Improving User Experience through Machine Learning

An approach using XGBClassifier

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Problem

E-commerce Food Entertainment

Predict and **personalize** user preferences across **three distinct domains** by analyzing user behavior and interactions.

Enhance user experience through **personalized recommendations**, which can significantly improve user satisfaction by suggesting relevant products, movies, and recipes based on histories and preferences.

Based on a technique called **boosting**
= EACH TREE CORRECTS THE ERRORS OF ITS PREDECESSORS

BASIC MODELS COMBINED FOR GREATER ACCURACY
Decision Tree

Missing values handling

Avoid overlearning

XGBoost

XGBClassifier
Classification problems

DISCRET TARGET VARIABLE

Multi-class problems handling
[0,1,2,3,4,5]

XGBRegressor
Régression problems

CONTINUOUS TARGET VARIABLE

Optuna

Automatic hyperparameter optimization tool

Why optimize hyperparameters?

- **Improve** model performance
- **Adapt** the model to the specifics of the data and the problem

Why Optuna?

Dynamic optimization :

Intelligent search based on **Bayesian** methods:

Explores **promising areas** of hyperparameter space

Efficiency:

- **Easy integration** with XGBoost
- **Faster** than Grid Search or Random Search
- Dynamic **pruning** functionality: abandons unpromising trials

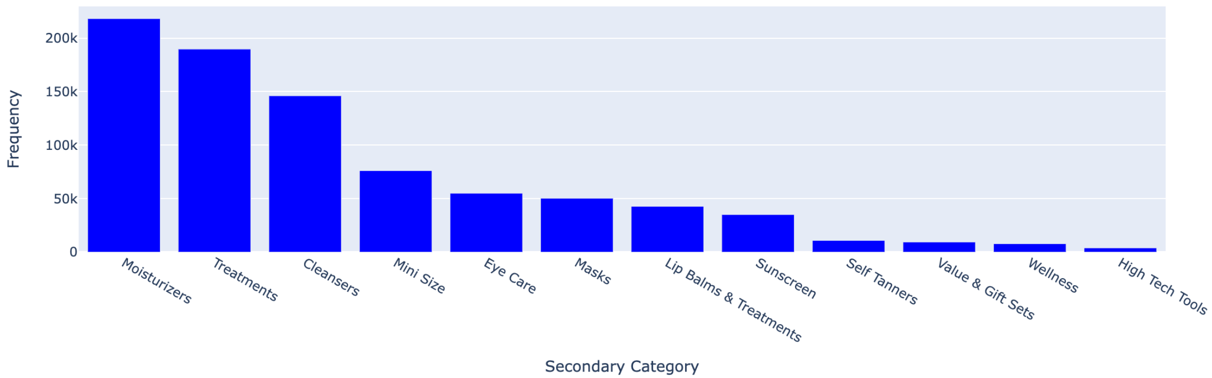
In this project

- **Objective**: maximize accuracy
- **Hyperparameters** explored: learning_rate, n_estimators, max_depth, etc.
- **Range** defined: n_estimators between 10 and 1000 (logarithmic)
- Number of **trials**: 30 (n_trials = 30)

