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Library Late Book Returns Use Case

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1. Business objective



The library is facing a problem with late book returns (books are considered late if not returned within 28 days of checkout), which affects book availability for other patrons and disrupts book management



- 1. Conduct root cause analysis to identify factors associated with late returns
- 2. Build a model to predict the likelihood of a late return of any book at checkout

2. Data analysis











TRAINING DATA
CONSISTS OF 4 CSV
FILES: LIBRARIES,
CHECKOUTS,
BOOKS AND
CUSTOMERS

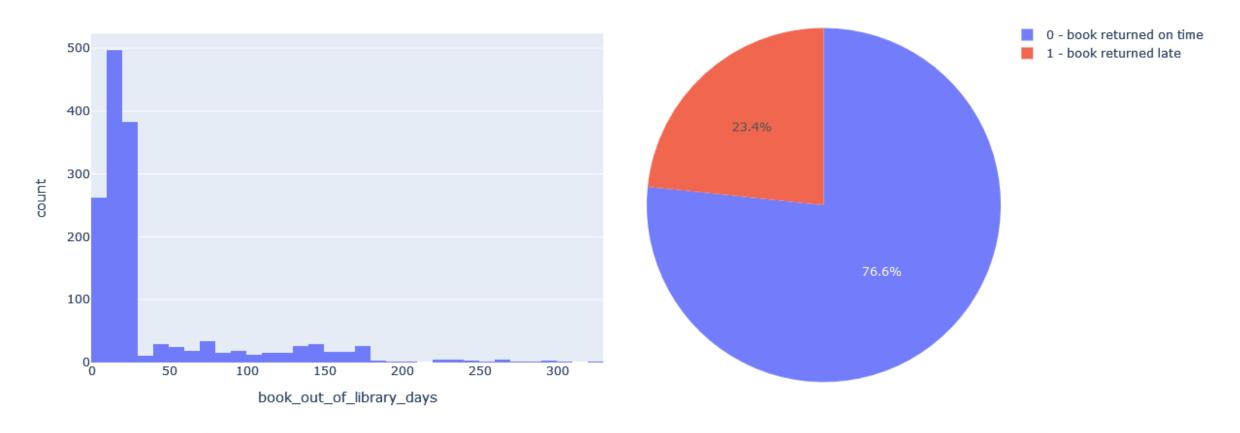
DATA QUALITY
ISSUE (MISSING
VALUES, DATA
INCONSISTENCIES)

DATA CLEANING
AND FEATURE
ENGINEERING ARE
PERFORMED
BEFORE
EXPLORATORY DATA
ANALYSIS

3 NEW FEATURES
ARE ADDED:
CUSTOMER AGE,
BOOK AGE AND
CUSTOMER
LIBRARY DISTANCE

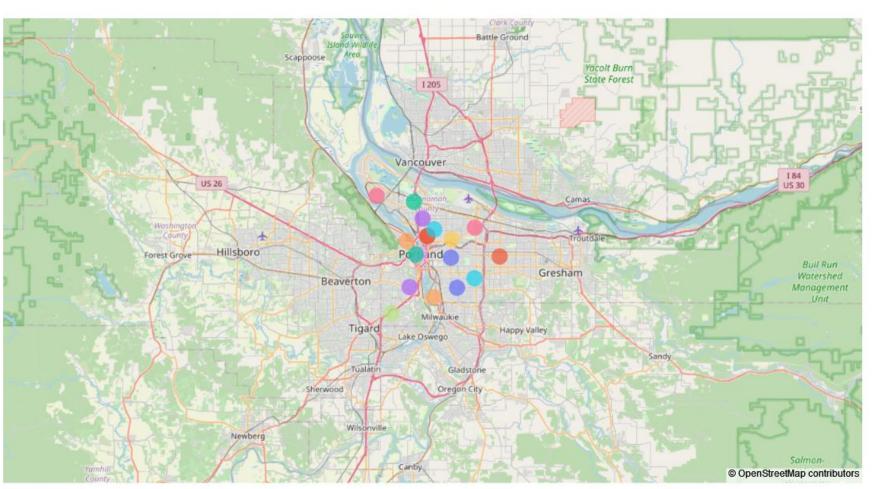
APPROXIMATELY 1500 INSTANCES ARE AVAILABLE FOR TRAINING THE MODEL

2.1 Target distribution



The mean borrowing period is 39.3 days. Half of the books are returned within 19 days of checkout and 75% of the books are returned within 27 days of checkout.

