Predicting Procurement Compliance Using KPI-Driven Machine Learning Models

Brittany M.D. Dowdle

Northwest Missouri State University
School of Computer Science and Information Systems
Maryville MO 64468, USA
S574362@nwmissouri.edu

Abstract. **Keywords:** procurement · compliance · prediction · product

1 Introduction

This project explores procurement performance using real-world data; the goal is to predict whether a purchase order will result in supplier compliance. Order compliance is critical in performance metrics. It reflects whether supplier contracts are meeting agreed-upon delivery schedules, product quality, and pricing terms. By building a predictive model based on attributes such as quantity, price deviation, or defect rates, the objective was to provide procurement teams with data-driven insights. This is useful to predict risk, improve supplier relationships, and enhance operational efficiency.

1.1 Goal of This Project

The final deliverables from this project include the following:

- ✓ Machine learning model predicting order compliance with supporting visualizations [6]
- ✓ A PDF report written in LaTeX via Overleaf
- ✓ A fully documented GitHub repository with Jupyter notebooks including EDA [6]

1.2 Project Resources

- **GitHub Repository:** https://github.com/Bdowdle4/Dowdle$_{A}nalytics_{C}apstone$
- **Overleaf Report:** https://www.overleaf.com/read/bszyhdxsnrsf
- **Pro Analytics 01:** https://github.com/denisecase/pro-analytics-01
  The guide used to follow a repeatable workflow for professional python projects [1]

2 Collect and Describe Data

The data set analyzed consists of 777 purchase order records with 11 original columns. Each row in the data set represents a unique transaction with attributes that relate to the identity of the supplier, the characteristics of the order, the pricing, the defects, and whether or not the supplier was compliant. The data set was publicly accessible on Kaggle; the link is in Section 2.2 Dataset Resource.

2.1 Dataset Overview

- **Data Type:** Structured (Avg of 10 key features per PO)
- **Source:** Kaggle
- **Size:** 68 KB
- **Rows:** 777
- **Columns:** 11
- **File Extension:** `.csv`
- **Tool for Ingestion:** `pandas` in Python

The data set was downloaded from Kaggle [4] and moved to the project folder. Then it was added to the GitHub project repository in the "Data" folder. Finally, it was read into two Jupyter notebooks using the pandas library (Cleaning and Modeling).

2.2 Data Attribute Dictionary

Column Name	Description	Data Type	Example
po_id	Unique identifier for the purchase order	String	PO-10231
supplier	Supplier name or identifier	String	Supplier_A
order_date	Date the order was placed	Date	2024-01-03
delivery_date	Date the order was delivered	Date	2024-01-11
item_category	Category or type of item ordered	String	Raw Materials
order_status	Status of the order (e.g., Delivered, Pending)	String	Delivered
quantity	Quantity of units ordered	Integer	500
unit_price	Price per unit paid	Float	12.75
negotiated_price	Contractually agreed price per unit	Float	12.00
defective_units	Number of defective units in the delivery	Integer	5
compliance	Binary indicator of contract compliance	Integer	1

Table 1. Original data attributes and examples.

2.3 Domain and Professional Description

Domain: Business Operations
Subdomain: Procurement / Supply Chain

This project would be important to:
1. Supply Chain Analysts - to identify patterns in KPI metrics
2. Procurement Managers - for supplier scorecards and vendor decisions
3. Chief Purchasing Officer (CPO) - to support strategic sourcing and policy decisions

This data set falls within the field of procurement analytics. Procurement professionals use analytics to track KPIs such as on-time deliveries, cost savings, and defect rates to measure supplier performance. When a supplier consistently does not meet the expected performance level, they are a financial and operational risk. Suppliers can be considered non-compliant for late deliveries, defective products, and violations of negotiated pricing. By identifying patterns in procurement data and predicting compliance outcomes, organizations can optimize sourcing strategies, negotiate better contracts, and reduce supply-side risk. [5]

2.4 Dataset Resource

Procurement KPI Analysis Dataset:
https://www.kaggle.com/datasets/shahriarkabir/procurement-kpi-analysis-dataset

