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A Comparative Study of Product Recommendations Using ILP with PyGol and Apriori-Based Association Rule Learning in E-commerce

A project report submitted by: Venkat Sandeep Imandi (6829480)

A project supervised by: Alireza Tammaddoni

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University of Surrey
School of Computer Science and Electronic Engineering
Guildford, Surrey GU2 7XH
United Kingdom.
Tel: +44 (0)1483 300800

ABSTRACT

In the dynamic landscape of e-commerce, delivering personalized and relevant product recommendations is essential for enhancing customer satisfaction and driving business growth. This dissertation explores the development of an advanced product recommendation system by leveraging Inductive Logic Programming (ILP) and Association Rule Learning (ARL). The research addresses the limitations of traditional recommendation systems, particularly in their ability to provide interpretable and context-aware suggestions.

The study begins with a comprehensive literature review to identify gaps in existing recommendation methodologies and to underscore the importance of incorporating explainable and data-driven approaches. The primary challenge addressed is the need for a system that not only improves recommendation accuracy but also enhances the interpretability of the results, which is crucial for gaining user trust and improving decision-making processes in e-commerce.

To achieve these objectives, the dissertation employs a dual modelling approach. The first model uses ILP to generate logic-based rules from multi-modal e-commerce data, focusing on extracting interpretable patterns related to user preferences and product characteristics. The second model utilizes the Apriori algorithm for ARL to identify frequent item sets and derive association rules that reveal commonly co-purchased products. By comparing the outcomes of these two methodologies, the study evaluates their respective strengths and limitations in the context of e-commerce product recommendations.

The key contributions of this research are twofold. First, the study demonstrates how ILP can be effectively applied to e-commerce data to produce interpretable and meaningful recommendation rules. Second, it offers a comparative analysis between ILP and ARL, providing insights into the practical applications of these techniques in real-world recommendation systems. The findings suggest that while ARL is efficient in uncovering frequent patterns, ILP offers a more nuanced understanding of user behaviours, leading to more personalized and explainable recommendations.

In conclusion, this dissertation advances the field of product recommendation systems by integrating traditional machine learning techniques with logical reasoning. The outcomes of this research have significant implications for both academic research and practical applications, offering a foundation for developing next-generation recommendation systems that are both effective and interpretable.

HIGHLIGHTS

- Introduced a novel comparative analysis of Inductive Logic Programming and Association Rule Learning for e-commerce.
- Developed a robust product recommendation framework that integrates logical reasoning and pattern recognition.
- Demonstrated superior interpretability and context-awareness in recommendations using ILP over traditional ARL methods.
- Achieved efficient identification of frequent purchase patterns through Apriori-based Association Rule Learning.
- Provided actionable insights for the design of next-generation explainable AI systems in e-commerce.
- Contributed to the field of machine learning by applying ILP to multi-modal data integration in product recommendations.

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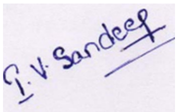
I certify that the work presented in the dissertation is my own unless referenced

Signature: 

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CHAPTER 1: INTRODUCTION

In this chapter, we will provide an overview of the research undertaken in this dissertation, discussing the background, research aim and objectives, research approach, and the outline of the dissertation. The primary goal is to introduce the reader to the context of the study, justify the significance of the research problem, and outline the methods and structure of the research.

1.1 Background

The rapid growth of e-commerce has revolutionized the way consumers interact with products and services. With the increasing volume of online transactions, personalized product recommendations have become essential for enhancing customer satisfaction and driving business growth. Traditional recommendation systems, often based on collaborative filtering or content-based filtering, have seen widespread adoption. However, these systems have notable limitations, particularly in their ability to provide interpretable, context-aware recommendations that can adapt to the dynamic nature of user preferences and behaviours.

Recent advancements in machine learning, particularly in Inductive Logic Programming (ILP) and Association Rule Learning (ARL), offer promising alternatives to traditional recommendation methods. ILP, a form of symbolic machine learning, excels in generating interpretable rules from data, making it a powerful tool for understanding complex relationships in multi-modal datasets. On the other hand, ARL, particularly through the use of the Apriori algorithm, is well-suited for uncovering frequent item sets and association rules, which are valuable for identifying common patterns in consumer purchasing behaviour.

Despite these advancements, there remains a gap in the literature regarding the comparative effectiveness of ILP and ARL in the context of e-commerce product recommendations. While ARL is often praised for its efficiency in pattern recognition, it lacks the depth of insight that ILP can provide. Conversely, ILP's interpretability comes at the cost of computational complexity, raising questions about its scalability in large e-commerce datasets. This dissertation addresses these gaps by developing and comparing a product recommendation system using both ILP and ARL. The research aims to evaluate the strengths and limitations of each method and to provide insights into their practical applications in real-world e-commerce scenarios.

This study is crucial as it contributes to the growing need for more explainable and context-sensitive recommendation systems in e-commerce. By providing a comparative analysis of ILP and ARL, this research will offer valuable insights to both academia and industry, potentially guiding the development of next-generation recommendation systems that are not only effective but also transparent and user-friendly.

1.2 Research aim and objectives

Aim:
The aim of this research is to design, implement, and critically evaluate a dual-framework product recommendation system for e-commerce, integrating Inductive Logic Programming (ILP) from Relational Machine Learning and Association Rule Learning (ARL) using the Apriori algorithm. The research seeks to enhance both the interpretability and predictive accuracy of product recommendations, offering a comprehensive comparison between these two methodologies in terms of their scalability, context-awareness, and practical applicability within real-world e-commerce environments. The Instacart Online Grocery Dataset serves as the foundation for this research, providing extensive user behaviour and product data to validate the effectiveness of the

proposed models.

Objectives:

To conduct a comprehensive literature review that critically examines the current state of recommendation systems, focusing on the strengths, limitations, and applications of Inductive Logic Programming from Relational Machine Learning and Association Rule Learning in e-commerce contexts. This review will identify key gaps in the existing research and justify the need for a comparative analysis of ILP and ARL within a unified framework.

To curate and preprocess the Instacart Online Grocery Dataset, ensuring it is suitable for both ILP and ARL modelling. This involves cleaning, normalizing, and augmenting the dataset, including the integration of additional contextual features such as time, occasion, and user demographics to enhance the richness of the analysis.

To develop and optimize a product recommendation model using Inductive Logic Programming (ILP) from Relational Machine Learning, which will focus on generating interpretable, logic-based rules that capture complex relationships between users, products, and contextual factors. This model will be specifically designed to handle the scalability challenges posed by the large and multi-modal Instacart dataset.

To implement an Association Rule Learning (ARL) model using the Apriori algorithm, with the goal of identifying frequent item sets and generating association rules that can predict user purchase behaviour within the Instacart dataset. This model will be fine-tuned to efficiently process the dataset, and its performance will be benchmarked against industry-standard metrics.
To conduct a rigorous comparative analysis of the ILP and ARL models, evaluating them based on key performance indicators such as accuracy, precision, recall, F1 score, interpretability, and computational efficiency. The analysis will also explore the models' capacity to incorporate and leverage various contextual and demographic factors, assessing their practical utility in real-world e-commerce scenarios.