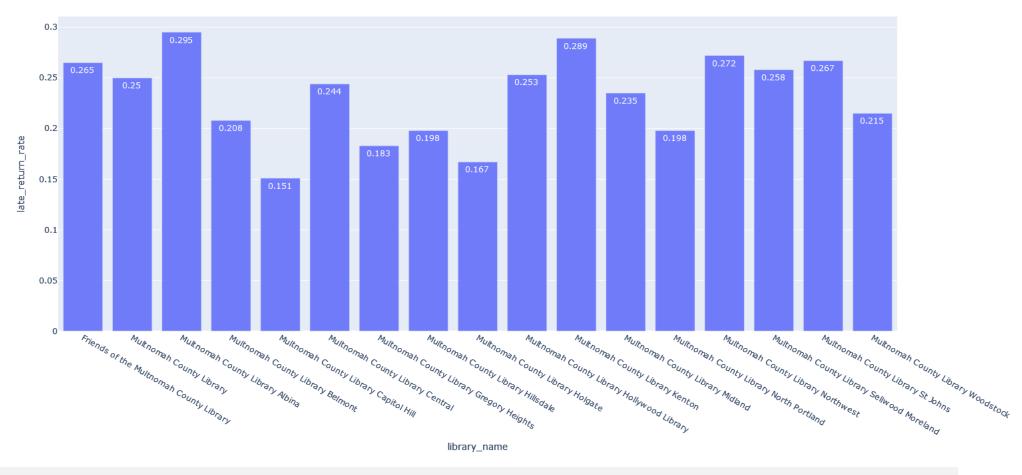
2.2 Libraries



library_name

- Multnomah County Library Woodstock
- Multnomah County Library
- Multnomah County Library Kenton
- Multnomah County Library North Portland
- Multnomah County Library Northwest
- Multnomah County Library Holgate
- Multnomah County Library Gregory Heights
- Multnomah County Library Capitol Hill
- Friends of the Multnomah County Library
- Multnomah County Library Hollywood Library
- Multnomah County Library Belmont
- Multnomah County Library Midland
- Multnomah County Library Central
- Multnomah County Library Hillsdale
- Multnomah County Library Sellwood Moreland
- Multnomah County Library Albina
- Multnomah County Library St Johns

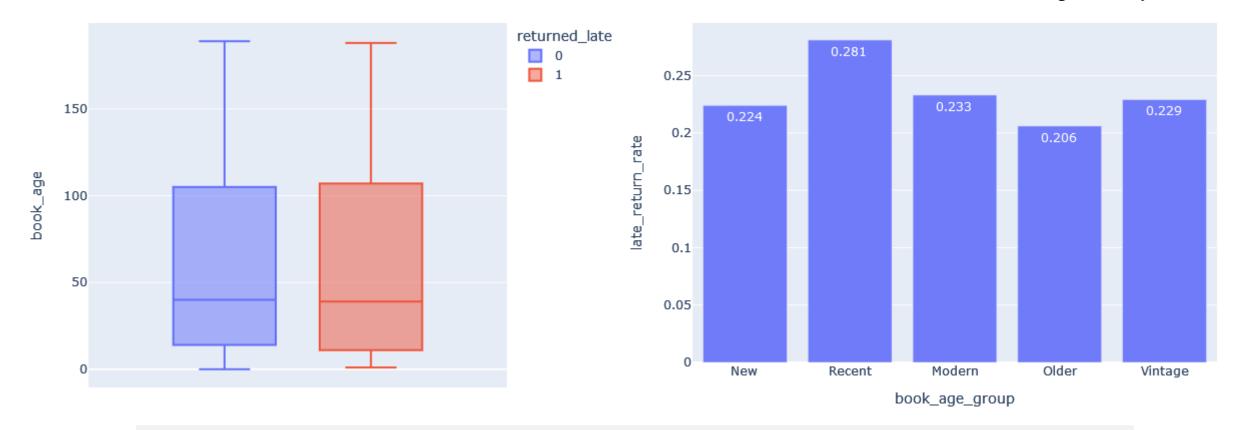
2.2 Libraries



Multnomah County Library Albina has the highest percentage of late returns (29.5%). Multnomah County Library Capitol Hill has the lowest percentage of the late returns (15.1%).

