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**PROJECT REPORT**

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1. **Summary**

**Takeaways:**

- Adding data: From open book, retrieve the subject of all books

- Cleaning data : fill missing values, remove blank spaces, change format date, remove duplicates, delete useless data, rename columns

- Securing the data : cross validation with excel workbook

- Analyzing data: plot all variables with statistical information, correlation checks

- Transforming data : create season and centuries from date, fusion of all English languages, transform into categories (from 1 to 5) the variables average\_rating, rating\_count, max\_pages, transform the subject from open book into a genre category

- Select the data : elimination of biased columns

- Model used: Random Forest & Adaboost algorithms

**-** Results : Recall 74,4% and Precision 75,7%

1. **Overview of the targeted problem**

The aim of this machine learning project is to build a model that can help Goodreads users get book recommendations based on authors, book types, and other relevant factors.

We believe that the problem at hand has an average complexity and will require a manageable number of features (independent variables) for the machine learning model.

*Questions to consider before starting the project?*

- missing information: subject, genre and cost

*How we intend to address the problem?*

- find the missing data on Google API and Open Books API

*Methodology*

The project is conducted with the following steps:

* **Exploratory data analysis** to understand the dataset and **data pre-processing** to clean and format the dataset to ensure it is in a suitable format for machine learning algorithms.
* **Feature engineering** by creating new features or extracting relevant features from the data to improve the model's predictive performance, and **Model selection** which will depend on the nature of the data and the required predictive accuracy for predicting book ratings.
* **Model training and evaluation**: Train the model on the training dataset, improve its performance and evaluate the performance of the model using the testing dataset.
* **Deployment:** Once the model is trained and evaluated, deploy it to a production environment.

1. **Exploratory Data Analysis and Data Preprocessing**

*About the dataset*

To achieve our objectives, we used a dataset containing approximately 11,000 rows of data scraped from the Goodreads API. This dataset includes customers' ratings of books, as well as other information such as author, book code, number of pages, count of text reviews, publication date, and publisher obtained from the Goodreads website[[1]](#footnote-1).

A picture containing qr code

Description automatically generatedHere, questions regarding the volume and accuracy of the data arise. While we believe that the collected dataset may be sufficient to build an ML model, it is crucial to ensure that the dataset is representative of the target population and contains a diverse range of books and ratings. The first step in determining the sufficiency of a dataset is to experiment with exploratory data analysis and data preprocessing techniques to validate the dataset.

It's important to note that the dataset used for this project was last updated in May 2019. This may have a significant impact on the accuracy of the machine learning model, as it may not reflect the current distribution of the target variable or account for new patterns or trends that have emerged since the data was collected. To mitigate this risk, we have decided to limit the scope of the project by focusing only on the period before mid-2019 and analyzing long-term trends that can be detected from the available data.

(on the right the main words apperaing in the title of books)

*Observations about data*

In this stage, we will be using Excel and Python to conduct EDA and DP processes.

1. ***Excel***

*We decided to use excel for two reasons:*

*- If the dataset is under 100k rows, it’s faster to get a quick overview of the dataset*

*- We can doublecheck the transformation of the data on Python and Excel and detect potential mistakes*

1. ***Python***

In Python, we installed all necessary libraries and imported the dataset using Pandas.

Subject data : We obtained it through open books API, you can check the code on the notebook GoogleAPIservice. (We tried to obtain information from google api but it failed because the data was not exhaustive and the number of interrogation of the database was limited.)

Table

Description automatically generated

We checked the data types using the code *"data.info()"* to get an overview of the dataset's dimensions and description. We identified two types of variables: Categorical variables & numerical variables.

In the same time we checked the missing values.

Chart, histogram

Description automatically generated

**Some observations:** We found that the dataset contains 11 123 records with 12 columns. There were no missing values, and the data types seemed coherent. We observed some redundancy in the “*titles*” (10 348 unique values) and “*authors*” (6 639 unique values), with Stephen King having the most works.

There were 27 unique “*languages*”, with English books dominating the dataset (8 908 values). There were 2 290 unique “*publishers*”, with Vintage being the most common (318 works).