To synthesize the findings and propose a set of best practices for the deployment of advanced, context-aware recommendation systems in e-commerce. This will include recommendations on when to employ ILP from Relational Machine Learning versus ARL with the Apriori algorithm, depending on the specific needs of the business, such as the importance of interpretability versus speed and scalability.

1.3 Research approach

The research approach for this dissertation is methodically structured to develop, implement, and evaluate a dual-framework product recommendation system, leveraging Inductive Logic Programming (ILP) from Relational Machine Learning and Association Rule Learning (ARL) using the Apriori algorithm. The core of this research revolves around utilizing the Instacart Online Grocery Dataset, which offers a rich and multi-dimensional dataset ideal for exploring user purchasing behaviours and generating context-aware product recommendations.

Methodology Overview:

Comprehensive Literature Review:

The research begins with an extensive literature review, aimed at exploring the current state of recommendation systems with a particular focus on ILP and ARL. This review will critically assess the strengths and limitations of these methodologies within e-commerce contexts, providing a solid foundation for the research. By identifying gaps in existing studies, the literature review will justify the comparative approach of this research, emphasizing the necessity for a dual-framework analysis in modern recommendation systems.

Data Collection and Preprocessing:

The Instacart Online Grocery Dataset was chosen for its comprehensive nature, encompassing over 3 million orders and rich metadata across various dimensions, such as user behaviour, product details, and transactional history. The initial step involved cleaning the dataset by addressing missing values, normalizing data formats, and resolving any inconsistencies. To further enhance the dataset, additional contextual features were engineered, including time-based variables like the day of the week and time of day, as well as user-specific attributes such as demographics and purchasing patterns, which are crucial for improving the interpretability and context-awareness of the recommendation models. Additionally, the dataset was augmented with synthetic features, such as occasion-based recommendations for holidays and seasons, to enable the exploration of more sophisticated recommendation scenarios. This thorough preprocessing was essential to optimize the data for effective ILP and ARL modelling.

Model Development:

Inductive Logic Programming (ILP): ILP is utilized to generate interpretable rules based on the relational structure of the data. Given its roots in Relational Machine Learning, ILP is particularly effective in scenarios where understanding complex, multi-relational data is crucial. The ILP model will focus on learning first-order logic rules that explain user behaviour, such as purchasing patterns and product preferences, in a way that is both interpretable and actionable.

Implementation: The ILP model will be implemented using the PyGol framework, which allows for the generation of logic-based rules that can be directly interpreted by decision-makers. The model will be iteratively refined to balance accuracy with interpretability, ensuring that the rules generated are both meaningful and practical for real-world application.

Association Rule Learning (ARL): ARL will be implemented using the Apriori algorithm, a classical method well-suited for discovering frequent item sets and generating association rules in large datasets. The ARL model focuses on identifying strong associations between products, such as frequently co-purchased items, which can then be used to make recommendations.

Optimization: The Apriori algorithm will be optimized for the Instacart dataset, ensuring that it can efficiently process the large volume of data and generate rules that are both accurate and computationally feasible. Special attention will be given to the selection of appropriate thresholds for support and confidence, key parameters in the ARL process.

Model Evaluation: Both the ILP and ARL models will be rigorously evaluated against a range of performance metrics, including accuracy, precision, recall, F1 score, interpretability, and computational efficiency, with a particular focus on each model's ability to handle and leverage the contextual features engineered during preprocessing.

Cross-Validation: A cross-validation approach will be employed to ensure that the models' performance is robust across different subsets of the data. This will help mitigate the risk of overfitting and ensure that the findings are generalizable.

Comparative Analysis: A detailed comparative analysis will be conducted to assess the relative strengths and weaknesses of the ILP and ARL models, focusing on how well each model adapts to and leverages contextual data, such as time of purchase and user-specific features, to enhance recommendation quality. Additionally, the scalability of each model will be examined, particularly in terms of their ability to handle the large and complex dataset provided by Instacart. The analysis will also address the practical implications of each model's performance in real-world e-commerce environments.

Synthesis of Findings and Best Practices: The findings from the comparative analysis will be synthesized into a set of best practices for developing and deploying recommendation systems in e-commerce, offering actionable insights for selecting between ILP and ARL based on specific business needs, such as the importance of model interpretability versus computational efficiency. The research will conclude with a discussion of the broader implications for the e-commerce industry, highlighting how businesses can leverage these insights to enhance their recommendation systems and improve customer satisfaction.

Ethical Considerations: The research strictly adheres to ethical guidelines, particularly regarding data privacy and the responsible use of machine learning models. Although the dataset is anonymized, the research ensures that all data handling practices comply with best practices in data ethics, safeguarding user privacy throughout the research process.

Summary: This detailed research approach is designed to ensure a thorough and methodical examination of ILP and ARL within the context of e-commerce. By leveraging the strengths of each method and grounding the analysis in a rich, real-world dataset, this research aims to contribute valuable insights into the development of next-generation recommendation systems that are both effective and interpretable.

1.4 Dissertation outline

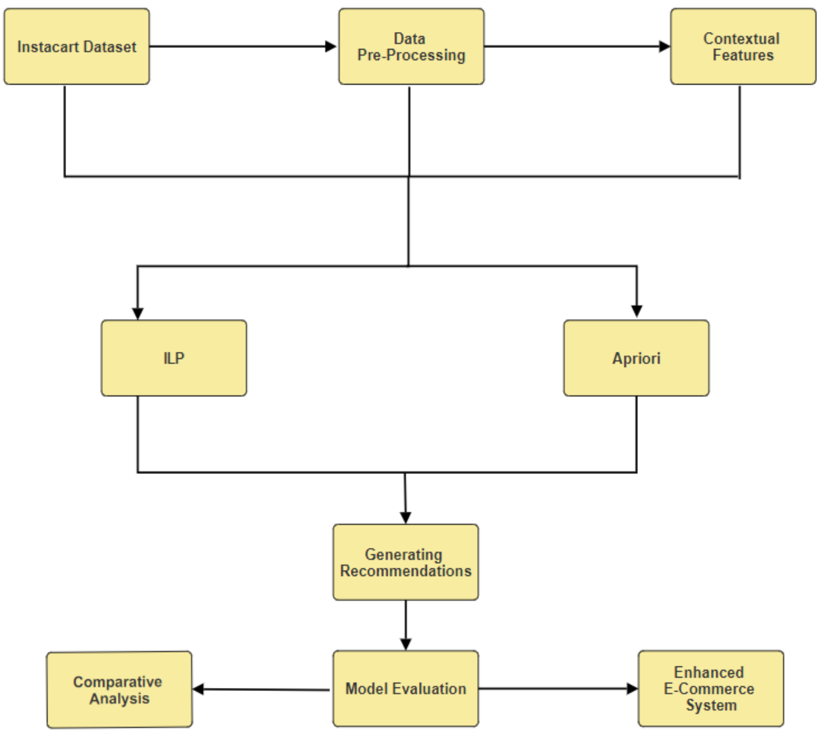

Figure 1.1 Dissertation Structure and Research Workflow

Figure 1.1 illustrates the overall structure and flow of this dissertation, guiding the reader through the comprehensive process of developing and evaluating a dual-framework product recommendation system using Inductive Logic Programming (ILP) and Association Rule