As mentioned in the Kaggle Data Card, this data set is anonymized to protect company and supplier identities and provides real-world transactions of 5 different suppliers from 2022-2023. This data set reflects challenges such as supplier delays, compliance gaps, defects, and inflationary price trends over time. It is not expected to be updated. [4]

3 Clean and Prepare Data

The raw procurement data set must be cleaned and preprocessed to ensure consistency, accuracy, and usability. This section outlines the data cleaning and preparation steps completed in the Jupyter notebook named `cleaning.ipynb`. The goal was to ensure that it was ready for EDA in the next section. The diagram below 1 summarizes the pre-processing pipeline [3].

Fig. 1. Cleaning Workflow Diagram (created by the author in PowerPoint).

3.1 Data Formatting and Standardization

To ensure consistency in data types and naming conventions:

- `order_date` and `delivery_date` were converted to datetime objects using

  `pd.to_datetime()`

- All column names were standardized to lowercase letters and any white space was removed using

  `str.strip().str.lower()`

3.2 Handling Missing Values

Missing data was identified and addressed with conditional logic using

`df.info`

- `defective_units` missing values were assumed to have no defects and replaced with 0 using

  `.fillna(0)`

- Missing `delivery_date` effected 87 rows and that seemed like a significant loss of data. So, instead, the rows that had an `order_status` of "Delivered" were kept and used a combined median imputation and a flag column to maintain data integrity.
- Each supplier's median `lead_time_days` was calculated using

  `.dropna(subset=['lead_time_days']).groupby('supplier')['lead_time_days'].median()`

- The column to flag missing delivery date was created using

  `df['delivery_date'].isnull() & (df['order_status'].str.lower() == 'delivered')`

– The column to flag missing delivery date was converted to an integer using

```
.astype(int)
```

– Imputed `delivery_date` used `order_date` + median lead time per supplier.
– 19 rows still had missing `delivery_date` after this and had an `order_status` of `"cancelled"`, `"pending"`, or `"partially delivered"`. They were removed because they represent incomplete transactions and could introduce bias or noise into the model.

3.3 Feature Engineering

Two more attributes were created to allow for a deeper analysis of procurement efficiency and quality because they will support more meaningful comparisons between suppliers and orders. These attributes were selected as independent variables for the model. The dependent variable for the model was `compliance`.

– `price_diff` measures the difference between the `negotiated_price` and the `unit_price`.
– `defect_rate` calculates the proportion of `defective_units` relative to the `quantity` ordered.

3.4 Outlier Detection and Treatment

Outliers were identified using the IQR method for the following 4 attributes: `quantity`, `unit_price`, `price_diff`, and `defect_rate`. Outliers were identified in 15 of 777 rows. This was equal to 1.93% and was assumed to be a natural variance. The treatment decided for these rows was to leave as is.