Chart

Description automatically generated with low confidenceThe mean “*average\_rating*” was 3.93, with 25% at 3.77, the median at 3.96, and 75% at 4.14. Ratings were mostly high, and the spread was small (0.35). Skewness seemed low. The mean “*num\_pages*” was 336, with the median at 299, and it exhibited some skewness because of outliers (with the top value of 6 576).

The mean “*ratings\_count*” was 1.79e+04, with the median at 7.45e+02, exhibiting strong skewness as the top value was > 1e+6. The mean “*text\_reviews\_count*” was 542, with the median at 47, exhibiting high skewness with a top value of 94 265.   
  
Graphical user interface, application

Description automatically generated

**Actions:**

* We renamed the columns correctly, converted everything to lowercase and removed blank spaces in the “num\_pages” column name.
* We converted every string to lowercase except for the ISBN since it is an identifier. We also corrected some data types, such as changing the "*publication\_date*" to MM-DD-YYYY format date (since it was assimilated as an object).
* We also inspected duplicates in the dataset and found 812 titles in duplicates. We decided to keep only the observation with the max “*average\_rating*” for each title.
* We decided to deal with the very low value of the number of pages by filling the "*num\_pages*" with the "*max\_pages*" value found in another row with the same book title, with the average pages of the author, with the average pages of the publisher, and with the number of pages found online. Additionally, we removed irrelevant data such as the value "not a book" from the "authors" column, and excluded any books with an average rating or rating count of 0.

Completing this step helped us gain a deeper understanding of the dataset and prepared it for the next steps of feature engineering and model selection.

1. **Feature engineering and Model selection**

The publication date can provide insight into the context in which the book was written, and books published in the winter season would have different ratings than those published in the summer season. The number of pages can also potentially affect the book rating, as readers may have different preferences for longer or shorter books. Additionally, the number of ratings a book receives can be an indication of its popularity and can help to identify books that are widely read, and so on.

Identifying such patterns or trends can be useful in creating predictive models to identify which books are likely to receive high or low ratings.

Therefore, we created some new features to include in our predictive model:

* For *“****publication\_date****”*, we opted to split the data by season[[2]](#footnote-2) and by century with corresponding numerical indications. The 'season' and 'century' columns could provide valuable insights into temporal patterns in book publishing and help identifying which periods and seasons are most popular for book releases.
* We found ‘***languages’*** with the values of “*en-us*”, “*en-gb*”, and “*en-ca*”, and grouped them into the “*language\_code\_ENgroup*” category. This column will be useful to see which English-speaking countries are most active in publishing books.
* For the *“****rating\_count****”* column, we transformed this into categories with a log function. We defined the bins using a logarithmic scale since the distribution of the “*ratings\_count\_updt*” column was highly skewed, making logarithmic bins a good choice for creating more evenly distributed categories. We then defined the labels for each category as ['very low', 'low', 'medium', 'medium-high', 'high', 'very high'], assigned a number (from 1 to 6) to each category, and created a new column with these category labels.

Chart, histogram

Description automatically generated

* Another new feature we created was to transform *“****max\_pages****”* into categories by using a classic splitting method. We decided to define bin ranges as [0, 50, 200, 400, and >= 1000], with corresponding labels of ['very low', 'low', 'medium', 'high', 'very high'].
* We transformed also the *“****average\_rating***” into discrete and more meaningful categories of ['very bad', 'bad', 'medium', 'good', 'very good'] - using a logarithmic function.
* Chart

  Description automatically generatedChart, pie chart

  Description automatically generatedWe identified the ‘***genres’*** using keywords found within the *'Subject\_list'* value. For any NA values, we filled them with *'not specified*'. We grouped all those whose genre couln't be classified into the group *'mixed'.* The 'genre' column in particular seems interesting as it was created by extracting subjects and topics dealt in the book and using them to identify the genres using some key words. This could help grouping and comparing books based on their genres and see which genres are most popular and successful.   
  The Genre is then transformed into numerical vues.

We re-verified the dataset. As a result, we obtained a well-prepared dataframe with 10283 observations and 60 columns with no missing values. The dataframe contains a lot of useful information about books and can be used to analyze various aspects of the book industry such as the prediction of book ratings.