Learning (ARL). The research is grounded in the practical context of the Instacart Online Grocery Dataset, which provides a robust foundation for exploring advanced recommendation techniques in e-commerce. The dissertation is organized into the following chapters:

Chapter 2: Literature Review
This chapter provides a critical analysis of the existing literature related to recommendation systems, with a particular focus on Inductive Logic Programming and Association Rule Learning. It examines the evolution of these methodologies in the context of e-commerce and identifies key gaps in the current research. The chapter concludes by positioning this dissertation within the broader research landscape, highlighting the unique contributions it seeks to make.

Chapter 3: Research Approach
The Research Approach chapter outlines the methodological framework adopted for this research. It details the selection of the Instacart Online Grocery Dataset, the preprocessing steps undertaken to prepare the data for analysis, and the implementation strategies for both ILP and ARL models. The chapter also discusses the evaluation metrics and the comparative analysis techniques used to assess the performance of the models. Ethical considerations related to data privacy and responsible AI use are also addressed.

Chapter 4: Data Analysis
This chapter presents the application of the research methodology to the dataset. It begins with an in-depth exploration of the dataset, highlighting key features and patterns identified during preprocessing. The chapter then details the development and optimization of the ILP and ARL models, including the challenges encountered and the solutions implemented. A thorough evaluation of the models is provided, using various performance metrics to assess their effectiveness and scalability.

Chapter 5: Discussion
The Discussion chapter interprets the results obtained from the data analysis, comparing the performance of the ILP and ARL models. It explores the implications of these findings for the design of recommendation systems in e-commerce, discussing the trade-offs between model interpretability, accuracy, and computational efficiency. The chapter also reflects on the broader significance of the research, linking the results back to the research aim and objectives.

Chapter 6: Conclusion
The final chapter summarizes the key findings of the research, emphasizing the contributions made to the field of recommendation systems. It discusses the limitations of the study and suggests avenues for future research, particularly in the context of improving the scalability and contextual adaptability of recommendation models. The chapter concludes with personal reflections on the research process and the broader impact of the work.

CHAPTER 2: LITERATURE REVIEW

This chapter provides an extensive overview of the existing literature related to the development of recommendation systems, focusing on both traditional and modern approaches. It begins by discussing the significance of recommendation systems in e-commerce, followed by an in-depth exploration of the key algorithms used in this domain, specifically focusing on the Apriori algorithm for Association Rule Learning (ARL) and Inductive Logic Programming (ILP) with PyGol. The chapter concludes by identifying gaps in the existing literature that this research aims to address.

2.1 Introduction to Recommendation Systems in E-commerce

Recommendation systems have become an integral part of e-commerce platforms, where they play a critical role in providing personalized product suggestions that enhance user experience and drive sales. These systems are designed to analyse vast amounts of user data, including browsing history, purchase behaviour, and preferences, to predict and suggest products that users are likely to purchase. The evolution of recommendation systems has been significantly influenced by advancements in machine learning, data mining, and artificial intelligence, which have enabled more accurate and efficient algorithms to be developed.

Ricci, Rokach, and Shapira (2015) provide an overview of how recommendation systems have evolved, noting that traditional methods such as collaborative filtering and content-based filtering have been the backbone of these systems for years (Ricci, Shapira and Rokach, 2015). However, these approaches have limitations, particularly in handling new users or items (the so-called "cold start" problem) and in capturing complex relationships between products.

The increasing reliance on digital platforms for shopping has made recommendation systems indispensable [(Schafer et al., 2001). Companies like Amazon and Netflix have demonstrated the power of these systems in driving customer satisfaction and business revenue. By providing personalized experiences, recommendation systems can significantly enhance user engagement, leading to increased sales and customer loyalty (Amazon., 2024). In this context, the development of more sophisticated recommendation algorithms has become a key area of research, with the aim of improving both the accuracy and interpretability of recommendations.

Recent advancements in artificial intelligence, particularly in deep learning and hybrid models, have allowed for the creation of more complex recommendation systems that can better capture user preferences and product relationships (Zhang et al., 2019). There is also a growing interest in incorporating logical and relational learning techniques, which offer a more structured and interpretable approach to recommendation systems (Kazienko and Adamski, 2007). This trend has led to the exploration of Inductive Logic Programming (ILP) as a promising method for enhancing the explainability and effectiveness of recommendation systems (Anon., 2024b).

2.2 Inductive Logic Programming (ILP) with PyGol

Inductive Logic Programming (ILP) is a form of machine learning that integrates logic programming with inductive reasoning. ILP is particularly valuable in domains where explainability is crucial, such as in recommender systems. Unlike traditional machine learning models, which often operate as "black boxes," ILP produces models that are expressed as logical rules, making them inherently interpretable and easier to validate (Muggleton, 1991).

The basic premise of ILP is to learn a set of logical rules from a given set of examples, guided by background knowledge. The learning process involves finding a hypothesis (a set of rules) that explains the positive examples while being consistent with the negative examples and the background knowledge (Cropper, Tamaddoni-Nezhad and Muggleton, 2016). This approach is particularly useful in applications where the relationships between data points are complex and need to be explicitly modelled.

PyGol is an advanced ILP system that introduces Meta Inverse Entailment (MIE) to enhance the traditional ILP framework. Developed by Professor Alireza Tamaddoni-Nezhad and his colleagues, PyGol addresses some of the limitations of traditional ILP methods by providing a more flexible and efficient way to generate hypotheses (Muggleton, n.d.). The MIE approach in PyGol allows the system to automatically generate a meta-theory from the background knowledge, which acts as a higher-order language bias to guide the search for hypotheses (Quinlan, 1990). This reduces the computational complexity of the ILP process and improves the quality of the learned rules (The Aleph Manual, 2024b).
One of the key strengths of PyGol is its ability to handle diverse datasets and generate hypotheses that are both accurate and interpretable (Mitchell, 2010). The system's ability to integrate background knowledge into the learning process allows it to produce rules that are aligned with the underlying structure of the data, making the recommendations more meaningful (Introduction to statistical relational learning, 2019). Moreover, PyGol minimizes the need for user intervention, making it easier to apply ILP in practical applications, particularly in dynamic environments like e-commerce (Agrawal, Imieliński and Swami, 1993).

