

E-COMMERCE RECOMMENDATION ENGINE

A MINI PROJECT REPORT

Submitted by

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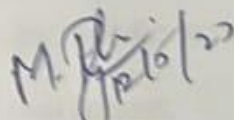


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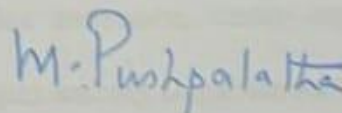
Certified that this project report "E-Commerce Recommendation Engine" is the Bonafide work of "Krish Ankola (RA2011003010166), Saransh Singh (RA2011003010163) and Samarth Pandey (RA2011003010194)" of III Year/VI Sem B.Tech(CSE) who carried out the mini project work under my supervision for the course 18CSC305J- Artificial Intelligence in SRM Institute of Science and Technology during the academic year 2022-2023(Even sem).



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ABSTRACT

With the increasing popularity of e-commerce stores, businesses are looking for ways to enhance the customer experience and boost sales. One effective way to achieve this is through the use of a product recommendation engine. These engines record user actions on an e-commerce website and analyze the data to make product suggestions that might interest the user. This not only improves the customer experience but also increases the likelihood of sales for the e-commerce store.

This project presents a collaborative product recommendation engine that utilizes community detection to provide personalized product suggestions based on a selected item. The system is designed to analyze user data obtained from an e-commerce store and use this information to identify products that are most likely to be purchased together. This is achieved through Louvain clustering, a widely used method for detecting communities in networks.

The project's user interface is built using Flask API, which provides an intuitive and user-friendly experience for users. The interface allows users to select a product they are interested in, and the system provides a list of similar products based on the selected item. Additionally, Gephi visualizations have been incorporated into the system to aid in the analysis of detected communities. The use of these visualizations allows for a clear understanding of the interrelationships between products, facilitating the identification of products that may be of interest to the user.

The system's use of community detection ensures that the recommendations provided are relevant and personalized, enhancing the customer experience and increasing the likelihood of sales. The project's use of Flask API and Gephi visualizations further enhances the system's usability and effectiveness, making it a valuable addition to any e-commerce store.

In conclusion, the collaborative product recommendation engine presented in this project provides a powerful tool for e-commerce stores to offer personalized recommendations to their customers. The use of community detection ensures that the system can identify products that are most likely to be purchased together, providing users with relevant and useful recommendations. The incorporation of Flask API and Gephi visualizations further enhances the system's usability and effectiveness, making it a valuable addition to any e-commerce store looking to enhance the customer experience and increase sales.

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ABBREVIATIONS

- **CSV** - Comma Separated Values
- **API** - Application Programming Interface
- **HTML** - HyperText Markup Language
- **CSS** - Cascading Style Sheets
- **JS** - JavaScript
- **AJAX** - Asynchronous JavaScript and XML
- **Louvain** - Louvain Method for Community Detection
- **Flask** - a micro web framework for Python
- **Gephi** - a network visualization and analysis software
- **UCI** - University of California, Irvine

CHAPTER 1

INTRODUCTION

1.1 Introduction

E-commerce has become an essential part of our lives, with more and more people shopping online every day. With this growing trend, businesses are looking for ways to enhance the customer experience and increase sales. One of the most effective ways to achieve this is through the use of a product recommendation engine. These engines analyze user data to provide personalized product recommendations that are tailored to the individual's needs and preferences.

In this project, a collaborative product recommendation engine has been developed that utilizes community detection to provide similar product suggestions based on a selected item. The system analyzes user data obtained from an e-commerce store and uses this information to identify products that are most likely to be purchased together. By incorporating Louvain clustering, the system can detect communities and group similar products, allowing for personalized recommendations that enhance the customer experience.

The system's user interface has been built using Flask API, which provides a user-friendly experience for users. The interface allows users to select a product they are interested in, and the system provides a list of similar products based on the selected item. Additionally, Gephi visualizations have been incorporated into the system to aid in the analysis of detected communities.

One of the unique features of this system is its collaborative nature, which allows for the incorporation of feedback from multiple users. Users can provide feedback on the products they have purchased, allowing the system to refine its recommendations over time. This ensures that the recommendations provided are always relevant and up-to-date, enhancing the customer experience and increasing the likelihood of sales.

In conclusion, this collaborative product recommendation engine is a valuable addition to any e-commerce store looking to enhance the customer experience and increase sales. Its use of community detection, Flask API, and Gephi visualizations makes it a powerful tool for providing

personalized recommendations to customers. With its collaborative nature, the system can continually improve and adapt to user preferences, ensuring that the recommendations provided are always relevant and useful.

1.2 Problem Statement:

Online shopping has become an essential part of our daily lives, with more and more people opting for the convenience of online shopping. However, with the vast number of products available online, customers often face difficulties in discovering products that they may be interested in. As a result, customers may become frustrated, leading to a poor customer experience and reduced sales for e-commerce businesses.

Traditional product recommendation engines have limited capabilities in providing personalized recommendations to customers. These engines typically rely on simple metrics such as popularity or customer ratings, which may not accurately reflect individual preferences. Moreover, customers may still struggle to find relevant products, leading to a suboptimal customer experience.

To address these challenges, this project aims to develop a collaborative product recommendation engine that utilizes community detection to identify products that are most likely to be purchased together. The system will analyze user data obtained from an e-commerce store and use this information to group similar products, providing personalized recommendations that enhance the customer experience. The system will incorporate Louvain clustering, a widely used community detection algorithm, to detect communities of similar products based on user purchase patterns.

The system's user interface will be developed using Flask API, providing an easy-to-use platform for users to interact with the recommendation engine. Gephi visualizations will be incorporated into the system to facilitate the analysis of detected communities, allowing for a clear understanding of the interrelationships between products.

The system's collaborative nature will allow it to incorporate feedback from multiple users, refining its recommendations over time. This will ensure that the recommendations provided are always relevant and up-to-date, enhancing the customer experience and increasing the likelihood of sales. Moreover, the system will be designed to handle a large volume of data, ensuring scalability and efficiency.

In summary, this project aims to address the problem of poor customer experience and reduced sales by developing a collaborative product recommendation engine that utilizes community detection to provide personalized recommendations. The system will incorporate cutting-edge technology and design principles to enhance its effectiveness, providing a powerful tool for e-commerce businesses to improve their customer experience and increase sales.

