demand for goods and services.[3-16]

In recent years, the management of supply networks has grown significantly and poses more challenges [17]. As peak shipping season approaches, companies face daily supply chain risks as the demand mounts to fulfil customer and delivery expectations without increasing costs[18]. Backorders at a well-structured company generally account for less than 1% of all orders received—however, when scaled, it amounts to a considerable number and results in massive losses in money and resources.

AI has been used to tactically reduce supply chain challenges through task automation to assist the industry in accomplishing its supply chain goals and adapting better to an unpredictable future. With AutoML, we intend to increase the system's efficiency and reduce the active supervision time of data scientists (discussion mentioned below).

Automated Machine Learning: AutoML is a machine learning system that strives to automate such learning by using machine compute time rather than human research time[4]. The task of automating the process of engineering a "machine learning pipeline" specifically tailored to a problem at hand, that is, to a dataset on which a (predictive) model should be induced in case of automated machine learning (AutoML). This comprises choosing, combining, and parameterising machine learning (ML) algorithms as fundamental components of the pipeline, which is the primary output of an AutoML tool that can then be used to train an accurate model on the dataset[5]. Using AutoML in the industry can help experts focus on model explainability and generate more transfer models, allowing stakeholders to trust the solution. Thus, the present study was conducted to predict backorders in the supply chain using the integration of automated machine learning.

Literature Study

A literature review was conducted to study related works. We split them into two broad categories: Supply Chain and Automated ML. We studied literature from 2019-2022 to keep up with the latest trends.

From the related work, we inferred that

(1) Research experts used various “clients” to incorporate AutoML in their implementation.

(2) These tools (mentioned in (1)) exhibited a lack of flexibility in different use cases.

(3) Points (2) and (3) have to be considered during implementation as all papers showed evidence of satisfactory results.

This leads to the research questions.

1. How can the Automated Machine Learning technique(s) predict backorder efficiently?

2. Address the issue of a lack of real-time datasets.

3. Technique Used

LightAutoML (LAMA):

LightAutoML is an open-source library that we used to automate most tasks of the traditional pipeline. We employed the LAMA technique for our dataset to investigate the significance of features on the classification and regression tasks.

TabularAutoML:

We used binary classification in TabularAutoML. The input for TabularAutoML: numeric features, categorical features, timestamps and a single target column with continuous values or class labels. It has advanced data preprocessing compared to the other popular open-source solutions. LightAutoML uses two classes (linear models and gradient boosting models) and three types of algorithms Linear Model with L2 penalty, the light GBM version of the GBM method and the CatBoost version of GBM.

TABLE [I]: Attributes of the dataset

Dataset Name	Attributes	Total Number of data	Numerical Features	Categorical Features	Target Features	Class Imbalance
Kaggle- Backorder Prediction	23	1687860	16	6	1	1:148

4. Dataset

We have included the information on the dataset we used for our project below.

4.1 Dataset Description:

TABLE [II]: Dataset Summary

No.	Feature Type	Feature Name	Description
1	Numerical	national_inv	Component's current inventory level
2		Sku(Stock Keeping unit)	The product id
3		Lead_time	the time it takes for a procedure to start and finish

4		In_transit_qty	In transit quantity(The difference between issued shipments and received shipments)
5		Forecast_3_month , Forecast_6_month , Forecast_9_month	Forecast sales for the next 3, 6 and 9 months
6		Sales_1_month , sales_3_month ,sales_6_month , sales_9_month	Sales quantity for the prior 1, 3, 6, 9 months;
7		Min_bank	Minimum recommended amount in stock
8		Pieces_past_due	Overdue parts from the source
9		Perf_6_month_avg , perf_12_month_avg	Source performance in last 6 and 12 months
10		Local_bo_qty	Amount of stock orders overdue
11	Categorical	Deck_risk , oe_constraint, ppap_risk, stop_auto_buy, rev_stop	General risk flags;
12		Potential_issue	Any flaws discovered in the product/part
13	Target	Went_on_backorder	Product went on backorder.

The dataset used is divided into two classes, “Yes” and “No”, which are present in the target column (went_on_backorder - pre-processed later; mentioned below). It is found that the data in the target column is highly imbalanced, with No: Yes being a 99.27%:0.72% ratio. The figure [I] below shows the previously mentioned in a graphical format.