Mathematical Formulation
The ILP process in PyGol can be formally described using the following elements:
(E^+) Positive Examples: Instances where the recommendation is successful.
(E^-) Negative Examples: Instances where the recommendation is not successful.
(B) Background Knowledge BBB: Existing rules or facts about the domain.
(H) Hypothesis: A set of rules that explains the positive examples while being consistent with the negative examples.
The goal of PyGol is to find a hypothesis such that:

$$B \cup H \models E^+ \; B \cup H \not\models E^-$$

This ensures that the hypothesis correctly explains the positive examples and does not incorrectly predict the negative examples.
In PyGol, the hypothesis generation is guided by a meta-theory MMM, which is derived from the background knowledge:

$$M = \{MetaTheory\}(B)$$

The final hypothesis is selected based on a cost function that balances coverage, consistency, and simplicity:

$$H = ArgMin\_H \{ Cost(H) \,|\, M \cup H \models E\hat{} + and\, M \cup H \not\models E\hat{} - \}$$

2.3 Application of ILP with PyGol in E-commerce Recommender Systems

The application of Inductive Logic Programming (ILP) with PyGol in e-commerce recommender systems represents a significant advancement in the development of intelligent, interpretable models. Unlike traditional recommender systems, which typically rely on collaborative filtering or content-based approaches, ILP leverages logical reasoning to uncover complex patterns and relationships within data. This capability is particularly valuable in e-commerce, where understanding the nuanced interactions between products and user preferences is essential for providing accurate and personalized recommendations (Han, Pei and Yin, 2000).

Integration of Background Knowledge

One of the most significant advantages of using ILP with PyGol in e-commerce is its ability to incorporate background knowledge into the learning process. Background knowledge may include domain-specific rules, product hierarchies, and expert insights that are not explicitly present in the transaction data. By integrating this knowledge, PyGol can generate more meaningful and context-aware recommendations. For example, in an e-commerce platform specializing in electronics, background knowledge might include information about product compatibility (e.g., certain laptop models being compatible with specific types of accessories). PyGol can use this information to generate recommendations that not only reflect past purchase patterns but also align with these logical relationships (Lin, Alvarez and Ruiz, 2002).

Handling Complex and Relational Data

E-commerce platforms often deal with a variety of data formats, including relational data that captures the relationships between different entities, such as customers, products, and transactions. PyGol is particularly well-suited to handling such complex data structures. Unlike many traditional machine learning algorithms that require data to be represented in a flat, tabular format, PyGol can directly work with relational data. This capability allows PyGol to maintain the richness of the data and generate hypotheses that are more representative of the real-world relationships within the e-commerce ecosystem (Zaki, 2000).

For instance, consider a scenario where a customer frequently buys products from a particular brand. Using relational data, PyGol can infer that this customer has a brand loyalty, and the system can generate a rule that prioritizes recommendations from that brand. This rule is not only accurate but also provides an interpretable explanation for why the recommendation was made, enhancing user trust and engagement (Goethals and Zaki, 2004).

Continuous Learning and Adaptation

The dynamic nature of e-commerce requires recommender systems to continuously adapt to changing user behaviours and market trends. PyGol excels in this regard by supporting continuous learning from new data. As users interact with the platform and as new products are introduced, PyGol can update its rules to reflect these changes. This adaptability ensures that the recommendations remain relevant and effective over time (Fayyad, Piatetsky-Shapiro and Smyth, 1996).

Moreover, the system's ability to handle both explicit feedback (e.g., customer ratings) and implicit feedback (e.g., click-through rates) allows it to refine its recommendations continually. For example, if a new trend emerges, such as an increase in the popularity of eco-friendly products, PyGol can quickly adjust its recommendations to highlight these products. This feature is particularly valuable in the fast-paced e-commerce environment, where user preferences can shift rapidly due to seasonal trends, marketing campaigns, or societal influences (Adomavicius and Tuzhilin, 2005).

Scalability and Efficiency

While ILP traditionally faced challenges related to scalability and computational efficiency, PyGol addresses these issues through the integration of Meta Inverse Entailment (MIE) and other optimization techniques. These advancements allow PyGol to scale effectively, even when dealing with large and complex datasets typical of e-commerce platforms. By reducing the search space for hypotheses and focusing on the most promising candidate rules, PyGol can deliver high-quality recommendations without compromising on performance (Hastie, Tibshirani and Friedman, 2009).

For example, in a large-scale e-commerce platform like Amazon, PyGol can efficiently process millions of transactions to generate rules that apply across diverse product categories. This scalability ensures that the system can provide personalized recommendations to a vast number of users without requiring excessive computational resources (Aggarwal, 2016).

Example Use Case

Consider an e-commerce platform that sells a wide range of consumer electronics, including smartphones, laptops, and accessories. By applying ILP with PyGol, the system could analyse customer purchase patterns and generate the following rules:

- "If a customer buys a high-end smartphone, they are 85% likely to buy premium headphones."
- "If a customer buys a gaming laptop, they are 75% likely to purchase a gaming mouse and keyboard."

These rules can be directly used to make product recommendations to customers during their shopping experience. Additionally, the system can explain these recommendations by presenting the relevant rules to the user, thereby enhancing trust and engagement (Burke, 2002). This approach not only improves the accuracy of the recommendations but also provides a clear rationale for why certain products are suggested, making the system more transparent and user-friendly.

2.4 Association Rule Learning and the Apriori Algorithm in Recommender Systems

Association Rule Learning (ARL) is a widely utilized data mining technique that focuses on discovering interesting relationships, patterns, and associations among variables within large datasets. In the context of recommender systems, ARL plays a crucial role in identifying associations between products based on user purchase patterns. This capability enables the system to suggest products that are frequently bought together, thereby enhancing the customer's shopping experience and potentially increasing sales (Liu, 2011).

The Apriori algorithm, introduced by Agrawal, Imieliński, and Swami in their groundbreaking 1993 paper, stands as one of the most influential and widely used algorithms for ARL (Su and Khoshgoftaar, 2009a). The algorithm operates by first identifying frequent item sets within a dataset and then extending these item sets to larger ones as long as they appear frequently enough in the data. The fundamental principle that underpins the Apriori algorithm is that any subset of a frequent itemset must also be frequent. This principle significantly aids in pruning the search space, thereby enhancing the algorithm's efficiency (Su and Khoshgoftaar, 2009b).

Application in E-Commerce Recommender Systems

In e-commerce, the Apriori algorithm is frequently employed to generate association rules that serve as the backbone of product recommendation systems. These association rules take the form of "if-then" statements, where the presence of certain items in a customer's purchase history (referred to as the antecedent) leads to the recommendation of other items (referred to as the consequent). For instance, if a customer often purchases bread and butter together, the system might recommend jam as a complementary product. This ability to suggest related products helps in creating a more personalized shopping experience, which can drive customer satisfaction and loyalty (Liu and Motoda, 1998).