Some observations at this stage :

* After removing duplicates, we have 10 283 unique ‘*titles’*;
* In terms of *‘authors’*: we now have 6 252 unique values in the ‘*authors’* column and 4164 unique values in the ‘*main\_author’* column. Stephen King was also the author with the most books in the dataset;
* We observed 27 unique ‘*languages’* in the dataset, with English books dominating (8908 books). We created an additional column to group languages related to English, and now there are 9736 English books in the dataset;
* There were 2262 unique ‘*publishers’*, with vintage being the most common (318 works). Even after processing the data, 'vintage' still appears to be the most frequent publisher with 293 observations;
* We found 31 unique *genres*, with *'novel-narrative'* being the most popular.
* Most books (3002) had a ‘*rating\_count’* that fell under the 'medium high' category, whereas the most frequent category for *'text\_reviews'* was 'low' with 4448 observations. If we consider the total number of reviews, the most popular category is 'medium high' with 3046 observations.
* The difference between *'num\_pages'* and *'max\_pages'* was very low. The most frequent category for both columns was *'medium*,' with 4 865 and 4 897 observations, respectively.
* Finally, with 9384 observations, ‘*good’* was the most frequently occurring *rating category* in the dataset.

We have selected the following parameters to address the challenge of predicting the average ratings of a book:

|  |  |
| --- | --- |
| Dataset use for simulations | Example |
| title | Twilight (Twilight #1) |
| Rating\_type | 2 |
| num\_pages\_cat | 3 |
| ratings\_count\_cat | 3 |
| text\_reviews\_count\_cat | 3 |
| Season | 4 |
| Year | 2006 |
| Publisher\_number | 1 |
| Main\_Author | 1 |
| Author\_average | 1 |
| average\_rating | 3,59 |
| num\_pages | 501 |
| rating\_count | 4597666 |
| text\_reviews\_counts | 94265 |
| genre\_T | 56872 |

1. **Model training and evaluation**

After doing the data cleaning and feature selection. We have decided to test models in order to predict the ratings of a book from different inputs. One of the main transformations that were performed was the transformation of the ‘*rating’* columns into 3 different categories. It would be interesting too to compare models that predict the initial ‘*average\_rating’*, when using SMOTE algorithm in order to balance the data.

First of all, we split the dataset into two parts: 20% for testing and the remaining 80% for training.

In terms of algorithms to choose for prediction of a variable, we have chosen the classic way of fitting data with a Linear Model - Ordinary Least Squares (OLS)[[3]](#footnote-3). It assumes that the relationship between the dependent variable and the independent variables is linear. OLS aims to find the line of best fit that minimizes the sum of the squared errors between the predicted and actual values. This line can then be used to make predictions for new values of the independent variables.

For classification purposes, we have selected the Random Forest & Adaboost algorithms[[4]](#footnote-4). Random Forest is a type of decision tree algorithm that combines multiple decision trees to improve the accuracy of the classification and the final prediction will be based on a majority vote of the individual tree predictions. Adaboost, on the other hand, is a boosting algorithm that combines multiple weak classifiers to create a strong classifier. It is particularly useful when dealing with imbalanced datasets or when the base classifiers are simple.

ADD SOME GRAPHS

1. **Deployment**

(to be completed)

1. **Results and recommendations**

(to be completed)

1. Goodreads is an American social cataloging website and a subsidiary of Amazon that allows individuals to search its database of books, annotations, quotes, and reviews. [↑](#footnote-ref-1)
2. The seasons were defined as follows: Winter (1), Spring (2), Summer (3) and Autumn (4) [↑](#footnote-ref-2)
3. Other options : **Polynomial Regression** (used when the linear model is not sufficient and a polynomial could help), **Elastic Net** (a linear model that takes into account features of both Lasso and Ridge Regressions), **Bayesian Regression** (which uses random variables to obtain a fully probabilistic model, where the output is assumed to be Gaussian distributed around Xw), and **Stochastic Gradient Descent** (useful when the number of features and samples is large). [↑](#footnote-ref-3)
4. For classification purposes, we have Gaussian Naive Bayes, Logistic Regression, AdaBoost, and Random Forest. [↑](#footnote-ref-4)