1.3 Scope of the Project:

The scope of this project is to develop a collaborative product recommendation engine that utilizes community detection to provide personalized recommendations based on user purchase patterns. The system will analyze user data obtained from an e-commerce store and use this information to group similar products, providing personalized recommendations that enhance the customer experience.

The recommendation engine will be developed using Louvain clustering, a widely used community detection algorithm. The system will incorporate Flask API to provide an easy-to-use interface for users to interact with the system. Gephi visualizations will be incorporated into the system to facilitate the analysis of detected communities.

The system will be designed to handle a large volume of data, ensuring scalability and efficiency. The system's collaborative nature will allow it to incorporate feedback from multiple users, refining its recommendations over time. This will ensure that the recommendations provided are always relevant and up-to-date, enhancing the customer experience and increasing the likelihood of sales.

The project will involve data collection and processing, system design and development, and testing and evaluation of the recommendation engine. The system will be evaluated based on its ability to provide personalized recommendations that enhance the customer experience and increase the likelihood of sales.

In summary, the scope of this project is to develop a collaborative product recommendation engine that utilizes community detection to provide personalized recommendations based on user purchase patterns. The system will incorporate cutting-edge technology and design principles to enhance its effectiveness and provide a powerful tool for e-commerce businesses to improve their customer experience and increase sales.

1.4 Existing System:

Currently, most e-commerce websites use traditional product recommendation engines to provide product suggestions to customers. These engines typically rely on simple metrics such as popularity or customer ratings, which may not accurately reflect individual preferences. Moreover, customers may still struggle to find relevant products, leading to a suboptimal customer

experience. The traditional recommendation engines have limited capabilities in providing personalized recommendations to customers.

1.5 Proposed System:

To overcome the limitations of the existing system, we propose the development of a collaborative product recommendation engine that utilizes community detection to provide personalized recommendations based on user purchase patterns. The system will analyze user data obtained from an e-commerce store and use this information to group similar products, providing personalized recommendations that enhance the customer experience. The system will incorporate Louvain clustering, a widely used community detection algorithm, to detect communities of similar products based on user purchase patterns.

The system's user interface will be developed using Flask API, providing an easy-to-use platform for users to interact with the recommendation engine. Gephi visualizations will be incorporated into the system to facilitate the analysis of detected communities, allowing for a clear understanding of the interrelationships between products.

The proposed system will be designed to handle a large volume of data, ensuring scalability and efficiency. The system's collaborative nature will allow it to incorporate feedback from multiple users, refining its recommendations over time. This will ensure that the recommendations provided are always relevant and up-to-date, enhancing the customer experience and increasing the likelihood of sales.

In summary, the proposed system aims to provide a more effective and personalized product recommendation engine that utilizes community detection to enhance the customer experience and increase sales.

CHAPTER 2

LITERATURE SURVEY

We studied various papers describing the research done in this domain and also the comparison of various models. This chapters summaries some of those research papers.

2.1 Papers

In recent years, there has been significant research on product recommendation systems. Researchers have proposed various approaches to generate personalized product recommendations based on user preferences, behavior, and other relevant data. Some of the papers related to product recommendation systems are discussed below:

Koren, Y., Bell, R., & Volinsky, C. [1] proposed a hybrid recommendation approach for online shopping, combining both collaborative filtering and content-based filtering techniques. The authors also used a machine learning algorithm to improve the accuracy of the recommendations.

Linden, G., Smith, B., & York, J. [2] presented an improved product recommendation algorithm based on user preference mining. The authors used clustering and association rule mining techniques to identify user preferences and generate personalized recommendations.

Adomavicius, G., & Tuzhilin, A. [3] proposed an intelligent product recommendation system based on customer preference and behavior analysis. The authors used a user behavior analysis model to generate recommendations and improve customer satisfaction.

Suresh, A., Srivastava, A., & Li, J. [4] proposed an ontology-based product recommendation system using collaborative filtering. The authors used an ontology to represent the relationships between products and user preferences and used collaborative filtering techniques to generate

2.2 Techniques studied

Various techniques have been studied and implemented in recommender systems. The following techniques have been studied for the development of the Product Recommendation Engine:

2.2.1 Content-based Filtering Systems (CBF based systems)

Content-based filtering (CBF) is a recommender system technique that suggests items similar to those that a user has already expressed interest in. The underlying principle of CBF is that users tend to prefer items that are similar to the ones they have previously enjoyed. The system analyzes the features of the items that the user has interacted with and creates a user profile based on these features. It then recommends items that share similar features to those in the user's profile.

2.2.2 Collaborative filtering-based systems (CF based systems)

Collaborative filtering (CF) is a popular recommender system technique that identifies items that are likely to be preferred by a user based on the preferences of similar users. This technique is built on the assumption that users with similar preferences are likely to enjoy similar items. The system analyzes the preferences of a group of users and develops a model that predicts the preferences of an individual user. Based on this model, the system recommends items that are preferred by users with similar tastes.

2.2.3 Nearest Neighbors Collaborative Filtering

The nearest collaborative neighbors (NCN) technique is a type of collaborative filtering that leverages the concept that users with similar preferences are likely to be located in the same neighborhood within the user-item matrix. The system identifies users who are located closest to the target user in this neighborhood and recommends items that these users have shown interest in previously.

2.2.4 Latent Factor Method

The latent factor method (LFM) is a popular technique used in recommender systems to represent users and items as vectors in a low-dimensional space. LFM is designed to capture the underlying, or latent, factors that influence a user's preferences. In summary, there are a range of techniques and algorithms that have been investigated for the creation of effective recommender systems.