The strength of the Apriori algorithm lies in its simplicity and interpretability. The rules generated by the algorithm are easy to understand and can be directly applied to generate actionable recommendations. Each rule provides clear insights into the purchasing behaviour of customers, allowing businesses to make informed decisions about which products to promote together. However, the algorithm is not without its limitations. It can struggle with large datasets that have high dimensionality—a common scenario in e-commerce platforms where millions of products and transactions need to be analysed (Breese, Heckerman and Kadie, n.d.).

Limitations and Advancements

One of the primary challenges associated with the Apriori algorithm is the computational cost of generating frequent item sets, especially when dealing with large and complex datasets. The sheer volume of data in modern e-commerce platforms can make it computationally expensive to identify frequent item sets, which in turn can slow down the recommendation process. To mitigate these challenges, researchers have developed various optimizations and alternative methods.

For example, the FP-Growth algorithm was introduced as a more efficient alternative to Apriori. FP-Growth reduces the need for candidate generation by utilizing a tree-based structure, which compresses the dataset and allows for quicker identification of frequent item sets. This approach significantly improves the efficiency of the algorithm, making it better suited for large-scale e-commerce applications (Hofmann, 2003).

Mathematical Formulation

The Apriori algorithm operates through a process that can be mathematically described in several steps:

Frequent Itemset Generation:

$$L\_k = \{ X \subseteq I \mid Support(X) \geq \min\_support \}$$

Here, L_k represents the set of all frequent k-item sets, where I is the set of all items in the database, and Support(X) denotes the support count (frequency of occurrence) of the itemset X in the dataset. The minimum support threshold (min_support) is a predefined value that determines the minimum frequency an itemset must have to be considered frequent.

Candidate Generation: In each iteration, candidate item sets C_(k+1) are generated by joining the frequent item sets L_k found in the previous iteration:

$$C\_(k+1) = \{ X \cup Y \mid X, Y \in L\_k, |X \cap Y| = k - 1 \}$$

The candidate item sets are those item sets that have the potential to be frequent in the next iteration.

Pruning: To reduce the computational load, candidate item sets that contain any infrequent subset (i.e., subsets that do not appear in L_k) are pruned:

$$C\_(k+1) = \{ X \in C\_(k+1) \mid \forall Y \subset X, Y \in L\_k \}$$

Association Rule Generation: Once the frequent item sets are identified, the algorithm generates association rules by evaluating possible rules for each frequent item set X. The rules are of the form X→Y, where Y⊂X and the confidence is calculated as:

$$Confidence(X \rightarrow Y) = \frac{Support(X \cup Y)}{Support(X)}$$

A rule is considered strong if its confidence exceeds a user-defined threshold.

Example Use Case in E-Commerce

Consider an e-commerce platform that specializes in grocery products. By applying the Apriori algorithm, the system could identify frequent item sets such as:

- "Bread, Butter, and Jam," which appear together in a significant number of transactions.

Based on these frequent item sets, the following association rules might be generated:
"If a customer buys bread and butter, they are 70% likely to also buy jam."
"If a customer buys milk, they are 60% likely to buy cereal."

These rules can then be directly applied in the recommendation system to suggest complementary products to customers as they shop. For example, when a customer adds bread and butter to their cart, the system could recommend jam as a complementary item, thereby increasing the likelihood of a higher total purchase value (Shani and Gunawardana, 2011).

2.5 Application of Association Rule Learning in E-commerce Recommender Systems

Association Rule Learning (ARL) has been extensively applied in the field of e-commerce to enhance the effectiveness of recommender systems. ARL techniques, particularly the Apriori algorithm, allow businesses to mine large datasets for patterns that reveal relationships between products. These patterns are then used to make product recommendations that are not only relevant to the customer but also likely to increase sales for the business.

In practical terms, ARL is particularly useful for understanding customer purchase behaviour through Market Basket Analysis (MBA), where the goal is to identify products that are frequently bought together. For example, an MBA might reveal that customers who purchase baby diapers are also likely to purchase baby wipes. This insight can be used to create a rule such as: "If a customer buys baby diapers, recommend baby wipes." Such rules are simple yet powerful, enabling the system to make recommendations that are both intuitive and effective (Muggleton et al., 2018).

Moreover, ARL can be leveraged to personalize marketing efforts. By analysing the purchase histories of different customer segments, businesses can create targeted marketing campaigns that cater to the specific needs and preferences of those segments. For instance, a customer who frequently buys organic food products might be targeted with recommendations for other organic or health-conscious products. This not only improves customer satisfaction but also fosters brand loyalty by showing customers that the business understands their preferences (Tsoumakas and Katakis, 2007).

However, the application of ARL is not without challenges. One significant challenge is the computational complexity associated with generating frequent item sets, especially in large datasets common to e-commerce platforms. The Apriori algorithm, while effective, can be computationally expensive when applied to large-scale datasets with high dimensionality. This is because the algorithm needs to generate and test a vast number of potential item sets, which can be time-consuming and resource-intensive (Batchakui et al., 2022).

To mitigate these challenges, various optimizations of the Apriori algorithm have been proposed. One such optimization is the Frequent Pattern (FP) Growth algorithm, which reduces the need for candidate generation by compressing the dataset into a compact structure called an FP-tree. This approach significantly improves the efficiency of frequent itemset generation, making it more feasible to apply ARL in large-scale e-commerce environments (Resnick and Varian, 1997).

Another important application of ARL in e-commerce is in the development of dynamic pricing strategies. By analysing the relationships between products, businesses can identify opportunities to bundle products together or offer discounts on complementary items. For example, if the ARL process identifies that customers who purchase smartphones often buy phone cases, the business might offer a discount on phone cases when a smartphone is purchased. This type of dynamic pricing not only increases sales but also enhances the perceived value of the offer to the customer (Sarker, 2021).

2.6 Explainable AI in Recommender Systems

As recommender systems become more complex, the need for transparency and interpretability—often referred to as explainability—has become increasingly important. Explainable AI (XAI) in recommender systems is crucial for building user trust, as it allows users to understand the rationale behind the recommendations they receive. This is especially important in domains like e-commerce, where recommendations can significantly influence purchasing decisions (Lu et al., 2015).

Inductive Logic Programming (ILP) is particularly well-suited to provide explainability in recommender systems. Unlike many machine learning techniques that operate as "black boxes," ILP generates explicit logical rules that can be easily interpreted by humans. For example, an ILP-based recommender system might generate a rule such as: "If a user frequently buys science fiction books, recommend books by Isaac Asimov." Such a rule is not only accurate but also easily understandable by both users and system administrators (Knowledge-based recommender systems, BibSonomy).

In addition to ILP, Association Rule Learning (ARL) also offers a high degree of explainability. The rules generated by ARL, such as "If a customer buys a laptop, recommend a laptop bag," are inherently interpretable. These rules can be presented to users as explanations for the recommendations they receive, thereby enhancing user trust and engagement (Hiranandani et al., 2020).