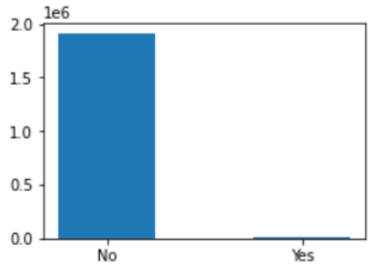
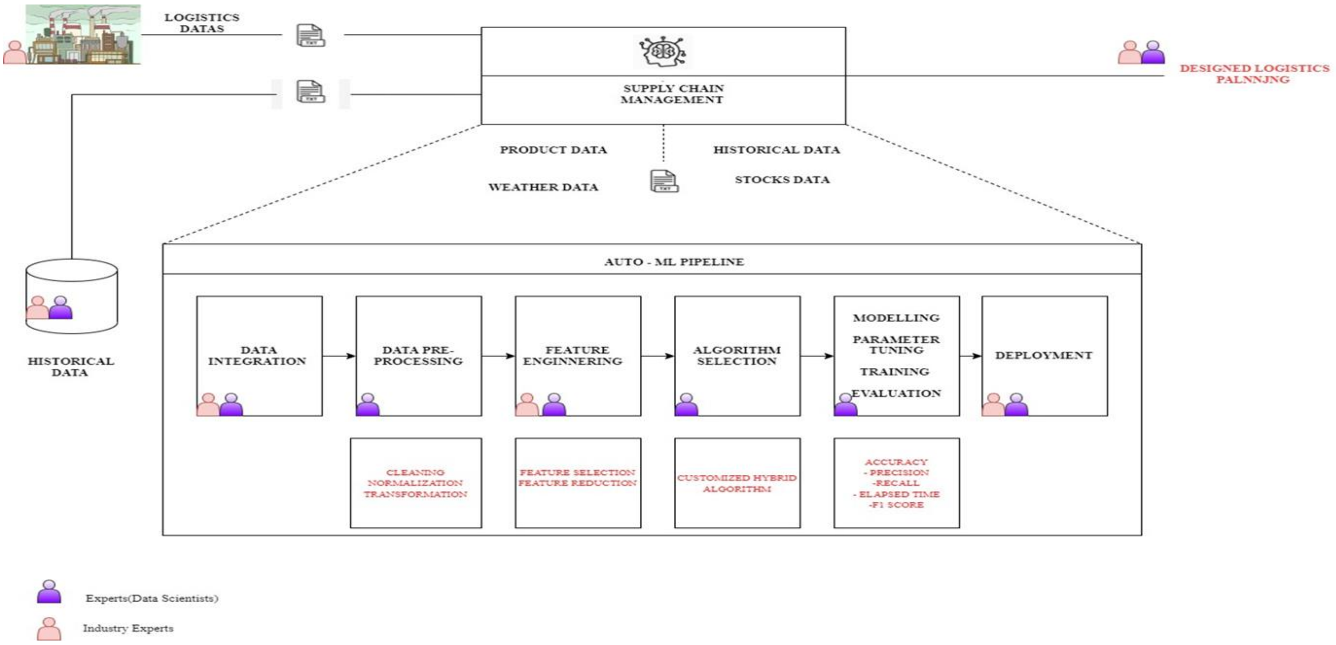


FIGURE [I]: Graphical representation of the target variable

4.2 Pre-processing

Generally, any data is manually pre-processed, leading to the wastage of time of a data scientist. The basic pre-processing via LAMA is directly automated, eliminating the above. Automatic data typing inference is used. “NormalisedGini Index” is used between target variable and encoded feature as a measure of encoding quality as it estimates the quality of sorting and could be computed



for classification.

Figure [II] shows a pictorial representation of industrial implementation.

5. Implementation

Dataset is divided into train and test, and appropriate weights were added to balance the data. This process, along with the aforementioned steps, is taken care of TabularAutoML preset.

5.1 Feature Selection

TabularAutoML uses three strategies for feature selection

1. No selection
2. Importance of cutoff selection (default)
3. Importance based forward selection

TabularAutoML has a built-in preset, which has a built-in function to know the scores called “get_feature_scores()”.

Figure [III] is available for better comprehension. The figure shows that both features “national_inv” and “3_month_forecasting” play a significant role in the backorder of products.

