Part 2 — Logistic Regression from Scratch

PDAN8412

ST10458509

Rick Jackson

30 October 2025

Emeris Cape Town

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Introduction

Top Goodreads Books Collection (1980–2023) dataset sourced from Kaggle has been selceted for this project.

www.kaggle.com/datasets/jealousleopard/goodreadsbooks

The 'client' is a **book press** that wants to predict **whether a book will be a bestseller**. This dataset contains features directly tied to **book success indicators** — such as:

- **Average rating (`Rating`)** → Quality perception
- **Number of voters (`Number of Voters`)** → Popularity
- **"Want to Read" and "Current Readers"** → Market interest and engagement
- **Genres, Publisher, Price, Pages** → Book characteristics affecting sales

These map perfectly to what a press might want to analyze *before release* or *for similar upcoming titles*.

- Clean structure (each row = one book)
- Good balance of **categorical**, **numerical**, and **textual** data
- No obvious privacy or licensing issues
- From a reputable data platform (Kaggle)

Dataset Overview

Columns:

> ISBN, Title, Series info, Authors, Publisher, Language, Description, Num Pages, Format, Genres, Publication Date, Rating, Number of Voters, Current Readers, Want to Read, Price, URL

Initial Cleaning Notes:

`num_pages` converted to numeric from strings with regex.

Cleaning the 'num_pages' column

```
# Handling all values as though they were string.

df['num_pages'] = df['num_pages'].astype(str)
```

```
# Checking whether conversion is successful from object

df['num_pages'].apply(type).value_counts()
```

Missing numeric values (`num_pages`, `price`, `current_readers`, `want_to_read`) filled with median.

Filling missing values

Filling missing values in the columns such as publisher/language/format with 'Unknown'

```
# Fill missing publisher with 'Unknown'

df['publisher'] = df['publisher'].fillna('Unknown')
```

```
# Fill missing language with 'Unknown'

df['language'] = df['language'].fillna('Unknown')
```

```
# Fill missing format with 'Unknown'

df['format'] = df['format'].fillna('Unknown')
```

Converted types: `num_pages` → int, `price`, `current_readers`, `want_to_read` → float.

Missing Values Summary

Column	Missing
isbn	594
series_title	2132
series_release_number	2144
publisher	116
language	26
description	2
num_pages	21
format	35

Column	Missing
current_readers	104
want_to_read	39
price	233

Exploratory Data Analysis (EDA)

Checked for skewed distributions.

Visualizing skewness:

```
import seaborn as sns
import matplotlib.pyplot as plt

num_features = ['num_pages', 'price', 'current_readers', 'want_to_read']
for col in num_features:
    sns.histplot(df[col], kde=True)
    plt.title(f'Distribution of {col}')
    plt.show()
```

Calculated correlations between numeric features and `bestseller`.

Observed outliers and handled scaling for numeric features.

Correlation heatmap.