2.3 Book age

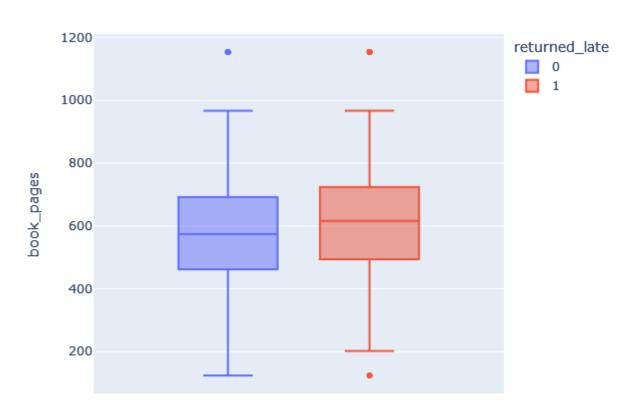
New 0-2 years
Recent 3-10 years
Modern 11-30 years
Older 31-50 years
Vintage 51+ years

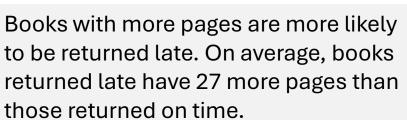


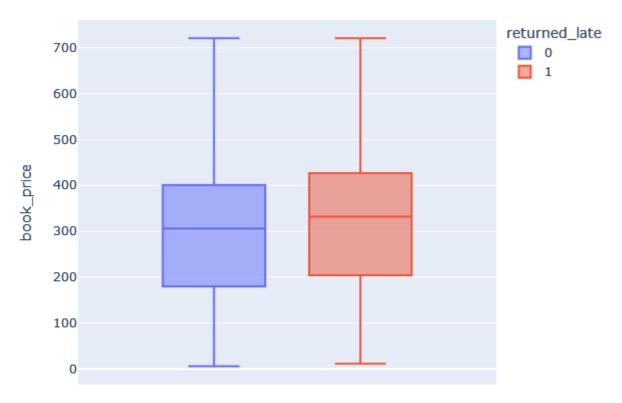
The mean book age is 59.5 years.

Books published within the last 3-10 years have the highest percentage of late returns (28.1%). Books published within the last 31-50 years have the lowest percentage of late returns (20.6%).

2.4 Book pages and price

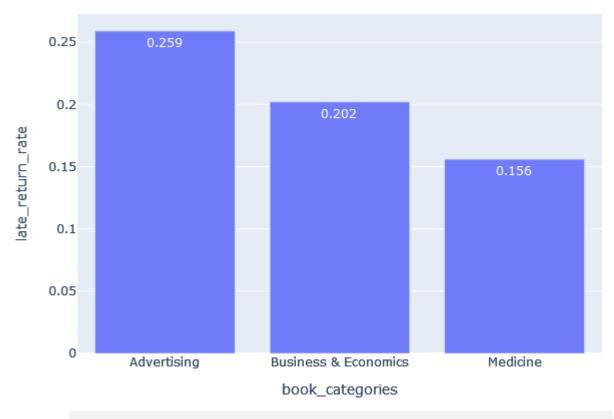




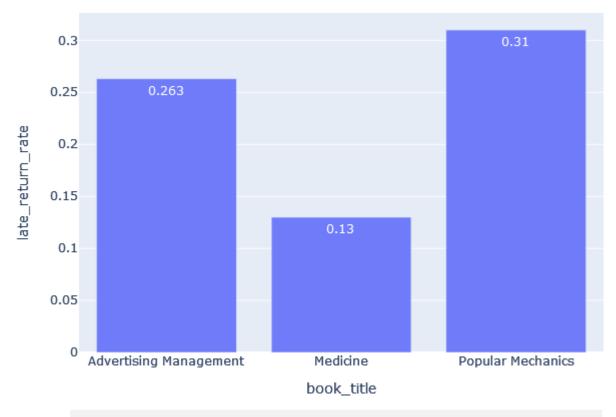


Books with higher prices are more likely to be returned late. On average, books returned late are 21\$ more expensive than those returned on time.