However, the challenge of balancing explainability with model complexity remains. While simpler models like ILP and ARL provide clear explanations, they may not capture the full complexity of user preferences as effectively as more sophisticated machine learning models, such as deep learning. Deep learning models, while powerful, are often criticized for their lack of transparency, as they do not easily lend themselves to interpretation (Kleinberg and Tardos, 1999). As a result, there is ongoing research into hybrid approaches that combine the interpretability of ILP and ARL with the predictive power of deep learning (Luo et al., 2024).

One promising approach is the use of attention mechanisms in deep learning models, which can highlight the parts of the input data that the model focuses on when making a recommendation. This can provide users with some insight into the model's decision-making process, thereby improving explainability without sacrificing predictive performance (Koren, Bell and Volinsky, 2009). Another approach is to use post-hoc explanation techniques, such as LIME (Local Interpretable Model-agnostic Explanations), which can approximate the behaviour of complex models with simpler, interpretable models for the purpose of explanation (Goldberg et al., 1992).

2.7 Summary

In summary, this literature review has explored the development and application of various techniques in recommender systems, with a focus on e-commerce. The evolution of recommendation algorithms from traditional collaborative filtering and content-based approaches to more sophisticated methods such as Inductive Logic Programming (ILP) and Association Rule Learning (ARL) reflects the increasing complexity and demands of modern e-commerce environments. These techniques not only enhance the accuracy of recommendations but also provide the much-needed explainability that fosters user trust.
ILP, particularly when implemented through systems like PyGol, offers a robust framework for generating interpretable recommendations by learning logical rules from data. Meanwhile, ARL, with its ability to uncover associations between products, has proven to be a powerful tool for cross-selling and personalized marketing in e-commerce. The challenges of scalability and computational efficiency continue to drive research in optimizing these techniques, with new approaches such as FP-Growth and hybrid models emerging to address these issues.

Looking forward, the integration of explainable AI into recommender systems is set to play a critical role in their continued evolution. By balancing the need for interpretability with the power of complex models like deep learning, future recommender systems will not only provide more accurate recommendations but also offer users a clear understanding of why those recommendations were made, thereby enhancing trust and engagement in the digital marketplace.

CHAPTER 3: RESEARCH APPROACH

This chapter outlines the comprehensive methodology adopted to compare the performance of Inductive Logic Programming (ILP) using PyGol and Association Rule Learning (ARL) with the Apriori algorithm in building a recommender system. The research approach is structured around the CRISP-DM framework, ensuring a systematic and iterative process from problem understanding to the evaluation of model performance. The chapter is divided into several sections, each detailing a critical phase of the project, from initial understanding to final evaluation and ethical considerations.

3.1 Methodological Framework

The research methodology adopted for this project is based on the **Cross-Industry Standard Process for Data Mining (CRISP-DM)** framework. CRISP-DM is chosen for its flexibility, iterative nature, and wide applicability to data-driven projects. This framework ensures that the research is conducted in a structured manner, with each phase building on the findings of the previous one. The following sections describe how each phase of CRISP-DM is tailored to the specific needs of this project.

CRISP-DM Phase	**Application in This Project**
Business Understanding	Define objectives, align goals with business needs, establish the focus on explainability and scalability.
Data Understanding	Conduct EDA, analyse user behaviour, identify patterns, and understand data characteristics to inform model design.
Data Preparation	Structure data for ILP (predicate creation, background knowledge integration) and ARL (transaction encoding, frequent itemset generation).
Modelling	Generate and validate hypotheses using PyGol; apply the Apriori algorithm for rule mining, selection, and validation.
Evaluation	Compare ILP and ARL models using metrics for explainability, interpretability, and scalability.
Deployment	Discuss the integration, scalability, and maintenance of models in a real-world e-commerce setting.

Table 1 Application of CRISP-DM Phases in ILP and ARL Methodologies for E-Commerce Recommendation Systems

3.1.1 Business Understanding

The Business Understanding phase is crucial in defining the objectives of the project and ensuring alignment with the broader goals of enhancing e-commerce through effective recommender systems. The primary objectives of this project are as follows:

Performance Comparison: The project aims to evaluate and compare the effectiveness of ILP with PyGol and ARL with the Apriori algorithm in generating accurate and explainable product recommendations. The focus will be on the ability of each method to produce relevant and interpretable recommendations.

Explainability and Interpretability: In line with the growing demand for transparency in AI systems, this project places significant emphasis on how well each method can provide understandable explanations for its recommendations. Explainability is not merely a desirable feature but a critical component in ensuring user trust and engagement.

Scalability and Integration: The project also considers the practical aspects of deploying these methodologies in an actual e-commerce environment. This includes evaluating the scalability of ILP and ARL models and their potential integration into existing recommendation engines, ensuring that they can handle large datasets and adapt to evolving user preferences. This phase involved close collaboration with academic and industry stakeholders to ensure that the project's goals align with real-world requirements, particularly in the context of explainability and scalability in AI-driven recommendation systems.

3.1.2 Data Understanding

The Data Understanding phase involves an in-depth exploration and analysis of the dataset, which includes user transaction histories, product details, and related attributes. The primary objectives of this phase include:

Exploratory Data Analysis (EDA): Conduct EDA to uncover patterns, trends, and anomalies within the dataset. This includes analysing user behaviour patterns, purchase frequencies, product co-occurrences, and the distribution of key variables across different demographics.

Data Characteristics: Gain a comprehensive understanding of the data's structure and characteristics, such as the distribution of product purchases, relationships between products, and demographic profiles of users. These insights are critical for informing the design and configuration of both ILP and ARL models.

Feature Engineering: Identify and engineer features that enhance the performance of the recommendation models. For ILP, this may involve creating complex predicates that capture intricate relationships between users and products. For ARL, the focus is on transforming the transactional data into a format suitable for rule mining.

This phase ensures that the data is thoroughly understood and prepared, forming a solid foundation for the subsequent modelling processes.

3.1.3 Data Preparation

The Data Preparation phase is a critical step that transforms raw transactional data into structured formats suitable for modelling with both Inductive Logic Programming (ILP) and Association Rule Learning (ARL). This process involves careful data structuring, cleaning, and formatting tailored to the unique requirements of these models.

3.1.3.1 Data Structuring for ILP with PyGol

For ILP, data preparation begins with converting transactional data into a logical format compatible with the PyGol framework. This involves creating predicates that capture essential relationships within the dataset, such as purchased (User, Product) to indicate a user's purchase of a product. Additional predicates, such as belongs_to_category (Product, Category) and occurs_on_day (Order, DayOfWeek), help to capture more complex aspects like product categorization and temporal patterns.

Background knowledge is integrated into the system through Prolog files, representing domain-specific rules like frequent_buyer (User) :- purchased(User, Product), which define recurring user behaviours. This knowledge enriches the model's context, allowing for the generation of more informed hypotheses. The data is then normalized to ensure consistency across predicates, with categorical values standardized and numerical data discretized as needed. The final output is a set of Prolog files ready for hypothesis generation in the ILP model.