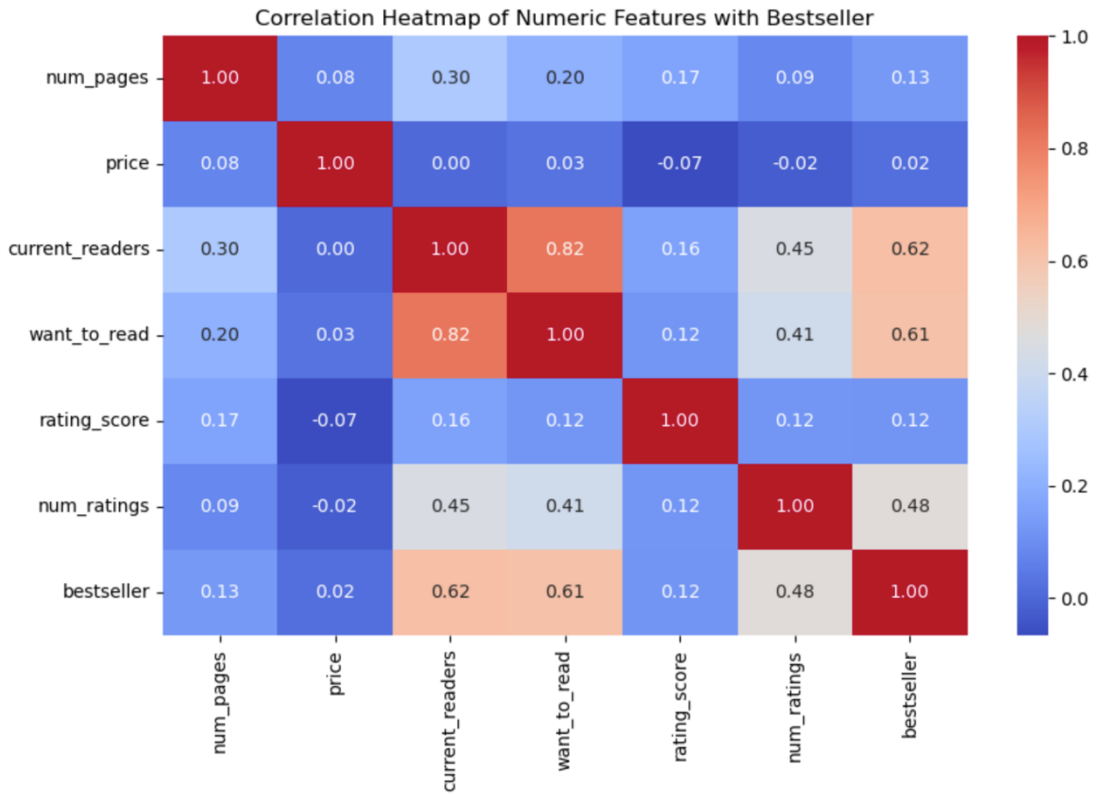
Boxplots for numeric features pre- and post-scaling.

Feature Engineering

Bestseller target variable:

`df['bestseller'] = (df['rating_score'] >= 4.0).astype(int)`

Author popularity: Mean ratings or counts of books per author.



Interaction features: e.g., `num_pages × current_readers`, `price × num_ratings`.

Descriptiong of features created:

1. **Bestseller target variable** (1 if rating ≥ threshold, else 0).
2. **Author popularity** (mean ratings or counts).
3. **Interaction features** (e.g., `num_pages × current_readers`).

Modeling Approach

The dataset is split into into 70% train, 30% test.

Logistic regression performed from scratch:

Forward propagation (sigmoid function).

Cost function (log-loss).

Backward propagation (gradients).

Gradient descent update.

```
# ----------------------------
    # STEP 1: Forward Propagation
    # ----------------------------

    m = X.shape[0]  # number of samples

    # Compute the linear combination of features and weights
    # z = Xw + b
    z = np.dot(X, w) + b

    # Apply the sigmoid activation function to get predicted probabilities
    # A = 1 / (1 + e^(-z))
    A = 1 / (1 + np.exp(-z))

    # Compute the cost function (log-loss)
    # Add a small epsilon (1e-9) to prevent log(0) errors
    cost = -(1/m) * np.sum(y * np.log(A + 1e-9) + (1 - y) * np.log(1 - A + 1e-9))

    # ----------------------------
    # STEP 2: Backward Propagation
    # ----------------------------

    # Compute the gradients of the cost function
    dw = (1/m) * np.dot(X.T, (A - y))  # Gradient w.r.t. weights
    db = (1/m) * np.sum(A - y)         # Gradient w.r.t. bias

    # ----------------------------
    # STEP 3: Store and Return Results
    # ----------------------------
    grads = {"dw": dw, "db": db}

    return grads, cost
```

Hyperparameters used learning rate, iterations and iterations are played to tune model.

```
# Split
from sklearn.model_selection import train_test_split
X_train_b, X_test_b, y_train_b, y_test_b = train_test_split(
    X_base, y, test_size=0.3, random_state=42, stratify=y
)

# Initialize weights and bias
w_b = np.zeros((X_train_b.shape[1], 1))
b_b = 0

# Logistic regression training (same gradient descent already built)
def model(X, y, w, b, num_iterations=1000, learning_rate=0.01):
    costs = []
    for i in range(num_iterations):
        grads, cost = propagate(w, b, X, y)
        w -= learning_rate * grads["dw"]
        b -= learning_rate * grads["db"]
        if i % 100 == 0:
            costs.append(cost)
    return w, b, costs

# Train baseline model
w_b, b_b, costs_b = model(X_train_b, y_train_b, w_b, b_b)
```