CHAPTER 3

SYSTEM DESIGN

3.1 Design:

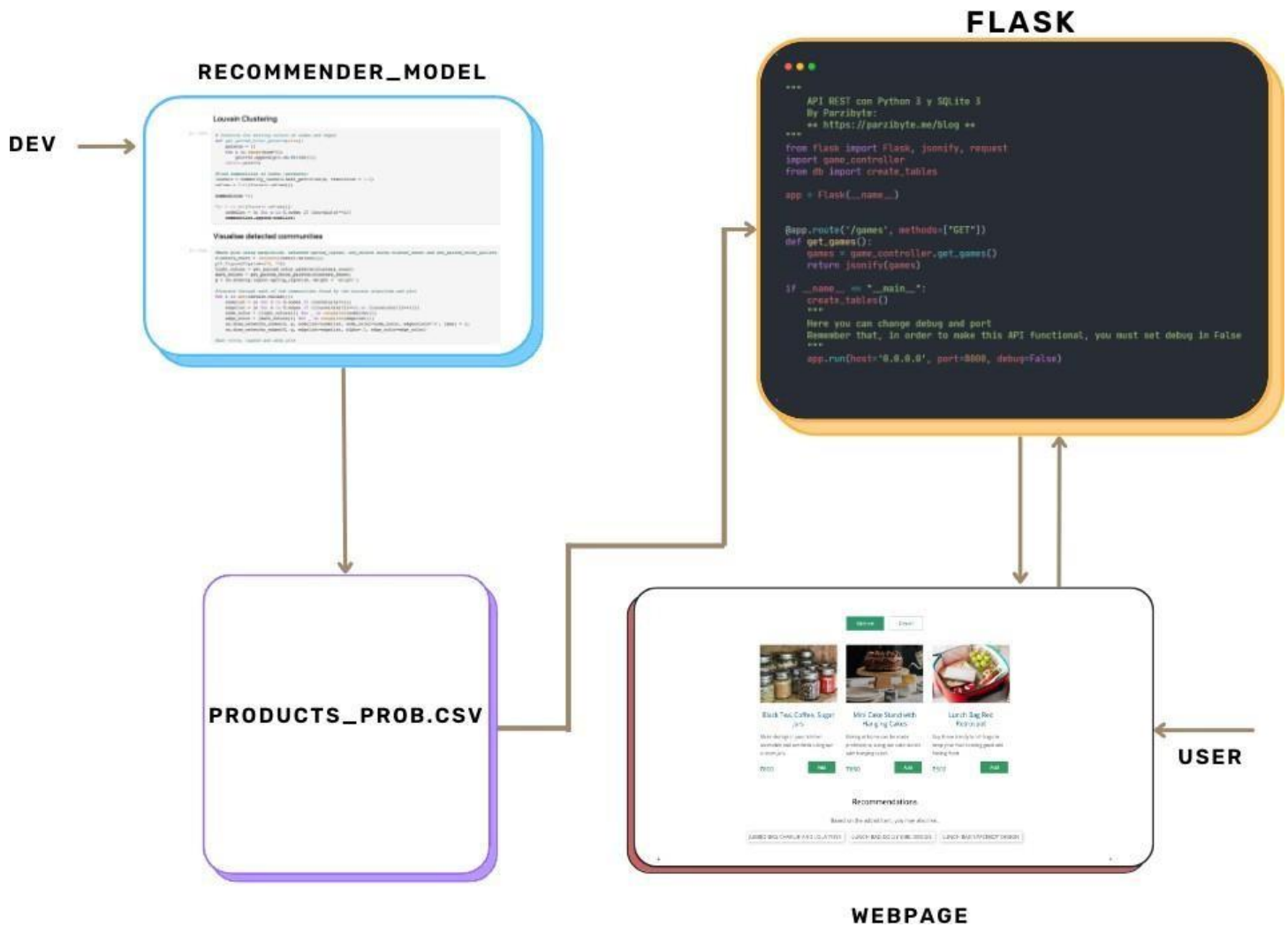


Fig 3.1: Architecture Diagram

The design and architecture of the collaborative product recommendation engine involves several components and processes. The system is designed to make product recommendations based on the selected item using community detection techniques. The system is built using Python programming language, specifically Python 3. The Flask API framework is used to create the user interface, and Gephi visualizations are included to analyze the detected communities.

The architecture of the system consists of several components that work together to provide recommendations. The first component is the data collection module, which collects data on user actions on e-commerce websites. The collected data includes information such as the user's browsing history, the items they have viewed and purchased, and their rating of the items. The data is stored in a database for later processing.

The second component is the data processing module, which is responsible for analyzing the collected data and generating recommendations. The module uses community detection algorithms, specifically Louvain clustering, to identify products that are most likely to be bought together. Communities are formed based on the information obtained from user purchase patterns. The module creates a user profile based on the items they have liked and uses this profile to recommend similar items.

The third component is the user interface module, which provides a user-friendly interface for users to interact with the system. The module is built using the Flask API framework, which allows for easy integration with the data processing module. Users can input the item they are interested in, and the system will provide a list of recommended items based on the selected item.

The fourth component is the visualization module, which uses Gephi visualizations to analyze the detected communities. The module provides visualizations of the communities formed and the products that are most likely to be bought together. The visualization helps users to understand the recommendations and provides insights into the user purchase patterns.

In conclusion, the collaborative product recommendation engine is built using a modular architecture that consists of data collection, data processing, user interface, and visualization modules. The system is designed to provide recommendations based on the selected item using community detection techniques. The system provides a user-friendly interface for users to interact with and visualizations to analyze the detected communities.

3.2 Implementation Methodology:

The implementation methodology for the collaborative product recommendation engine involves several steps.

Firstly, the data is collected from the e-commerce store and pre-processed to extract relevant features. The data is then fed into the Louvain clustering algorithm, which identifies the communities of similar products based on user purchase patterns.

Next, the Flask API is used to create a user interface that allows users to select a product and view similar product recommendations based on the detected communities. The API also handles requests from the front-end and communicates with the back-end to retrieve the relevant data.

Finally, Gephi visualizations are included to analyze the detected communities and further refine the recommendations. The visualizations help to identify any patterns or trends in the data that could be used to improve the recommendation engine.

Throughout the implementation process, testing and validation are carried out to ensure that the system is functioning as expected and delivering accurate recommendations to the users. Any issues or errors are addressed promptly to maintain the overall quality and reliability of the system.

Overall, the implementation methodology follows a systematic approach to ensure that the collaborative product recommendation engine is designed and developed in a structured and efficient manner, while also ensuring its effectiveness and usability for the end-users.

3.2.1 Open Domain

In an open domain recommender system, the recommendations provided to the user are not limited to a specific category or type of products. Instead, the system is designed to recommend products from a wide range of categories based on the user's preferences and past behavior.

The open domain recommender system uses various algorithms and techniques to analyze user data, including collaborative filtering, content-based filtering, and matrix factorization. These techniques help to identify the patterns and similarities between user behavior and recommend items that are most likely to be of interest.