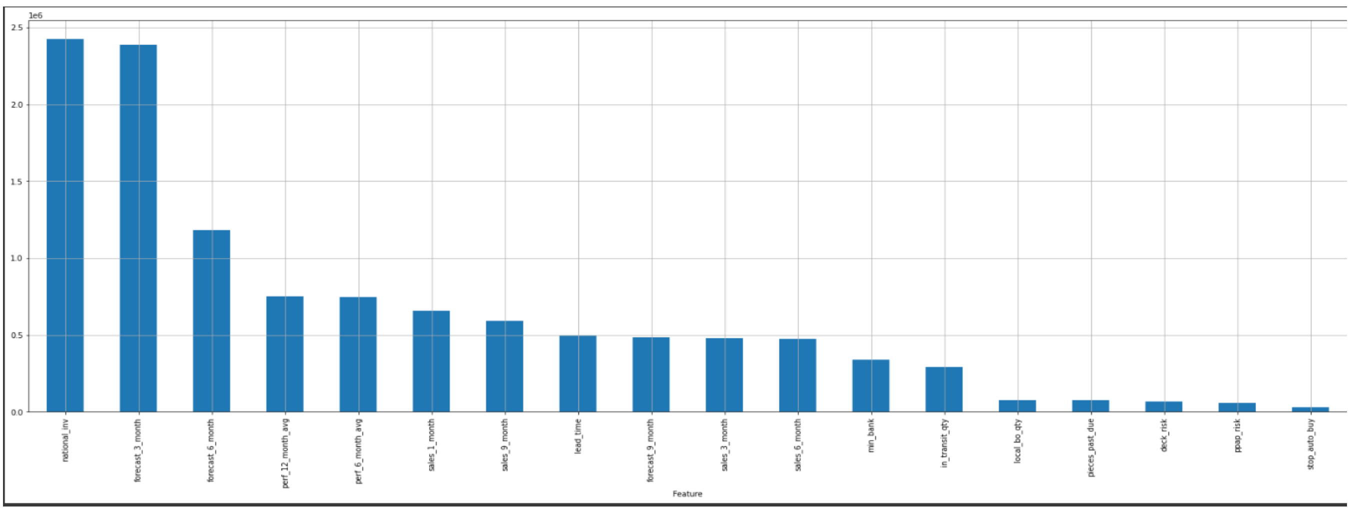


FIGURE [III]: Graph on feature importance

5.2 Evaluation metrics

Evaluation metrics evaluate the model's performance on train and test data. As discussed earlier, the dataset ishighly imbalanced, and hence we need proper metrics to assess. Typically, “Accuracy” is used to evaluate models with balanced data. However, the use of accuracy is not advised when data is highly imbalanced. The metrics used to assess the model thus change.

TABLE [III]: Evaluation metrics

S.no	Metric Name	Description	Formula
1	Precision(Pcs)	measures the correctness/accuracy of the Classifier.	Pcs = $(T_P + F_P) / T_P$
2	Recall(RC)	Recall is used to evaluate the completeness or sensitivity of a classifier.	RC=$T_P / (T_P+F_N)$
3	F1 Measure (F)	Represents a good mix of Pcs and RC.	F=2*(Pcs*RC) / (Pcs+RC)
4	ROC_AUC_score	Compute Area Under the Receiver Operating Characteristic Curve	

f1_score, roc_auc score, precision and recall.

Where TP defines True Positive, TN defines True Negative, FP defines False positive, and FN defines False Negative.

In the data section [], we had mentioned the size of data to be very extensive. Therefore, we had given every model a max—runtime of two hours (7200s).

5.3Coding Environment

The research was conducted with clean windows 1,0 installation. The system configurations are as follows.

1. Intel i3 7th gen dual-core four-thread processor clocked at 3.9 Ghz.
2. 16GB RAM clocked at 2400 MHz.
3. NVIDIA GTX 1060 6GB Graphics card.

Information on software/ libraries.

Google Colaboratory - IDE

Mozilla Firefox - Browser used

LIghtAutoML - Primary python library used.

And other standard libraries and features.

6. Findings

The findings of the ML models' evaluation are reported in this section. Appropriate metric scores employed in this investigation are shown in Table [IV, V], along with their hyper parameter tuning.

TABLE [IV]: Scores obtained using LightAutoML - train data

S.No	Time (in min)	Precision (%)	Recall (%)	F1 score (%)	roc_auc score (%)	Threshold
1	66	62.06	79.96	67.05	96.9	0.5

2	66	70.62	70.38	70.50	96.9	0.8

TABLE [V]: Scores obtained using LightAutoML - test data

S.No	Time (in min)	Precision (%)	Recall (%)	F1 score (%)	roc_auc score (%)	Threshold
1	66	62.11	81.38	67.31	97.1	0.5
2	66	70.55	69.4	69.95	97.1	0.8

It is seen that class weighting plays a vital role in handling imbalanced data, thus increasing the performance of the model. "f1-score" is a better tool to seek a balance between recall and precision. In the f1-score, we choose macro-averaged to treat both classes equally.