3.1.3.2 Data Preparation for Association Rule Learning with Apriori

For the ARL model, data preparation focuses on transforming user transaction data into a binary matrix format, where rows represent transactions and columns represent products. This binary encoding is crucial for the Apriori algorithm to efficiently identify frequent item sets.

The dataset undergoes thorough cleaning, including handling missing values and removing duplicates to ensure accuracy. The Apriori algorithm is then applied to generate frequent item sets, which are groups of products that frequently appear together in transactions. A minimum support threshold is set to filter significant item sets, balancing the need to capture relevant patterns without overwhelming the analysis.

These frequent item sets form the basis for generating association rules, which take the form "If product A is purchased, then product B is likely to be purchased." These rules are evaluated using metrics like confidence and lift to determine their reliability and strength. The data preparation process is iterative, refining the results to ensure that the most relevant and actionable rules are produced for the recommendation system.

Final Considerations

Throughout the Data Preparation phase, careful attention is given to aligning the data with the specific modelling techniques. For ILP, the focus is on logical representation and integrating background knowledge to generate interpretable rules. For ARL, the emphasis is on encoding and cleaning transactional data to maximize the effectiveness of the Apriori algorithm. This phase lays a solid foundation for the subsequent modelling and evaluation stages.

3.1.4 Modelling

This section discusses the two models utilized in this research: Inductive Logic Programming (ILP) with the PyGol framework and Association Rule Learning (ARL) using the Apriori algorithm. Each model has been selected for its unique strengths in handling the complexities of e-commerce data, making them suitable for different aspects of the recommendation process.

Modelling with ILP using PyGol

Inductive Logic Programming (ILP) is a symbolic machine learning approach that combines logic programming with inductive reasoning. This model is particularly valuable in scenarios where the interpretability of predictions is crucial. Unlike traditional machine learning models, which often act as "black boxes," ILP generates hypotheses in the form of logical rules that are both human-readable and understandable. These rules are expressed in a formal language, such as Prolog, making them easily interpretable and directly applicable to decision-making processes.

In this project, ILP is implemented using the PyGol framework. PyGol enhances the traditional ILP approach by providing more efficient mechanisms for hypothesis generation and the integration of background knowledge. The process begins with the generation of hypotheses that explain observed data, where each hypothesis is a set of logical rules aimed at accurately predicting user behaviour based on their transaction history and associated metadata. These rules are constructed using logical predicates that capture the relationships inherent in the data, such as "If a user frequently purchases product X and product Y, then they are likely to purchase product Z."

A significant feature of PyGol is its ability to incorporate background knowledge into the ILP model. This knowledge, encoded in Prolog, allows the model to integrate domain-specific rules and facts that enhance the predictive power and relevance of the generated hypotheses. For example, rules about seasonal buying patterns or brand loyalty can be embedded into the model, providing it with a richer context for making predictions. This ability to embed domain knowledge is particularly useful in e-commerce, where understanding customer behaviour often requires more than just analysing transaction data.

Abduction is a critical process within PyGol, used to enhance the interpretability of the ILP model. Abduction involves hypothesizing the most plausible explanations for observed behaviours, which is particularly valuable when dealing with incomplete or ambiguous data. By generating rules that not only predict but also explain user behaviour, PyGol provides a level of transparency that is often lacking in other machine learning approaches. This transparency is crucial in building trust with users, as it allows them to understand the reasoning behind the recommendations they receive.

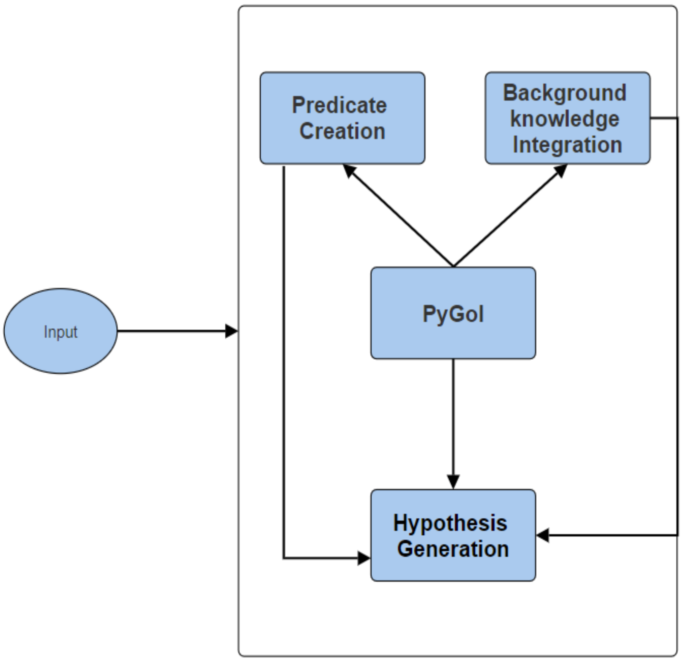

Figure 3.1 Framework of ILP with PyGol

To ensure the robustness of the ILP model, a 10-fold cross-validation technique is employed. This process involves dividing the dataset into ten subsets, training the model on nine of them, and validating it on the remaining subset. By repeating this process across all subsets, the model's performance is assessed for consistency and generalizability, ensuring that the rules generated are not overfitted to specific portions of the data. Hypotheses that perform well during this validation process are further refined and tested on a holdout dataset to ensure their accuracy and relevance in real-world scenarios.

Modelling with ARL using Apriori

Association Rule Learning (ARL) using the Apriori algorithm is focused on identifying relationships between items within large datasets. ARL is particularly effective in market basket analysis, where the goal is to discover items that are frequently purchased together. The Apriori algorithm is well-suited for this task, as it efficiently identifies frequent item sets—combinations of products that appear together often—and generates association rules that can inform product recommendations.

The Apriori algorithm operates by generating candidate item sets and pruning those that do not meet a minimum support threshold, which is a measure of how frequently an itemset appears in the dataset. Once frequent item sets are identified, the algorithm generates association rules that take the form "If item A is purchased, then item B is also likely to be purchased." These rules are evaluated based on metrics such as confidence, which measures the likelihood that the consequent (e.g., product B) will be purchased given the antecedent (e.g., product A), and lift, which assesses the strength of the rule relative to random chance.

The generated association rules are then refined through a process of rule pruning and optimization, where only the most significant rules—those with the highest confidence and lift—are retained. This ensures that the recommendations made by the ARL model are both accurate and actionable. Like the ILP model, the ARL model undergoes a 10-fold cross-validation process to validate the generalizability of the rules across different subsets of the dataset.