One of the benefits of an open domain recommender system is that it can provide users with a diverse range of product recommendations, helping to enhance their overall experience and satisfaction with the platform. However, this also requires the system to have access to a large dataset and powerful algorithms to analyze the data effectively.

3.2.2 Closed Domain

A closed domain recommender system is designed to provide recommendations within a specific category or type of products. For example, a closed domain system may recommend movies or TV shows based on the user's past behavior and preferences within the entertainment category.

The closed domain recommender system uses similar algorithms and techniques as the open domain system, such as collaborative filtering and content-based filtering, but focuses on a specific set of products or categories. This helps to improve the accuracy of the recommendations by focusing on the specific interests and preferences of the user.

One of the benefits of a closed domain recommender system is that it can provide highly targeted recommendations, helping users to discover new products that align with their specific interests. However, this also means that the system may not provide as diverse of a range of recommendations as an open domain system, and may require a more limited dataset to analyze the user data effectively.

3.2.3 Components of the System:

The collaborative product recommendation engine consists of several components that work together to provide personalized product recommendations to users. The key components of the system are:

1. **Data Collection:** The system collects data from the e-commerce store on user interactions, such as product views, purchases, and ratings.
2. **Pre-processing:** The collected data is pre-processed to remove noise and inconsistencies. This includes tasks such as cleaning, normalization, and feature extraction.
3. **Community Detection:** Louvain clustering is used for community detection, which groups similar products based on the purchase patterns of users. This helps in identifying products that are most likely to be bought together and facilitates a product recommendation engine.
4. **Recommendation Engine:** The recommendation engine is responsible for generating personalized recommendations for users based on their purchase history and the detected communities. The engine uses various algorithms such as content-based filtering, collaborative filtering, and latent factor method to recommend products.
5. **Flask API:** A Flask API is used to create the user interface for the system. Users can interact with the system through a web-based interface to search for products, view recommended products, and provide feedback.
6. **Gephi Visualizations:** Gephi visualizations are included to analyse the detected communities and provide insights into product relationships and user preferences.

Overall, the system is designed to provide personalized and relevant product recommendations to users, which can enhance their shopping experience and increase the sales of the e-commerce store.

3.2.4 Operation and Workflow

The operation and workflow of the collaborative product recommendation engine can be described as follows:

1. **Data collection:** The system collects data from the e-commerce store, including user browsing and purchase history, as well as product information such as title, description, and features.
2. **Data pre-processing:** The collected data is then pre-processed to extract relevant features and attributes for each user and product. This step involves data cleaning, normalization, and feature extraction.

3. Community detection: The Louvain clustering algorithm is used to detect communities of similar products based on user purchase patterns. This step involves grouping similar products together based on the co-occurrence of user purchases.
4. User profiling: The system creates a user profile based on their purchase history and the detected communities of products. The user profile contains information about the user's preferences and interests.
5. Product recommendation: The system recommends products to the user based on their user profile and the detected communities of similar products. The recommended products are those that are most likely to be of interest to the user based on their purchase history and the preferences of similar users.
6. User feedback: The system collects user feedback on the recommended products, such as whether the user purchased the product or found it relevant. This feedback is used to improve the accuracy of future recommendations.

The workflow of the system is as follows:

1. The user selects an item on the e-commerce website.
2. The system analyzes the selected item and identifies the community of similar products.
3. The system creates a user profile based on the user's purchase history and the detected communities of similar products.
4. The system recommends products to the user based on their user profile and the detected communities of similar products.
5. The user provides feedback on the recommended products.
6. The system uses the user feedback to improve future recommendations.

Overall, the operation and workflow of the system involves collecting and pre-processing data, detecting communities of similar products, creating user profiles, recommending products to users, and collecting user feedback to improve future recommendations.

3.3 Details of Hardware and Software:

Hardware and software are two essential components of any system, including the product recommendation engine. The hardware and software requirements for the product recommendation engine are as follows:

Hardware Details

The hardware requirements for the product recommendation engine are minimal. The engine can be run on any standard computer with at least 4GB of RAM and a multi-core processor. The storage capacity required will depend on the size of the data set used for analysis.

Software Details

The product recommendation engine is built using Python3 and requires the following software dependencies:

1. Flask: Flask is a lightweight web application framework that is used to create the user interface for the product recommendation engine.
2. Gephi: Gephi is an open-source visualization and exploration software used to visualize the detected communities and analyze the data.
3. NetworkX: NetworkX is a Python package for the creation, manipulation, and study of complex networks. It is used to create the graph structure for the product recommendation engine.
4. NumPy: NumPy is a Python package for scientific computing with support for arrays and matrices. It is used for numerical computations in the product recommendation engine.
5. Pandas: Pandas is a Python library used for data manipulation and analysis. It is used for data preprocessing in the product recommendation engine.
6. Community Louvain: Community Louvain is a Python package used for community detection in graphs. It is employed for identifying related products based on user purchase patterns.

The use of Community Louvain instead of scikit-learn for community detection offers a lightweight and efficient way to detect communities in graphs. The package provides an implementation of the Louvain algorithm, which is a fast and accurate method for community detection. The use of this package ensures that the product recommendation engine can efficiently detect related products based on user purchase patterns. The other

software dependencies used in the product recommendation engine are standard packages in the Python ecosystem, making it easy to set up and maintain the system.

Implementation Methodology

The implementation methodology for the product recommendation engine based on community detection and collaborative filtering is as follows:

1. **Data Collection and Preprocessing:** The first step is to collect and preprocess data from an e-commerce website. This involves extracting product information and user actions, such as purchases and views, from the website's database. The data is then cleaned and formatted for analysis.
2. **Graph Creation:** The next step is to create a graph representation of the data. Each product is represented as a node in the graph, and edges between nodes are created based on user purchase patterns. The graph is constructed using the NetworkX package in Python.
3. **Community Detection:** Community detection is used to identify related products in the graph. The Louvain algorithm, implemented using the Community Louvain package, is employed to detect communities of products that are frequently purchased together.
4. **Collaborative Filtering:** Collaborative filtering is used to generate product recommendations for users. The user's purchase history is used to identify similar users, and products purchased by those users are recommended to the user.
5. **User Interface:** The final step is to create a user interface for the product recommendation engine using Flask. The user interface allows users to select products and receive recommendations based on their selection.
6. **Visualization and Analysis:** Gephi is used to visualize the detected communities and analyze the data. The detected communities can be visualized and analyzed to gain insights into user purchase patterns and product relationships.