Scaling approach was then used for baseline model and the feature engineered model and the accuracy shot up considerably.

```
scaler = StandardScaler()
X_enh_scaled = scaler.fit_transform(df[enhanced_features])
```

Model Evaluation

Metrics used: Accuracy, Precision, Recall, F1-score.

Baseline vs.Enhanced model metrics:

Metric	Baseline (Scaled)	Enhanced Features
Accuracy	0.8833	0.9250
Precision	0.85	0.8942
Recall	0.75	0.7939
F1-score	0.80	0.8411

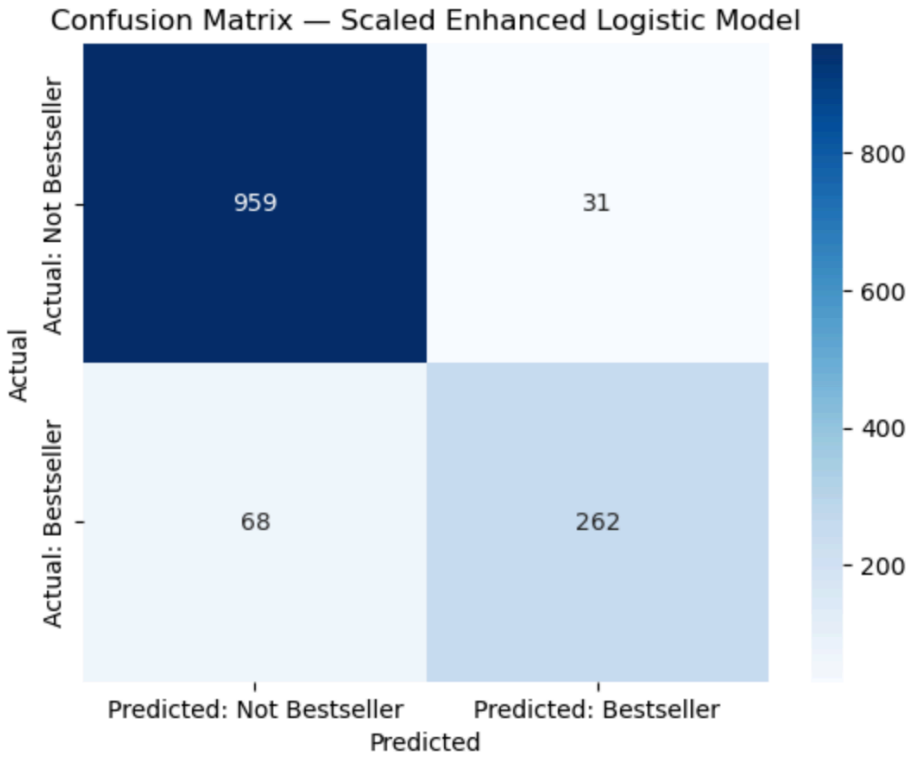
Visuals:

The enhanced model with interaction features and author popularity shows a clear improvement over the baseline in all metrics, particularly in accuracy and precision

```
Classification Report:
                precision    recall  f1-score   support

Not Bestseller       0.93      0.97      0.95       990
    Bestseller       0.89      0.79      0.84       330

      accuracy                           0.93      1320
     macro avg       0.91      0.88      0.90      1320
  weighted avg       0.92      0.93      0.92      1320
```



Conclusion

Engineered features improved model performance, but only slightly.

Scaled numeric features were crucial for gradient descent stability and lead to the best model performance overall.

Limitations:

- Some features may be noisy.
- Threshold for `bestseller` is arbitrary.

- Recommendations:
  - Could include NLP on book descriptions for deeper insights.
  - Test other models like Random Forest or XGBoost for potential further improvements.

References

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