2.5 Book categories and titles

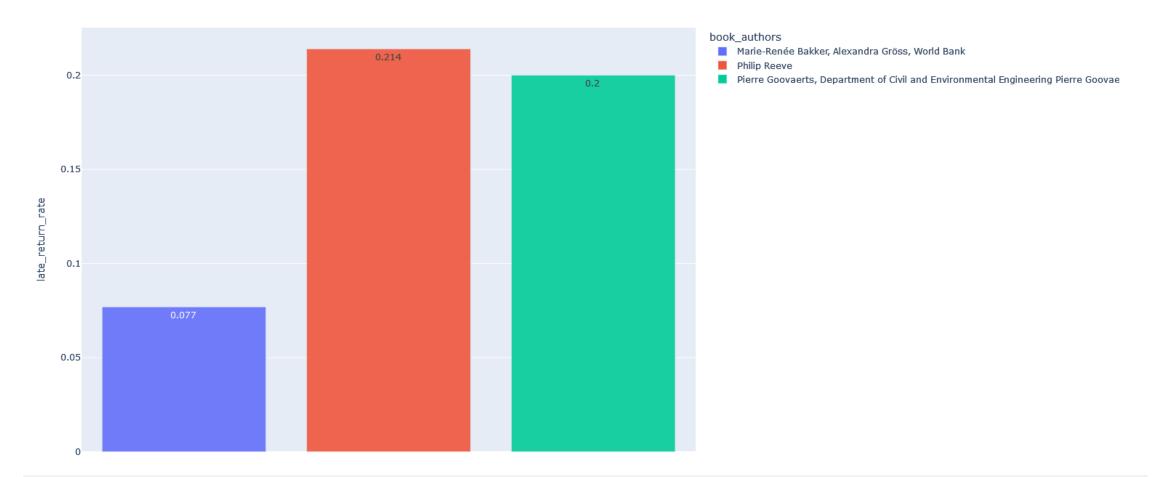


Top 3 most frequent book categories. Medicine has the lowest late return rate (15.6%). Advertising has the highest late return rate (25.9%).



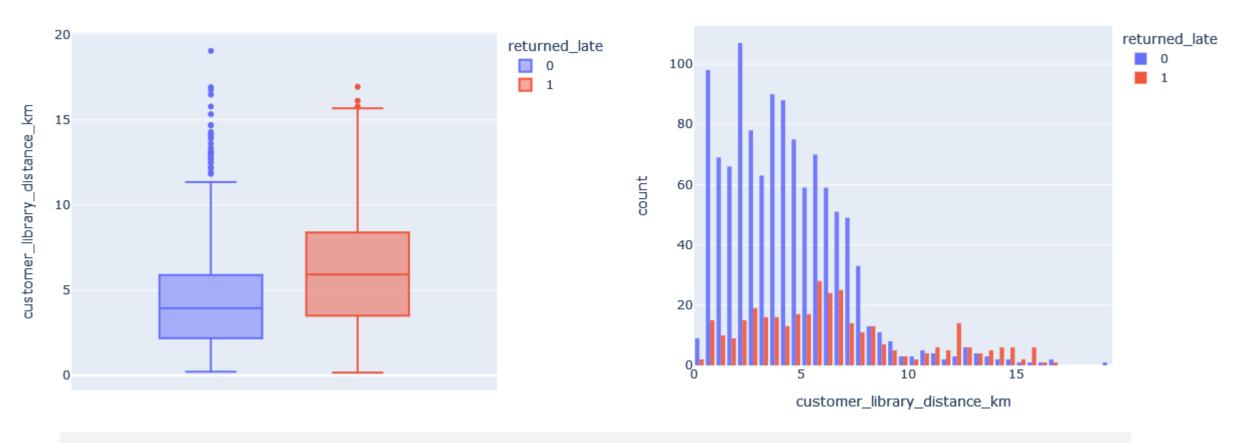
Top 3 most frequent book titles. Medicine has the lowest late return rate (13%). Popular Mechanics has the highest late return rate (31%).

2.6 Book authors



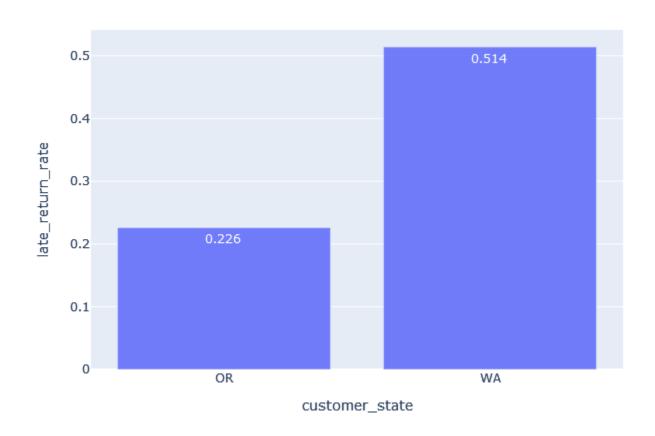
Top 3 most frequent book authors. Books written by Marie-Renée Bakker, Alexandra Gröss, World Bank have the lowest late return rate (7.7%). Books written by Philip Reeve have the highest late return rate (21.4%).