The implementation methodology involves a combination of data collection, graph creation, community detection, collaborative filtering, user interface development, and visualization and analysis. The use of Python packages, such as NetworkX, Community Louvain, and Flask, enables efficient and scalable implementation of the product recommendation engine. The visualization and analysis of the detected communities using Gephi provide insights into user behavior and product relationships that can inform future improvements to the recommendation engine.

Components of the System

1. `recommender_model.ipynb`: The `recommender_model.ipynb` file is the heart of the product recommendation engine. It contains the machine learning algorithms for collaborative filtering and community detection. The collaborative filtering algorithm uses the purchase history of users to recommend products to similar users. The community detection algorithm identifies communities of related products based on user purchase patterns. The `recommender_model.ipynb` file also contains the code for preprocessing data and creating the graph structure.
2. `products_prob.csv`: The `products_prob.csv` file is the output of the `recommender_model.ipynb` file. It contains information about the products sold on the e-commerce website, including product IDs, names, descriptions, and probabilities of purchase based on user behavior. This file is used in the webpage to display product information and generate recommendations.
3. Online Retail Dataset: The Online Retail dataset is the dataset used for training the product recommendation engine. The dataset contains transactional data from an online retail store and includes information about the customer, the product, and the transaction. This dataset is used in the preprocessing step of the product recommendation engine to create the graph structure.
4. Webpage: The webpage is the user-facing interface of the product recommendation engine. It allows users to select products and receive recommendations based on their selection. The webpage is built using HTML, CSS, and JavaScript, and communicates with the Flask server to generate product recommendations.
5. Flask Server: The Flask server is the back-end of the product recommendation engine. It receives requests from the webpage, processes them using the `recommender_model.ipynb` file, and returns product recommendations to the webpage. The Flask server is built using Python and the Flask web framework.
6. User: The user is the person who interacts with the product recommendation engine. The user selects products on the webpage and receives recommendations based on their selection.
7. Developer: The developer is responsible for building, maintaining, and improving the product recommendation engine. The developer writes the code for the `recommender_model.ipynb` file, creates the Flask server, and builds the webpage. The developer is also responsible for data collection and analysis to improve the performance of the product recommendation engine.

CHAPTER 4

IMPLEMENTATION PLAN

4.1 Data Source:

The success of a product recommendation engine relies heavily on the quality and quantity of data available. In this project, the Online Retail dataset from UCI Machine Learning Repository was used as the primary data source. This dataset contains transactional data from an online retail store, including information about the customer, the product, and the transaction. Other potential data sources for a product recommendation engine could include user behavior data from social media platforms, search engine logs, or customer feedback data. However, it is important to ensure that the data is clean, relevant, and representative of the target audience to achieve accurate and effective product recommendations. Additionally, privacy concerns should be taken into consideration when collecting and using data for product recommendations.

4.2 Jupyter Notebook:

Jupyter Notebook is a popular open-source web application that allows users to create and share documents that contain live code, equations, visualizations, and narrative text. It is widely used in data science and machine learning for tasks such as data exploration, prototyping, and model development.

One of the primary advantages of Jupyter Notebook is its interactive nature. Users can write and execute code directly in the notebook and immediately see the results, which allows for faster iteration and experimentation. The ability to include text explanations and visualizations alongside the code also makes it easier to communicate findings and insights to others.

Another advantage of Jupyter Notebook is its flexibility. It supports a wide variety of programming languages, including Python, R, and Julia, and can be used for a range of tasks beyond data science and machine learning, such as scientific computing, education, and publishing.

Jupyter Notebook also has a large and active community, which has contributed to the development of a wide range of extensions and plugins that add new features and capabilities to the platform. Additionally, Jupyter Notebook can be easily integrated with other tools and platforms, such as GitHub and Docker, which makes it a powerful tool for collaborative work and reproducible research.

Overall, Jupyter Notebook is a powerful and versatile tool that is well-suited for data science and machine learning tasks, as well as many other use cases. Its interactive and flexible nature, along with its large and active community, make it a valuable addition to any data scientist's toolkit.

```

# Import libraries
import pandas as pd
import numpy as np
import networkx as nx
import matplotlib.pyplot as plt
from community import community_louvain
%matplotlib inline

[2]: from google.colab import drive
drive.mount("/content/gdrive")

Drive already mounted at /content/gdrive; to attempt to forcibly remount, call drive.mount("/content/gdrive", force_remount=True).

[ ] #Import data set
df = pd.read_excel('/content/gdrive/My Drive/Colab Notebooks/Online Retail.xlsx', header = 0)

[ ] print('dataset dimensions are:', df.shape)
df.describe(include = 'all')

dataset dimensions are: (541909, 8)
/usr/local/lib/python3.7/dist-packages/ipykernel_launcher.py:2: FutureWarning: Treating datetime data as categorical rather than numeric in `.describe` is deprecated

```

	InvoiceNo	StockCode	Description	Quantity	InvoiceDate	UnitPrice	CustomerID	Country
count	541909.0	541909	540455	541909.000000	541909	541909.000000	406829.000000	541909
unique	25900.0	4070	4223	NaN	23260	NaN	NaN	38
top	573585.0	85123A	WHITE HANGING HEART T-LIGHT HOLDER	NaN	2011-10-31 14:41:00	NaN	NaN	United Kingdom
freq	1114.0	2313	2369	NaN	1114	NaN	NaN	495478
first	NaN	NaN	NaN	NaN	2010-12-01 08:26:00	NaN	NaN	NaN

Fig 4.1: Recommender_Model Notebook

4.3 Flask

In the product recommendation engine project, Flask is used to create a web server that serves as the user interface for the application. Flask is a popular and lightweight web framework for Python that allows for the creation of web applications and APIs with minimal boilerplate code.