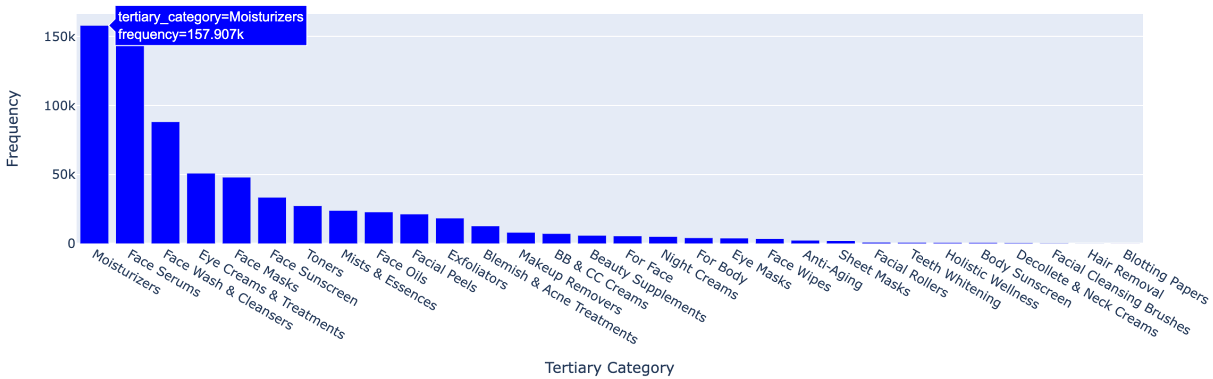
First experiment: E-commerce

Sephora

Distribution of Secondary Categories



Distribution of Tertiary Categories



6 287
products

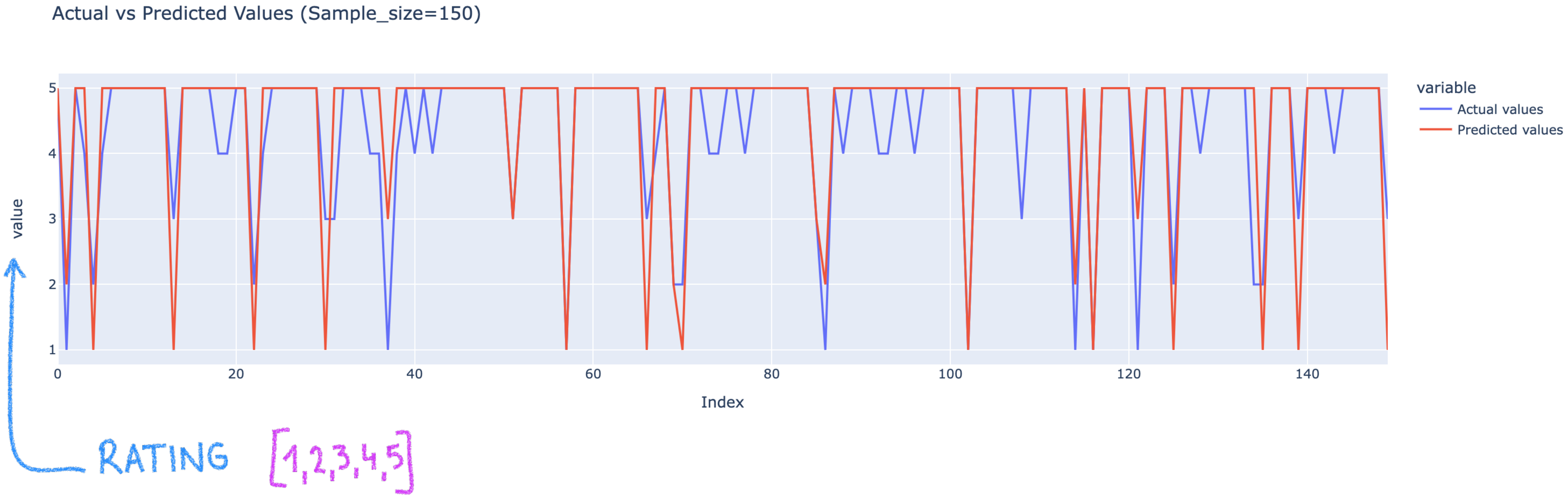
2000
Skin-Care

926 423
reviews

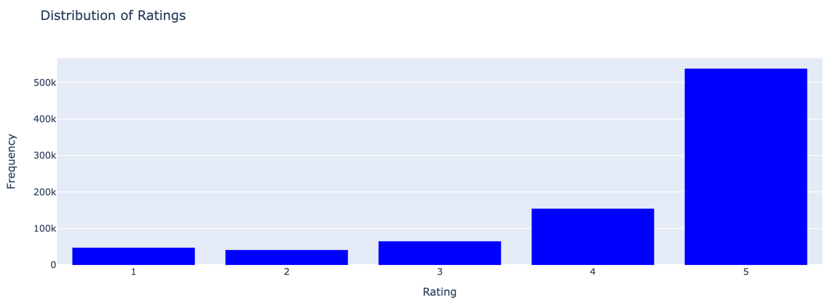
product_id	Unique product ID
product_name	Full name of the product
brand_name	Full name of the product brand
price_usd	Price of the product in US dollars
highlights	A list of tags or features that highlight the product's attributes
secondary_category	Second category in the breadcrumb section
tertiary_category	Third category in the breadcrumb section