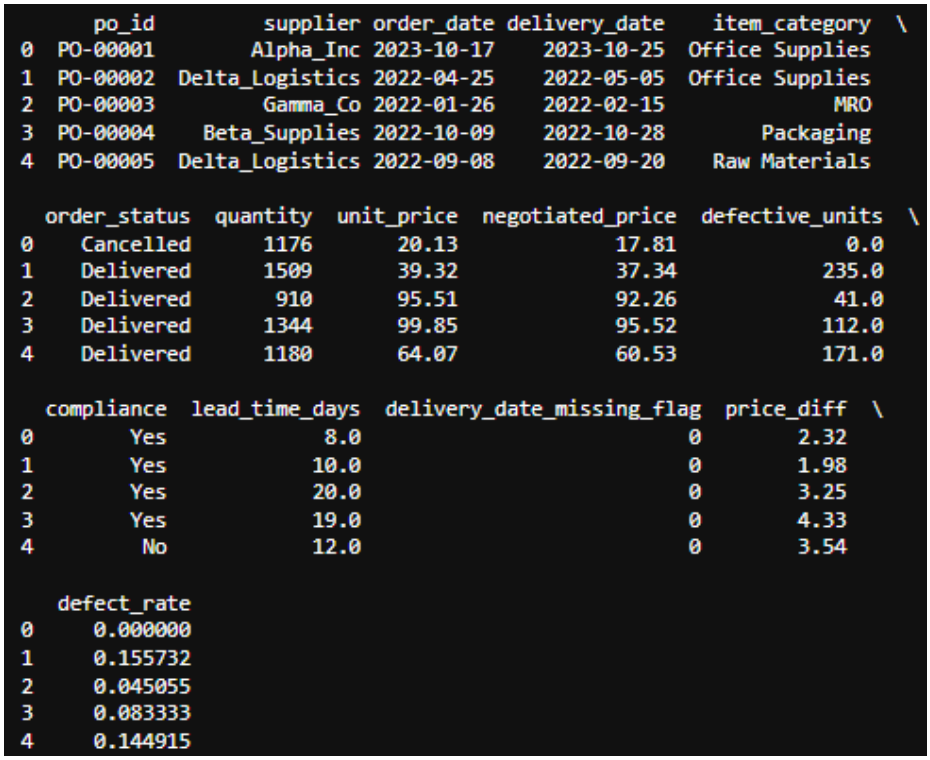
3.5 Exporting Cleaned Dataset

The cleaned data set contained 15 attributes and 758 records. It was exported as a CSV file using

```
df.to_csv()
```

It is saved as `cleaned_procurement_data.csv` in the project repository Data folder. The image below 2 shows the first five rows of the cleaned dataset as output from the Jupyter notebook [2]. This preview was generated using:

```
print(df.head())
```



	po_id	supplier	order_date	delivery_date	item_category	\
0	PO-00001	Alpha_Inc	2023-10-17	2023-10-25	Office Supplies	
1	PO-00002	Delta_Logistics	2022-04-25	2022-05-05	Office Supplies	
2	PO-00003	Gamma_Co	2022-01-26	2022-02-15	MRO	
3	PO-00004	Beta_Supplies	2022-10-09	2022-10-28	Packaging	
4	PO-00005	Delta_Logistics	2022-09-08	2022-09-20	Raw Materials	

	order_status	quantity	unit_price	negotiated_price	defective_units	\
0	Cancelled	1176	20.13	17.81	0.0	
1	Delivered	1509	39.32	37.34	235.0	
2	Delivered	910	95.51	92.26	41.0	
3	Delivered	1344	99.85	95.52	112.0	
4	Delivered	1180	64.07	60.53	171.0	

	compliance	lead_time_days	delivery_date_missing_flag	price_diff	\
0	Yes	8.0	0	2.32	
1	Yes	10.0	0	1.98	
2	Yes	20.0	0	3.25	
3	Yes	19.0	0	4.33	
4	No	12.0	0	3.54	

	defect_rate
0	0.000000
1	0.155732
2	0.045055
3	0.083333
4	0.144915

Fig. 2. Cleaned Dataset Head (created by the author in VSCode).

References

1. Case, D.: Git add, commit, push guide. bluehttps://github.com/denisecase/pro-analytics-01/blob/main/03-repeatable-workflow/06-git-add-commit-push.md (2023), accessed: 2025-06-29
2. Dowdle, B.: Cleaned dataset preview from jupyter notebook (2025), created using `df.head()` in VSCode
3. Dowdle, B.: Cleaning workflow diagram (2025), created in Microsoft PowerPoint
4. Kabir, S.: Procurement kpi analysis dataset. bluehttps://www.kaggle.com/datasets/shahriarkabir/procurement-kpi-analysis-dataset (2022), accessed: 2025-06-23
5. Team, T.E.: Why procurement is a good career: Key reasons to consider this path. bluehttps://www.techneeds.com/2025/04/05/why-procurement-is-a-good-career-key-reasons-to-consider-this-path/ (April 2025), accessed: 2025-06-29
6. Team, U.E.: Top 100 data science project ideas for beginners. bluehttps://www.upgrad.com/blog/data-science-project-ideas-topics-beginners/ (2024), accessed: 2025-06-23