2.7 Distance between customer and library



Customers who live farther from the library are more likely to return books late. On average, customers who return books late live 2.24 km farther from the library than those who return books on time.

2.8 Customer state



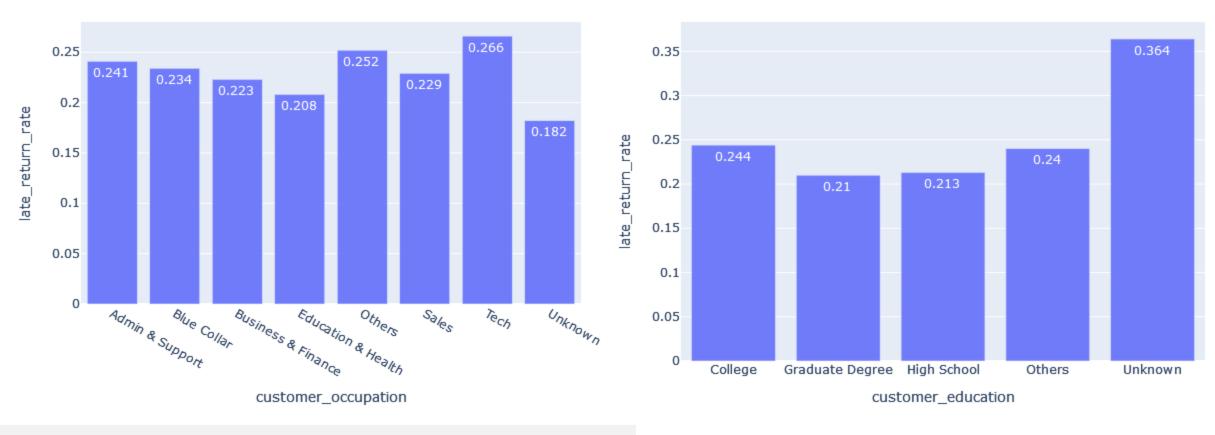
Customers from Washington (2.5%) have a much higher late return rate than those from Oregon, 51.4% compared to 22.6% (which is expected, as all libraries are located in Oregon).

2.9 Customer age



The lowest percentage of late returns is found among older customers (19.2%) - likely retirees, with more time for reading. The highest percentage of late returns is found among 35 to 60-year-olds, who are typically working and have less time for daily reading (25.7%).

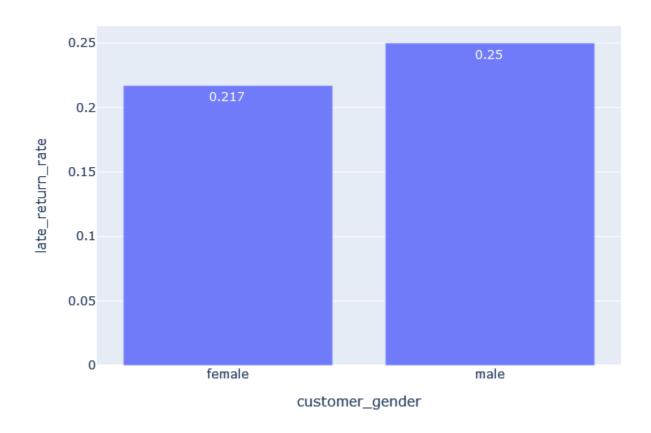
2.10 Customer occupation and education



The highest percentage of late returns is found in the group of customers with tech occupations (26.6%). The lowest percentage of late returns is found in the group of customers with education and health occupations (20.8%).