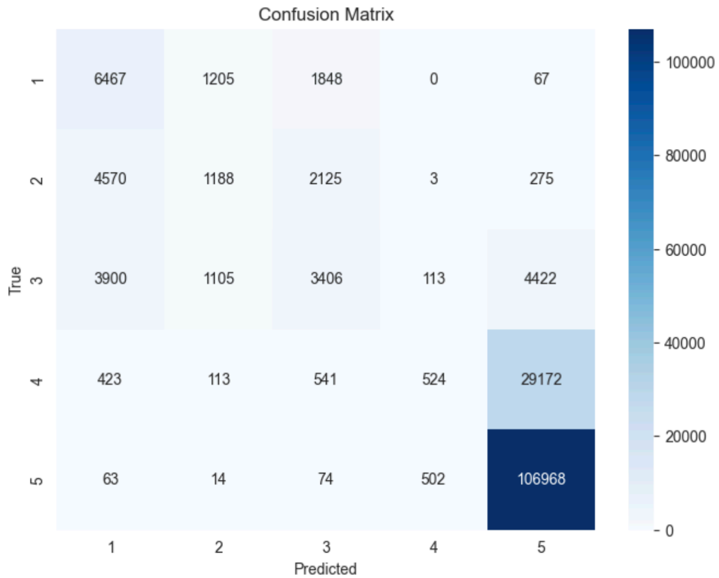
author_id	Unique author ID
is_recommended	Indicates if the author recommends the product or not (1-true, 0-false)
rating	The rating given by the author for the product on a scale of 1 to 5
product_id	Unique product ID
brand_name	Full name of the product brand
product_name	Full name of the product

Actual vs Predicted values



Metrics





Detection of 99% of class 5 instances

	precision	recall	f1-score	support
1	0.42	0.67	0.52	9587
2	0.33	0.15	0.20	8161
3	0.43	0.26	0.33	12946
4	0.46	0.02	0.03	30773
5	0.76	0.99	0.86	107621
accuracy			0.70	169088
macro avg	0.48	0.42	0.39	169088
weighted avg	0.64	0.70	0.62	169088

Accuracy: 70%

Balanced Accuracy: 42%

Grades are correctly classified around 42% of the time, taking class imbalances into account.

Multi-Class Precision:

[0.41930882 0.32772414 0.42606955 0.45884413 0.75915517]

Rating **1**: 42% of correct predictions

Rating **2**: 33%

Rating **3**: 43%

Rating **4**: 46%

Rating **5**: 76%

Macro-averaged Precision: 48%

On average, only 48% of predictions in all classes are correct.

2nd experiment: Entertainment

MovieLens

80 505

movies

movieId	Unique movie ID
title	Title of the movie
genres	All associated genres. This is a pipe-separated list.