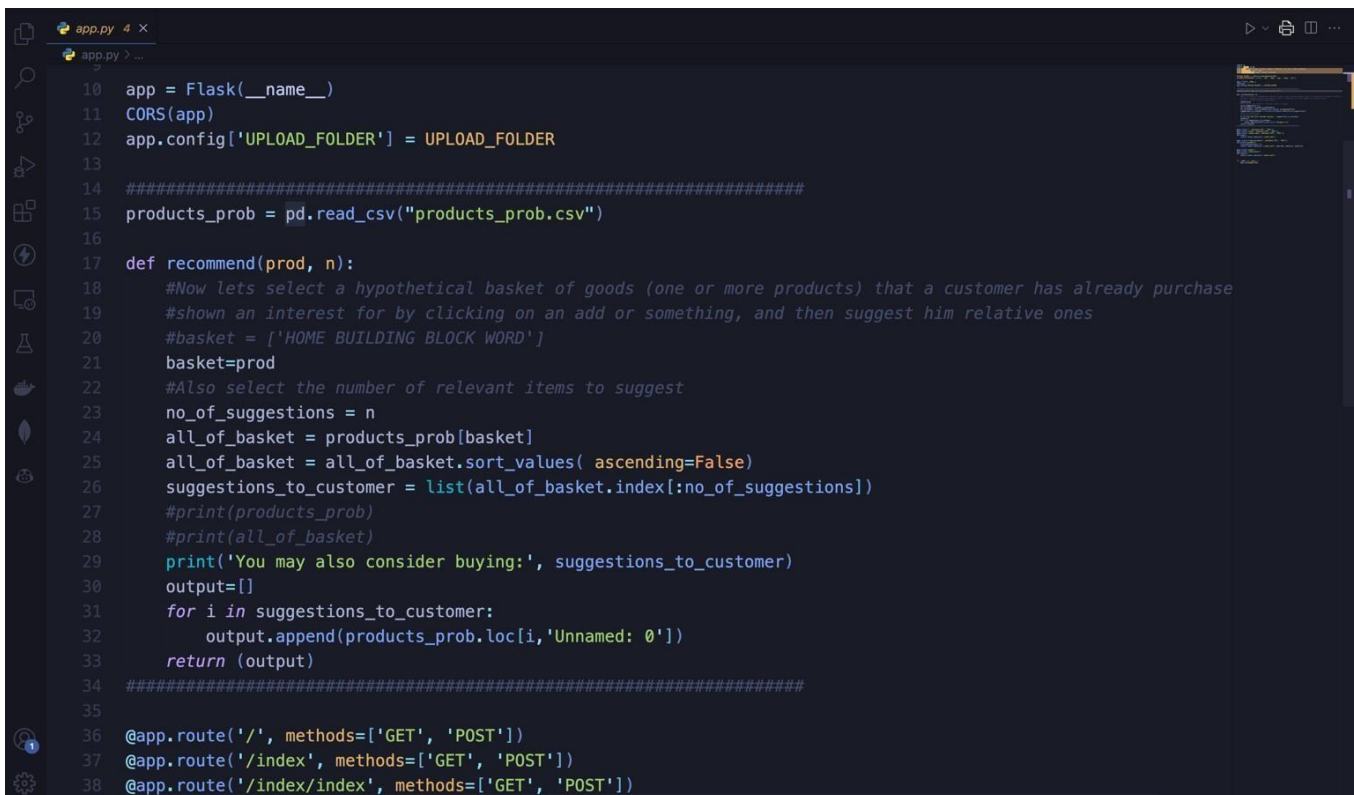
The Flask server in this project serves several purposes. Firstly, it provides a way for users to interact with the product recommendation engine by allowing them to input their preferences and receive recommendations in real-time. Secondly, it allows for the deployment of the recommendation engine as a web application that can be accessed from anywhere with an internet connection.

The Flask server in this project is responsible for several key tasks. Firstly, it receives input from the user in the form of product IDs and sends this information to the recommendation engine to generate a list of recommended products. Secondly, it retrieves product information from the dataset and sends it to the user interface for display. Finally, it handles errors and exceptions that may occur during the recommendation process and provides feedback to the user.

One of the advantages of using Flask in this project is its simplicity and ease of use. Flask allows for the creation of a lightweight and efficient web server that can handle a high volume of requests with minimal overhead. Additionally, Flask's modular design allows for easy integration with other

Python libraries and frameworks, which makes it well-suited for use in data science and machine learning applications.

Overall, the Flask server is a crucial component of the product recommendation engine project, as it provides the interface for users to interact with the engine and receive personalized recommendations. Its simplicity and flexibility make it an ideal choice for this application, and its ease of use makes it accessible to developers with varying levels of experience.

A screenshot of a code editor window titled 'app.py 4 x'. The code is for a Flask application. It imports Flask, CORS, and pandas. It configures the application with a CORS policy and an upload folder. It reads a CSV file 'products_prob.csv'. It defines a 'recommend' function that takes a product and a number of suggestions. The function selects a hypothetical basket of goods, sorts them by value, and returns a list of suggestions. It also defines three routes: a root route, an index route, and an index/index route.

```
10 app = Flask(__name__)
11 CORS(app)
12 app.config['UPLOAD_FOLDER'] = UPLOAD_FOLDER
13
14 #####
15 products_prob = pd.read_csv("products_prob.csv")
16
17 def recommend(prod, n):
18     #Now lets select a hypothetical basket of goods (one or more products) that a customer has already purchase
19     #shown an interest for by clicking on an add or something, and then suggest him relative ones
20     #basket = ['HOME BUILDING BLOCK WORD']
21     basket=prod
22     #Also select the number of relevant items to suggest
23     no_of_suggestions = n
24     all_of_basket = products_prob[basket]
25     all_of_basket = all_of_basket.sort_values( ascending=False)
26     suggestions_to_customer = list(all_of_basket.index[:no_of_suggestions])
27     #print(products_prob)
28     #print(all_of_basket)
29     print('You may also consider buying:', suggestions_to_customer)
30     output=[]
31     for i in suggestions_to_customer:
32         output.append(products_prob.loc[i,'Unnamed: 0'])
33     return (output)
34 #####
35
36 @app.route('/', methods=['GET', 'POST'])
37 @app.route('/index', methods=['GET', 'POST'])
38 @app.route('/index/index', methods=['GET', 'POST'])
```

Fig 4.2: app.py Flask app

4.3.1 Gephi visualisation

Gephi is an open-source software for visualizing and analyzing complex networks and graphs. In the product recommendation engine project, Gephi is used to visualize the communities detected by the Louvain clustering algorithm.