6.1Comparative Analysis

A comparative analysis was performed to establish a baseline to quantify our experiment. We used this report to compare the effectiveness of our model amongst others. All parameters used in the execution of LAMA are maintained, and appropriate metrics are used to obtain comparable scores.

Traditional model:

For this analysis, we used algorithms commonly mentioned in the literature survey. The necessary pre-processing is done to emulate the one handled by LAMA and added weights accordingly. The table below shows the results obtained from this experiment.

TABLE [VI]: Scores obtained without weights TABLE [VII]: Scores obtained with weights

S.No	Algorithm	Time (in min)	Train f1 score (%)	Test f1 score (%)	roc_auc score
1	SVM	90	99	1	0.5
2	kNN	183	99	1	0.56
3	Rf	7	99	20	0.63
4	Log. Reg.	2	99	40	0.49
5	LGBM	1	-	-	0.5

TABLE [VI]: Scores obtained without weights TABLE [VII]: Scores obtained with weights

S.No	Algorithm	Time (in min)	Train f1 score (%)	Test f1 score (%)	roc_auc score
1	SVM	-	-	-	-
2	kNN	-	-	-	-
3	Rf	5	99	35	0.63
4	Log. Reg.	3	99	12	0.55
5	LGBM	-	-	-	-

We can deduce from the above tables [VI, VII] that a high imbalanced dataset without any addition of weights/ feature engineering skews the result. LightGBM's score neither declined nor improved and maintained 0.5 throughout. After adding weights, a slight increase in value was noticed amongst Random Forest and Logistic Regression. However, models like SVM, kNN, and LGBM expended more than 120 minutes (2 hours) to run, a time cap we had established earlier. Thus, we were unable to obtain values for the above algorithms.

7. Results and Discussion

7.1 Inference

From the experiment, we can infer that the scores obtained for LAMA are better than the conventional counterparts. For instance, the random forest classifier has an f1_score of 35% with a roc_auc score of 63%, while scores for LightAutoML are 69.95% and 97.1%, respectively.

7.2 A discussion on datasets from the industry

We could hypothesize a few reasons why real-time data is absent from other studies and why we could not obtain satisfactory results. During the preliminary stages of the project, we acquired a dataset from the company Tecno doors Pvt. Ltd. Comparing the two datasets, we found a ratio of 1:2880. Backorders being rare, amounted to very few in number. We found the data to be insufficient; and found the model to be very inconsistent. Therefore, we concluded that the obtained scores were unsatisfactory (shown in table [VIII, IX]). Perhaps, more extensive data with variety had the possibility of being handled better.

TABLE [VIII]: Scores obtained using LightAutoML - train data

S.No	Time (in min)	Precision (%)	Recall (%)	F1 score (%)	roc_auc score (%)	Threshold
1	0.75	67.09	76.06	70.54	78	0.5

TABLE [IX]: Scores obtained using LightAutoML - test data

S.No	Time (in min)	Precision (%)	Recall (%)	F1 score (%)	roc_auc score (%)	Threshold
1	0.75	48.72	50	49.35	38	0.5

7.3 Conclusion

To answer our questions stated above, we can confirm with evidence that the use of Automated Machine Learning, i.e. LightAutoML, can be used to predict backorder effectively. Our primary goals: fast, efficient, and consistent, are accomplished here. In addition to this, active time and resources used are being saved here.

Moving forward with our case -firstly, LAMA is designed to handle large datasets, a tag mentioned in their documentation. Secondly, the inherent nature of the data available. The fine-tuning process for scenarios of this nature has proven to be extremely difficult and is not our primary objective.

7.4 Future Work

Future work can be extended in this research and is possible considering the rapid development in science and technology. Firstly, the hardware used is sufficient but not cutting edge. There is a possibility that cutting edge hardware could influence the overall performance. Secondly, external parameters must be considered to predict backorders –weather (meteorological data), traffic (transportation dataset), etc. In addition to this, we require large pools of data for LAMA to be consistent, which is hard to procure in this sector. Fine-tuning/ custom pipelining or switching to a different AutoML technique should be explored further. Also, deep learning models and other methods are to be considered.

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