32 000 204

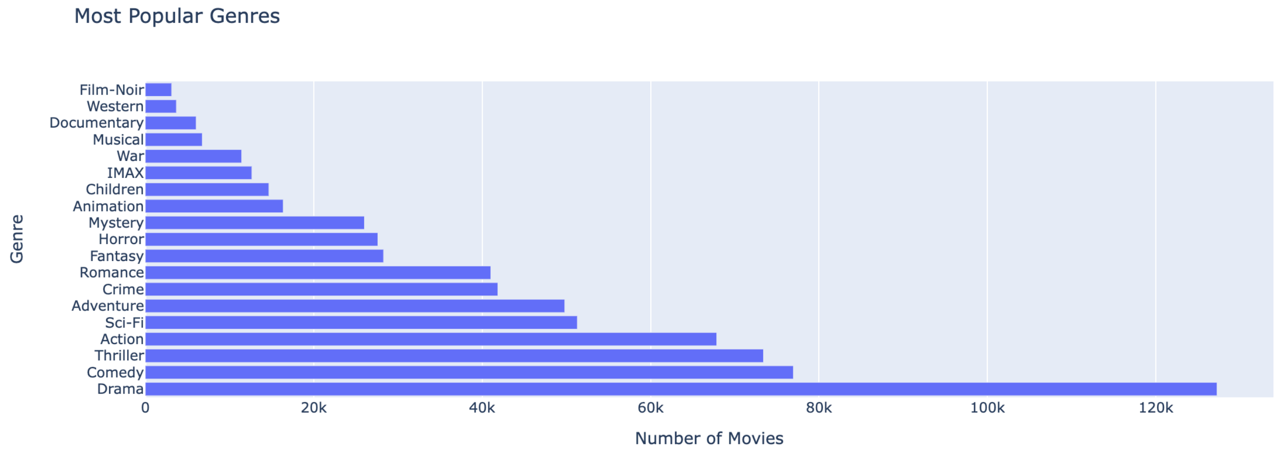
ratings

userId	Unique viewer ID
movieId	Unique movie ID
rating	Rating given on a 5-star scale, with half-star increments (0.5 stars - 5.0 stars)

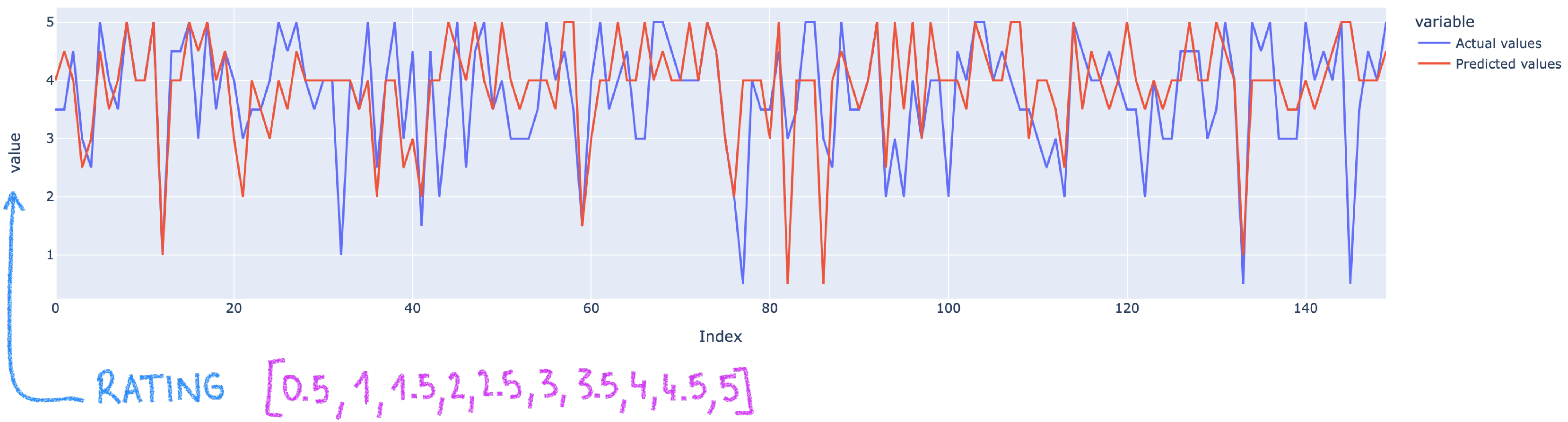
350 042

tags

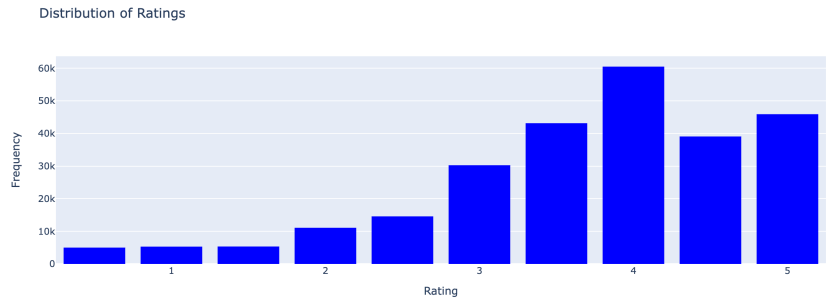
userId	Unique viewer ID
movieId	Unique movie ID
tag	User-generated. They usually consist of a single word or a short phrase.