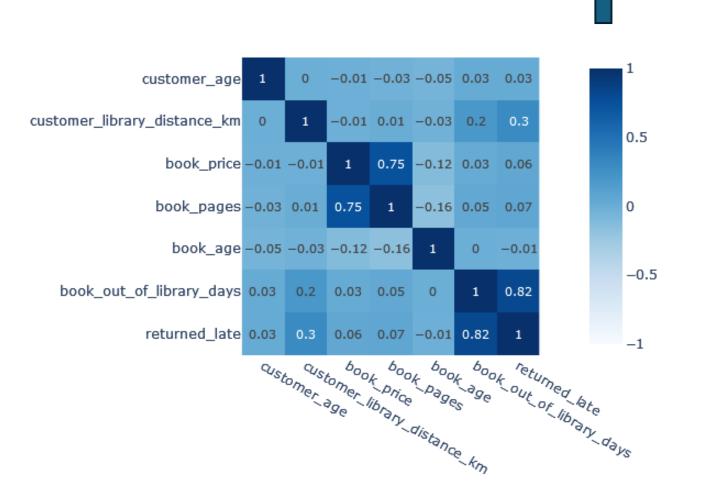
Customer education is missing in 5.2% of cases. Graduates have the lowest late return rate (21%).

2.11 Customer gender

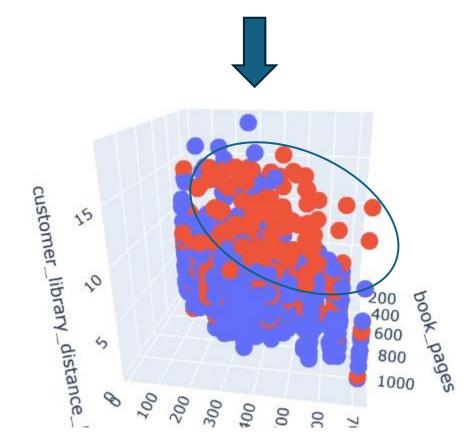


Men return books late more frequently (25% late return rate compared to 21.7% for women).

2.12 Correlation



Features customer_library_distance, book pages and book price are the most correlated with the target variable (returned_late).



2.13 Key observations

75% of the books are returned within 27 days of checkout.

Customers
who live farther
from the library
are more likely
to return books
late.

Books with more pages are more likely to be returned late as they require a longer time to read.

Books with higher prices are more likely to be returned late.

Customers aged 60 and over tend to return books on time, likely because they are retirees and have more time for reading.

Men return
books late
more
frequently than
women.

Medicine books have the lowest late return rates.

3. Model selection



Dataset is split into train and test sets, taking class imbalance into account.



Data preprocessing includes scaling numerical features and encoding categorical features.



Several ML models are tested, considering class imbalance: Logistic Regression, Random Forest, XGBoost and CatBoost. Building a global model – one model for all libraries.



Hyperparameters tuning is performed using grid search and cross validation.



Used model evaluation metrics are ROC AUC, balanced accuracy and weighted f1 score (imbalanced dataset).

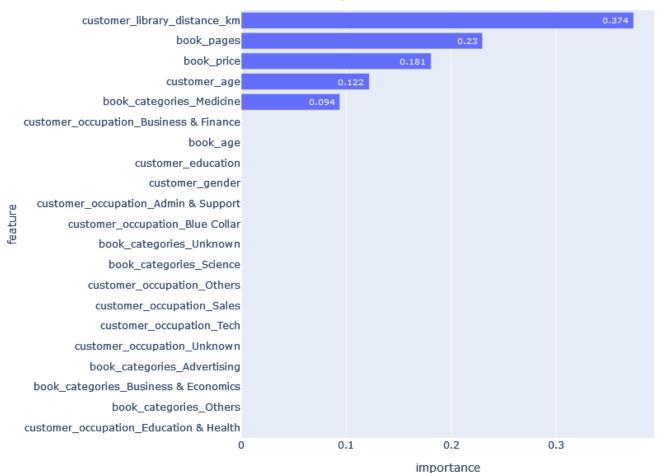
3.1. Models overview

	Logistic Regression		Random Forest		XGBoost		CatBoost	
	train	test	train	test	train	test	train	test
ROC AUC	0.69	0.67	0.72	0.7	0.72	0.67	0.71	0.69
BAL ACC	0.63	0.67	0.65	0.63	0.65	0.64	0.64	0.65
WEIG F1	0.68	0.7	0.69	0.7	0.72	0.71	0.7	0.72

All models show similar performance. XGBoost is selected as go-to model because it operates with the smallest number of features (next slide). Model explainability.