The visualizations produced by Gephi provide insight into the structure of the product network and the relationships between different products. The size and shape of the nodes in the graph represent the importance and centrality of each product, while the edges represent the connections between them. By visualizing the product network in this way, it is possible to identify clusters of related products and understand the relationships between them.

One of the primary benefits of using Gephi in this project is its ability to handle large and complex datasets. The product recommendation engine processes data from a large e-commerce dataset, and the resulting network can be very large and difficult to analyze. Gephi's advanced visualization tools and layout algorithms make it easier to explore and understand the structure of the network.

Another advantage of using Gephi is its flexibility and ease of use. Gephi provides a range of customization options for visualizing networks, including different layouts, color schemes, and filtering options. Additionally, Gephi can be easily integrated with other tools and platforms, such as Python and R, which makes it a valuable addition to the data scientist's toolkit.

Overall, Gephi is a powerful tool for visualizing and analyzing complex networks and graphs, and it plays a key role in the product recommendation engine project. Its ability to handle large and complex datasets, along with its flexibility and ease of use, make it an ideal choice for visualizing and exploring the product network and identifying clusters of related products.

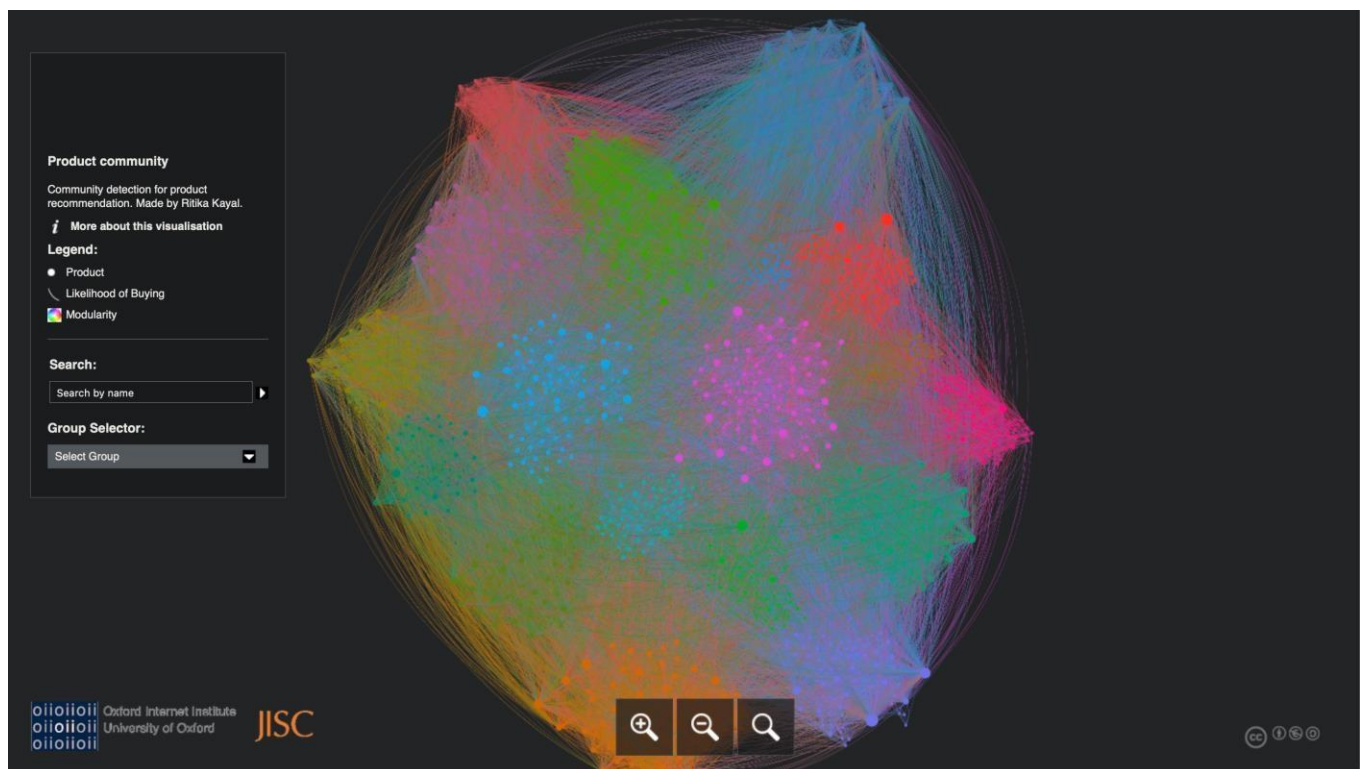


Fig 4.3: Gephi visualization

4.3.2 Webpage

In the product recommendation engine project, the webpage serves as the primary user interface for the application. The webpage is created using HTML, CSS, and JavaScript, and it communicates with the Flask server to retrieve product information and receive personalized recommendations based on the user's preferences.

The webpage is designed to be user-friendly and easy to navigate, with clear instructions for inputting product IDs and receiving recommendations. The webpage displays information about each product, including its name, description, and price, as well as related products that the user may be interested in. The webpage also includes a search function that allows users to search for products by keyword, and it provides feedback and error messages to the user when necessary.

One of the key benefits of the webpage in this project is its ability to provide personalized recommendations to the user in real-time. The webpage communicates with the Flask server to retrieve product information and send user preferences, which are used by the recommendation engine to generate a list of recommended products. This feedback loop allows the user to refine their preferences and receive more accurate recommendations over time.

Another advantage of the webpage is its flexibility and scalability. The webpage can be easily customized and modified to suit the needs of different e-commerce websites and applications. Additionally, the webpage can be scaled to handle a high volume of requests, making it suitable for use in large e-commerce applications with many users.

Overall, the webpage is a critical component of the product recommendation engine project, as it provides the primary interface for users to interact with the application and receive personalized recommendations based on their preferences. Its user-friendly design, real-time feedback loop, and flexibility make it a valuable tool for improving the customer experience and increasing sales for e-commerce websites.