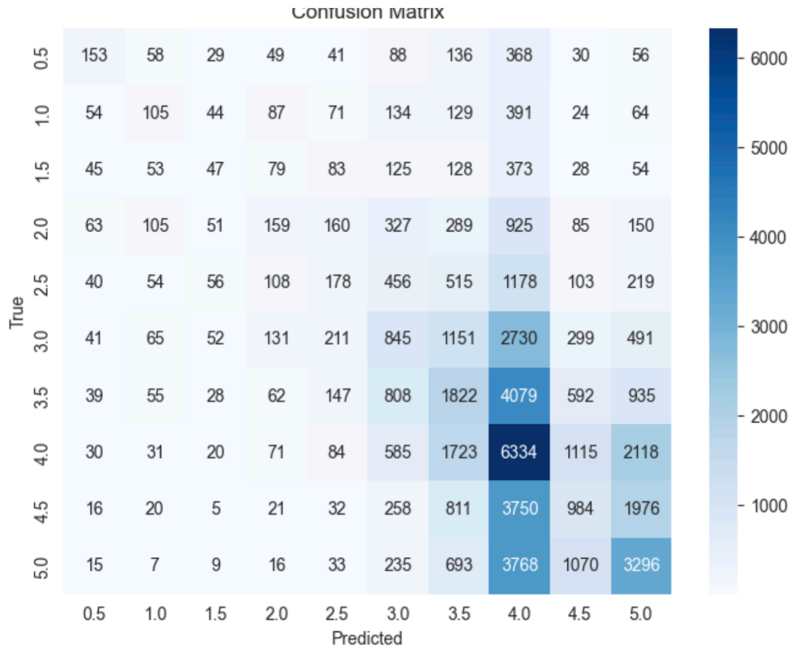


Actual vs Predicted values



Metrics





	precision	recall	f1-score	support
0	0.31	0.15	0.20	1008
1	0.19	0.10	0.13	1103
2	0.14	0.05	0.07	1015
3	0.20	0.07	0.10	2314
4	0.17	0.06	0.09	2907
5	0.22	0.14	0.17	6016
6	0.25	0.21	0.23	8567
7	0.27	0.52	0.35	12111
8	0.23	0.12	0.16	7873
9	0.35	0.36	0.36	9142
accuracy			0.27	52056
macro avg	0.23	0.18	0.19	52056

Accuracy: 27%

Balanced Accuracy: 20%

Grades are correctly classified around 20% of the time, taking class imbalances into account.

Multi-Class Precision:

[0.30846774 0.18987342
0.13782991 0.20306513
0.17115385 0.21885522
0.24631607 0.26506528
0.22725173 0.35217438]