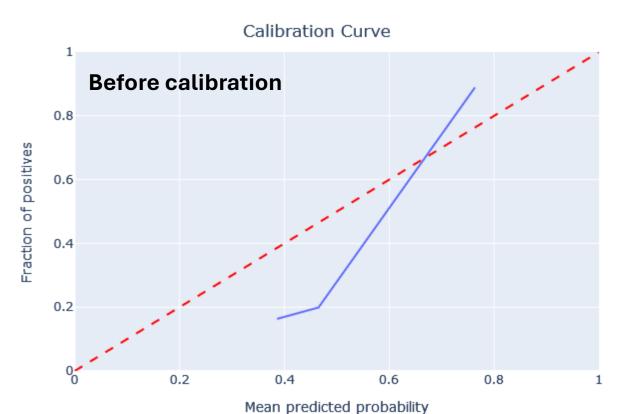
3.2 Final model - XGBoost



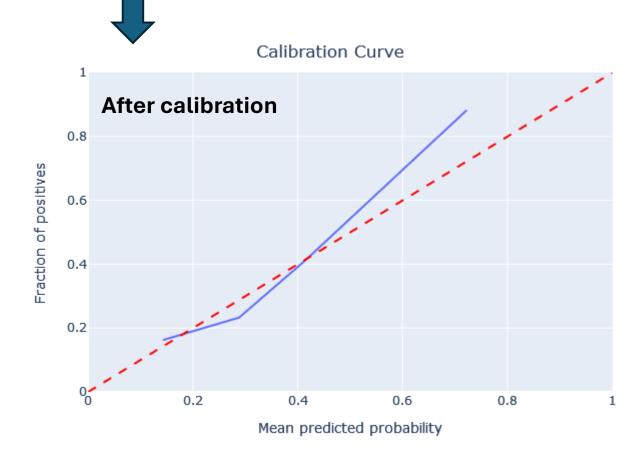


	XGBoost trained with top features				
	train	test			
ROC AUC	0.72	0.66			
BAL ACC	0.65	0.63			
WEIG F1	0.71	0.7			

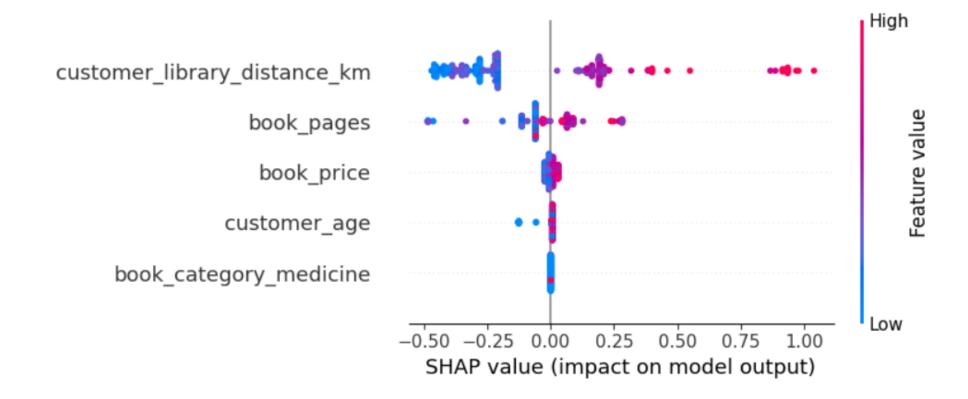
3.3 Model calibration



Calibrated model achieves weighted f1 score of 0.77, which is 7% higher than the uncalibrated model (0.7). Calibration is essential in this case because we are interested in the likelihood of book late returns.



3.4 Global model interpretability (SHAP)



3.5 Local model interpretability (SHAP)

Late return instance



On time return instance



4. Solution

- We identified key factors related to late book returns: distance between the customer and the library, the number of book pages, book price, customer age and books belonging to medicine category.
- To mitigate the risks of late returns, we propose using developed library ML model in day-to-day
 operations to assess the likelihood of a late return at checkout for any customer. If the model classifies
 a customer as a high-risk, the library can offer them some rewards for on time book returns, such as
 discount on the library subscription for the next month or another relevant benefit. Implementing a
 penalty system is not recommended, as it may negatively affect customer retention.
- Library model is available via API endpoint (appendix) and it can be integrated into the library app. This
 internal web-based application will provide valuable insights to library staff. It may include a simple
 dashboard highlighting high-risk customers, real-time prediction functionality, book tracking and a
 built-in notification system to alert employees for return deadlines.
- Business value: optimization of library operations, reduced late return rate, increased book availability and enhanced customer satisfaction.