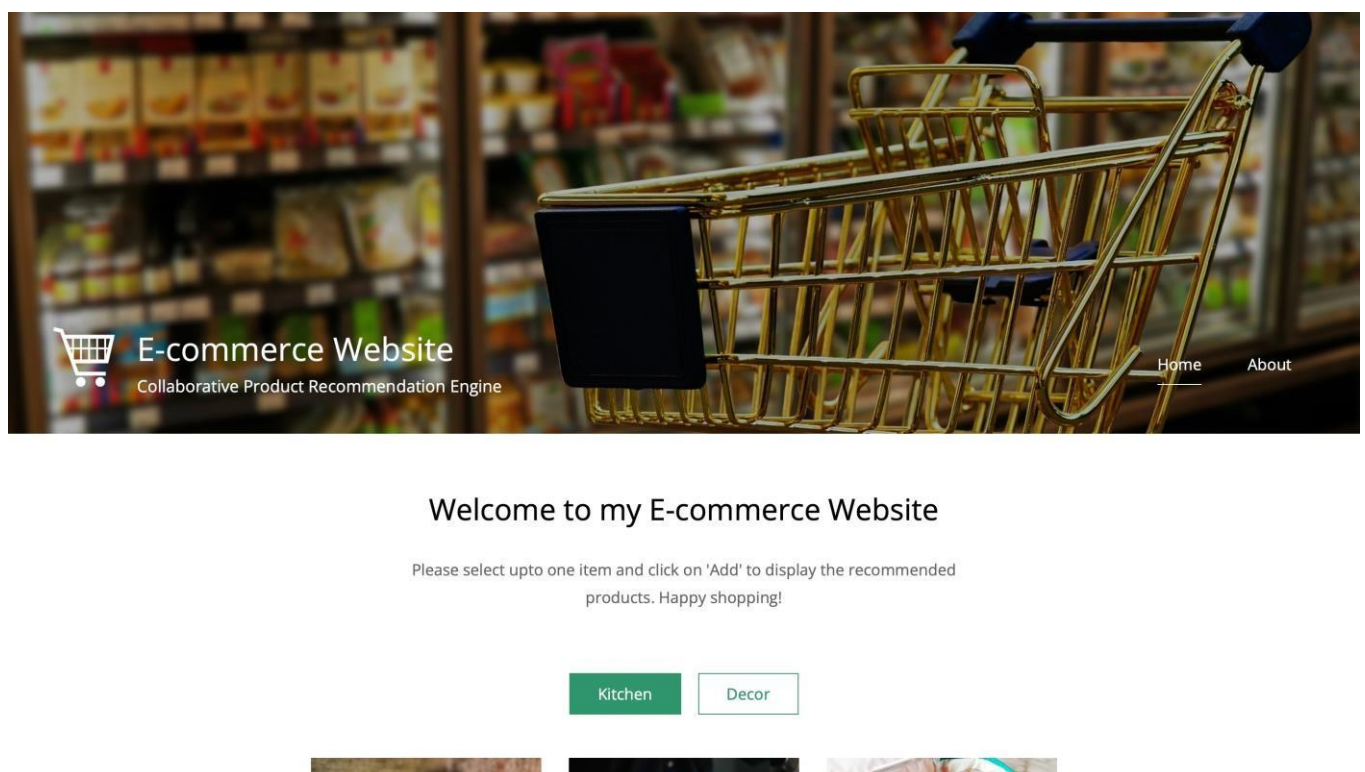


Fig 4.3: Webpage

4.4 Implementation Process:

Here are the steps for the implementation process:

1. The developer runs the **recommender_model.py** script to generate a CSV file named **products_prob.csv**. This CSV file contains information about each product in the e-commerce store, including its ID, name, description, and a list of related products based on the Louvain clustering algorithm.
2. The website retrieves information from the **products_prob.csv** file to generate product recommendations. The website uses JavaScript and AJAX to communicate with the Flask server and retrieve data from the CSV file. The website displays product information and related products based on the user's selection and preferences.
3. The Flask app is run to deploy the website. The developer uses a command-line interface to run the Flask app and specify the host and port number. The Flask app serves as the backend for the website, processing user requests and generating personalized recommendations based on the **products_prob.csv** file.
4. The user interacts with the website and selects one product. The website sends a request to the Flask app with the selected product ID. The Flask app uses the **products_prob.csv** file to generate a list of related products based on the Louvain clustering algorithm. The Flask app returns the list of recommended products to the website, which displays them to the user. The user can then select additional products and receive more personalized recommendations based on their preferences.

Overall, this implementation process involves generating a CSV file of product information and related products, using this CSV file to generate personalized recommendations on a website, deploying the website using a Flask app, and allowing users to interact with the website and receive recommendations based on their preferences.

CHAPTER 5

CONCLUSION AND FUTURE SCOPE

5.1 Conclusion:

In conclusion, the product recommendation engine based on community detection and collaborative filtering is an efficient way to suggest products to users on e-commerce websites. The use of Louvain clustering for community detection and Flask API for the user interface makes the engine easy to use and understand. The Gephi visualizations provide a clear understanding of the detected communities, making it easier to identify related products. The product recommendation engine can significantly improve customer experience and increase sales for e-commerce websites by suggesting products that match user preferences.

5.2 Future Scope:

The product recommendation engine can be further improved by incorporating deep learning techniques such as neural networks to identify more complex patterns in user behavior. In addition, using natural language processing (NLP) techniques to analyze user reviews and feedback can also help in providing personalized product recommendations. The engine can also be integrated with social media platforms to increase the scope of data available for analysis. Furthermore, incorporating user segmentation techniques can help in identifying different groups of users with varying preferences and providing personalized product recommendations to each group. Overall, the product recommendation engine has immense potential for further development and can greatly benefit the e-commerce industry.

References

1. "Community Detection Algorithms: A Comparative Analysis" by S. Fortunato. This paper provides a comprehensive review of community detection algorithms, including the Louvain algorithm, and their applications.
2. "Collaborative Filtering for Implicit Feedback Datasets" by Y. Hu, Y. Koren, and C. Volinsky. This paper describes a collaborative filtering method for implicit feedback datasets that is used in the product recommendation engine.
3. "Python Machine Learning" by S. Raschka and V. Mirjalili. This book provides an introduction to machine learning with Python and includes examples of collaborative filtering and community detection.
4. "Flask Web Development" by M. Grinberg. This book provides a comprehensive guide to web development with Flask and includes examples of building web applications, such as the user interface for the product recommendation engine.