Rating **0,5**: 30,8% of correct predictions

Rating **1**: 19%

Rating **5**: 35,2%

Rating **4**: 26,5%

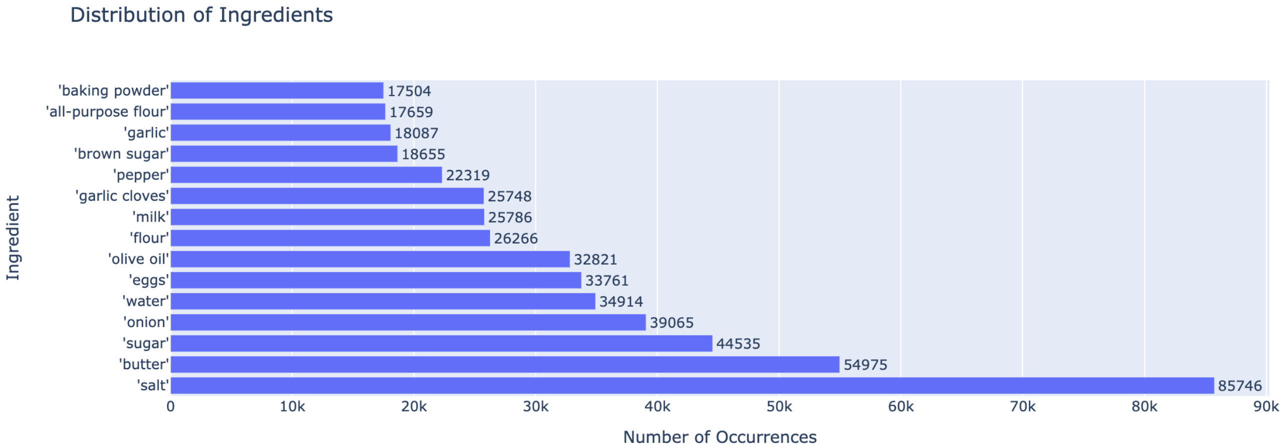
Macro-averaged Precision:

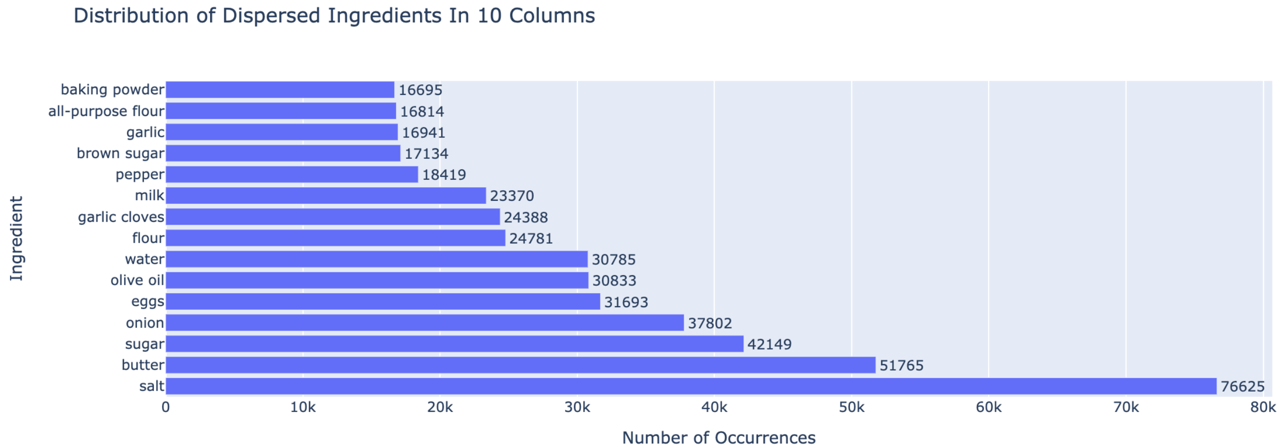
23%

On average, only 23% of predictions in all classes are correct.