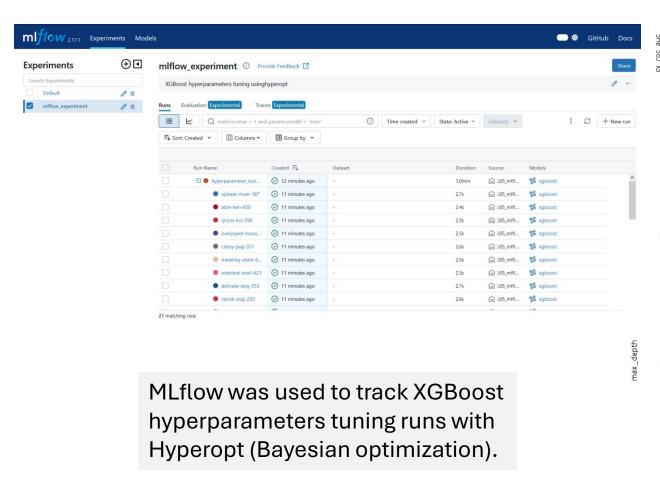


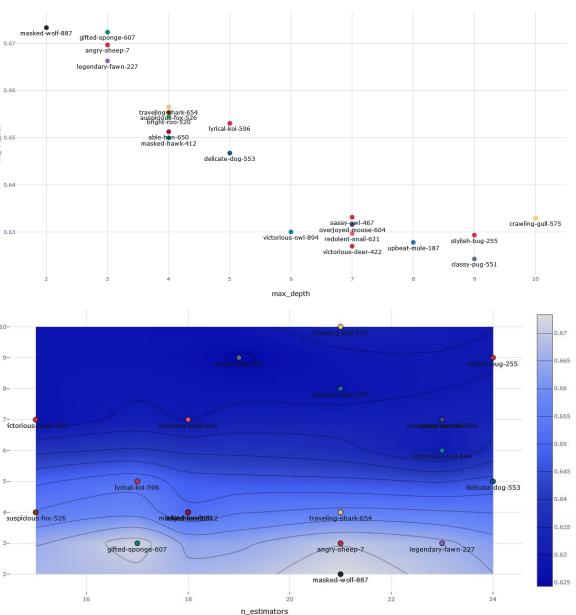


5. Next steps

- 1 Go/No-go decision. If go, proceed with the following.
- ML: Implement Airflow for ML workflow orchestration (Train/Predict/Refit DAGs). Set-up a database for storing model predictions (batch prediction).
- 3 ML: Build a model monitoring system to track production model performance on real-world data.
- SW: Backend/Frontend development of the library application.
- 5 QA and app deployment.
- 6 Cost/effort estimation for the above tasks.
- Generate the project plan with milestones/timelines and kick-off the work.

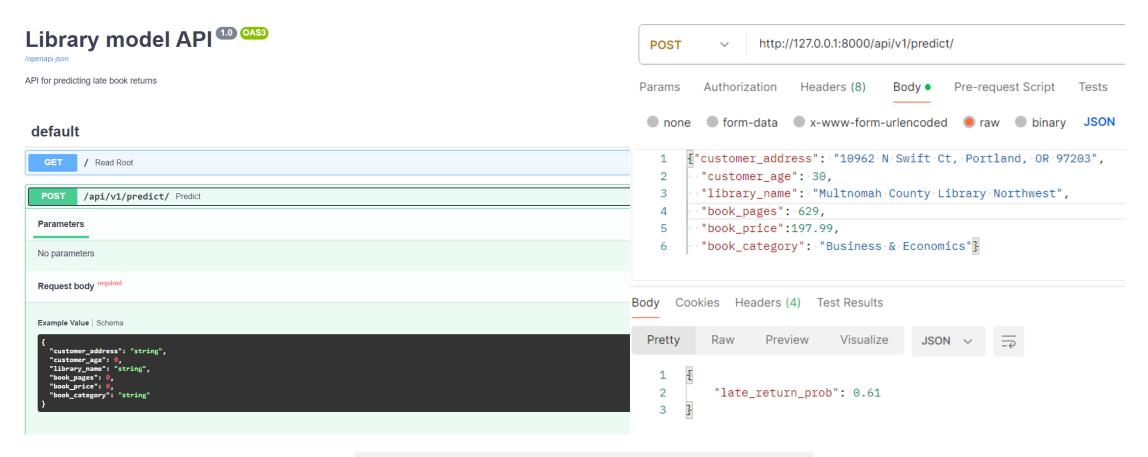
Appendix 1 - MLflow





Appendix 2 - API

Late return instance



FastAPI endpoint for real-time predictions.

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Thank you!