3rd experiment: Food

Food.com





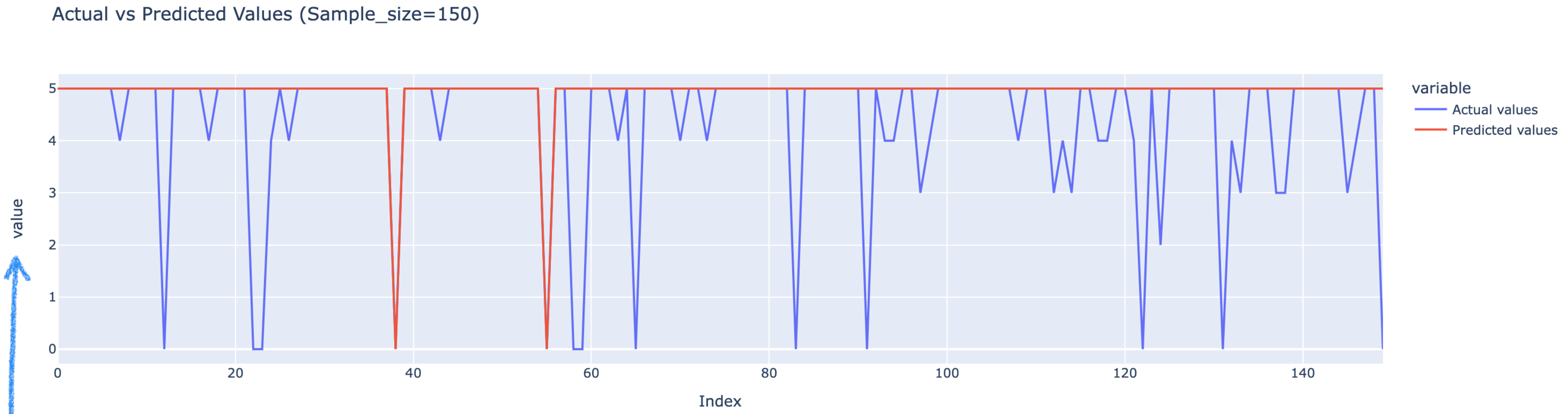
1 116 492
reviews

user_id	Unique user ID: the person who wrote the review
rating	The rating given by the author for the product on a scale of 0 to 5
recipe_id	Unique recipe ID

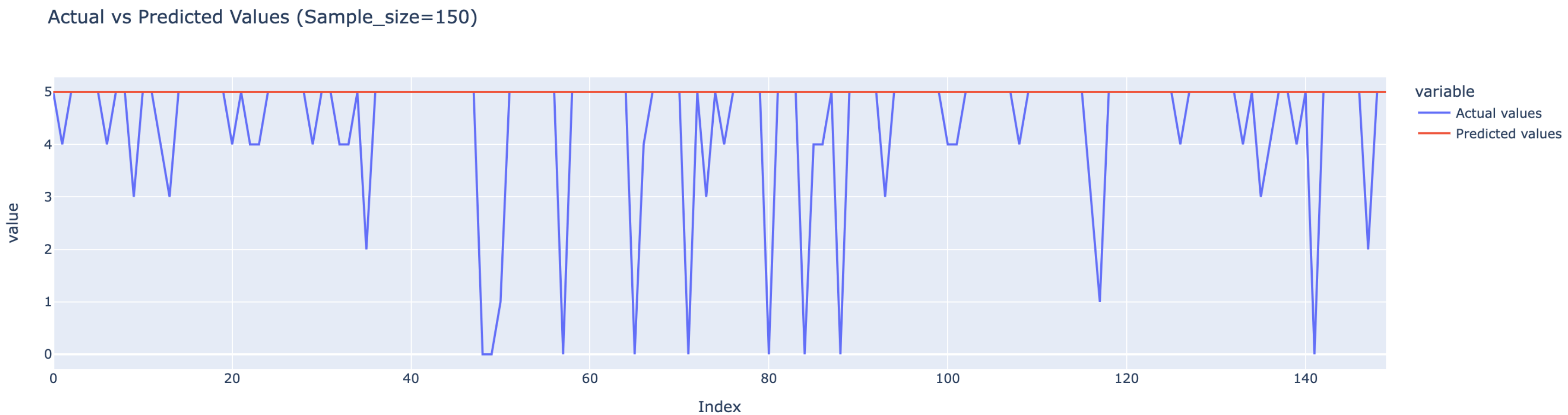
231 636
recipes

name	Recipe name
recipe_id	Unique recipe identifier
minutes	Preparation time (in minutes)
tags	Qualifying tags recipe
nutrition	Nutritional values
n_step	Number of steps to complete the recipe
ingredients	Ingredients needed to make the recipe

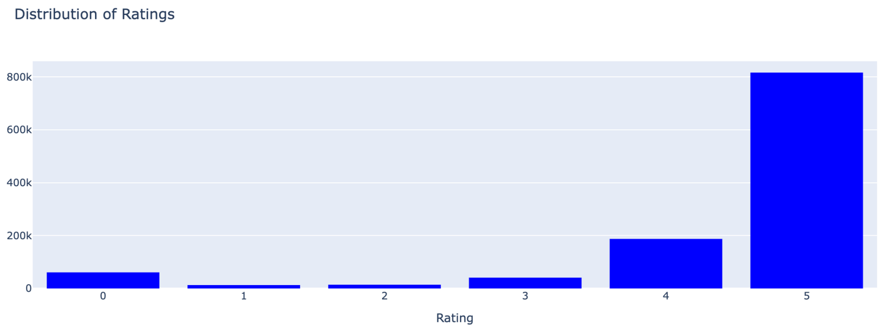
Actual vs Predicted values

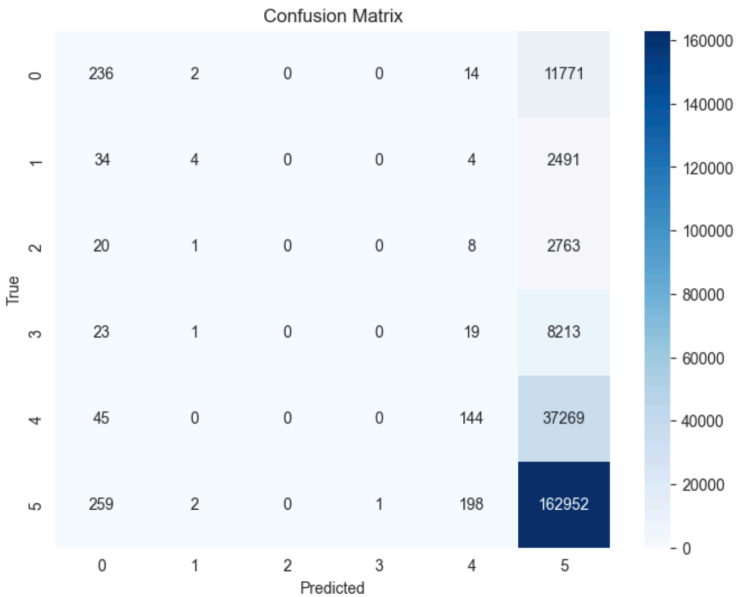


RATING
[0,1,2,3,4,5]



Metrics





	precision	recall	f1-score	support
0	0.38	0.02	0.04	12023
1	0.40	0.00	0.00	2533
2	0.00	0.00	0.00	2792
3	0.00	0.00	0.00	8256
4	0.37	0.00	0.01	37458
5	0.72	1.00	0.84	163412
accuracy			0.72	226474
macro avg	0.31	0.17	0.15	226474
weighted avg	0.61	0.72	0.61	226474

Detection of 100% of class 5 instances

Accuracy: 72%

Balanced Accuracy: 17%

Grades are correctly classified around 17% of the time, taking class imbalances into account.

Multi-Class Precision:

[0.38249595 0.4
0. 0.
0.37209302 0.72275669]

Rating **0**: 38% of correct predictions

Rating **1**: 40%

Rating **2 & 3**: 0 predictions

Rating **4**: 37%

Rating **5**: 72%

Macro-averaged Precision:

31,28%

On average, only 31% of predictions in all classes are correct.

Concluding remarks

ENTERTAINMENT : Movies

+ **Diversity of ratings**

+ **Ease of access** :leading to better distinction between liked and disliked films

- Performance is affected by **limited** richness in explanatory **columns** (e.g., genres, tags)

E-COMMERCE : Skincare Products

FOOD : Recipes

- **Anticipated satisfaction:** reinforce a bias towards high ratings

+ **More columns** giving product and recipe information

- **Financial** aspect encourages careful selection minimizing disappointment

- **Taste preferences** influence choices

LIMITATIONS

- **Unbalanced** data skews predictions toward **majority classes**
- Explanatory columns lack diversity, failing to capture nuances in minority classes

IMPROVEMENTS

- Diversify data with **contextual** or **emotional** variables
- Use **Natural Language Processing (NLP)** to analyze sentiment in reviews
- **Rebalance** data by **reducing** majority class dominance or **enriching** minority classes

Thank you

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