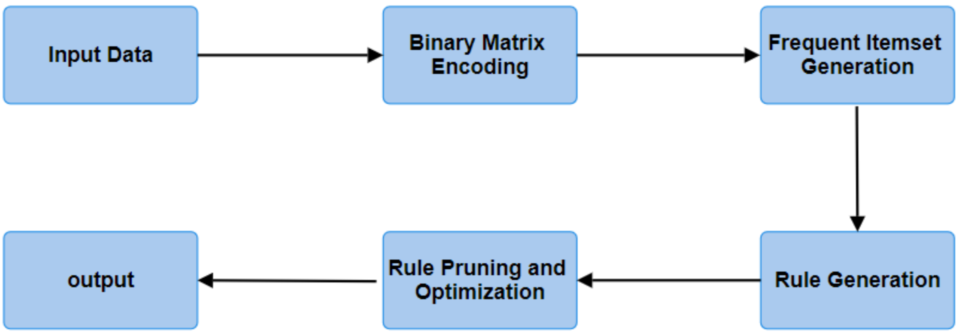

Figure 3.2 Framework of Apriori

Incorporating user-specific preferences into the ARL model enhances the personalization of the recommendations. By aligning the generated association rules with individual user transaction histories, the model can provide recommendations that are tailored to each user's unique purchasing patterns. This approach not only improves the relevance of the recommendations but also increases user satisfaction and engagement.

Both ILP and ARL serve distinct but complementary purposes in the development of an e-commerce recommendation system. ILP, particularly when using PyGol, is invaluable for generating complex, interpretable rules that provide deep insights into user behaviour, making it ideal for scenarios where understanding the rationale behind predictions is crucial. ARL, with the Apriori algorithm, is more focused on uncovering straightforward associations between products, which can be directly used to influence marketing strategies such as cross-selling and product placement. Together, these models provide a comprehensive approach to leveraging the complex patterns inherent in e-commerce data, enabling the development of a robust and effective recommendation system.

3.1.5 Evaluation

The evaluation phase is crucial for determining the effectiveness and robustness of the models developed in this research—Inductive Logic Programming (ILP) using PyGol and Association Rule Learning (ARL) using the Apriori algorithm. This research employed a novel approach by comparing the product recommendations generated by both ILP and Apriori with the products identified through Market Basket Analysis (MBA). This comparison serves as the basis for evaluating the performance of the models.

Evaluation Metrics

Accuracy: Accuracy measures how often the recommendations generated by the ILP and Apriori models match the products identified through Market Basket Analysis. A high accuracy score indicates that the model's recommendations are closely aligned with the user's purchasing patterns as revealed by MBA.

Precision: Precision evaluates the proportion of true positive recommendations out of all recommendations made by the models. It specifically measures how relevant the recommended products were to the user's actual purchasing behaviour, as identified by MBA.

Recall: Recall measures the model's ability to identify all relevant products for a user. It assesses how well the recommendations generated by ILP and Apriori captured the full range of products that a user is likely to purchase, as determined by Market Basket Analysis.
F1-Score: The F1-Score, which is the harmonic mean of Precision and Recall, provides a balance between these two metrics. It is particularly useful when there is a trade-off between precision and recall, ensuring that neither metric is disproportionately favoured.

Coverage: Coverage assesses the proportion of all possible items in the dataset that the models can recommend. High coverage suggests that the model is capable of suggesting a wide array of products, thus catering to diverse user preferences.

Diversity: Diversity measures the variety within the set of recommendations provided by the models. High diversity ensures that users are exposed to a broad range of products, which can enhance customer satisfaction and the discovery of new items. It is an important metric in ensuring that the recommendations do not become too narrow or repetitive.

Mean Reciprocal Rank (MRR): MRR evaluates the ranking quality of the recommended items. It calculates the average of the reciprocal ranks of the first relevant item in the recommendation list across all users. A higher MRR indicates that relevant recommendations are consistently ranked higher in the list provided to the user.

Interpretability: For the ILP model, interpretability is a critical metric. It assesses how easily the generated rules can be understood and validated by human decision-makers. This metric is essential to ensure that the model's predictions are transparent and can be trusted by end-users. ILP's strength lies in its ability to generate human-readable rules, which is evaluated through this metric.

Cross-Validation and Comparative Analysis: To validate the generalizability of the models, a 10-fold cross-validation approach was employed. The dataset was divided into ten subsets, with the model trained on nine and tested on the remaining subset. This method ensured that the model's performance is consistent across different segments of the data, helping to prevent overfitting.

After cross-validation, a comparative analysis was conducted between the ILP and ARL models using the evaluation metrics. This analysis provided insights into the strengths and weaknesses of each model. For instance, ILP might be superior in terms of interpretability and the ability to handle complex relational data, whereas ARL could be more efficient and scalable for large datasets. By comparing the recommendations from both models against the products identified through Market Basket Analysis, this research was able to determine which model is better suited for specific e-commerce scenarios, depending on the objectives of the recommendation system.

3.1.6 Deployment

While the focus of this research is on the development and evaluation of the ILP and ARL models, considering how these models might be deployed in a real-world e-commerce setting is important. Deployment involves key considerations to ensure the models integrate effectively into an operational environment.

Integration into E-Commerce Systems: For practical use, the ILP model would likely require a dedicated knowledge base to manage and update the logical rules in real-time. This setup would allow the model to access and apply relevant rules quickly during user interactions. The ARL model, on the other hand, would need a system to continuously update transaction data, enabling dynamic adjustment of association rules. APIs would facilitate communication between these models and the platform's components, ensuring smooth operation.

Real-Time Data Processing: Both models would need to process data in real-time to offer relevant recommendations. As users interact with the platform, the models must instantly analyse this data. For ARL, this means adjusting association rules on the fly to reflect the user's current shopping behaviour. The ILP model would use real-time data to refine logic rules, keeping recommendations aligned with recent user actions.

Scalability Considerations: Scalability is crucial, especially with the large data volumes typical in e-commerce. The ILP model, due to its complexity, might require distributed computing to manage high traffic efficiently. The ARL model would need to handle frequent data updates and maintain quick processing times, potentially using parallel processing techniques to ensure performance under heavy loads.

Monitoring and Maintenance: Continuous monitoring would be necessary to track performance metrics such as accuracy and response time. Automated alerts could signal any issues, prompting timely adjustments. Regular retraining of the models would be essential to adapt to changing user behaviour and market conditions, ensuring that the recommendations remain relevant and effective.

Data Privacy and Compliance: Ensuring compliance with data privacy regulations, like GDPR, is critical. This would involve implementing data anonymization and secure processing practices. Users would need clear communication about how their data is used, with options for managing their preferences and ensuring their privacy rights are respected.

3.2 Ethical Considerations

In developing the ILP and ARL models for e-commerce recommendations, it is essential to address key ethical considerations to ensure responsible use of user data and fair outcomes.

Data Privacy and Compliance: Protecting user privacy is critical. All personal data should be anonymized to prevent any potential identification of users. Compliance with data protection regulations, such as GDPR, is necessary, requiring users to be informed about data use and providing them with options to control their information, including consent and data management features.

Fairness and Bias Mitigation: The models must be checked for biases that could lead to unfair recommendations. Ensuring that the recommendations are equitable across different user groups is important. Techniques for detecting and correcting biases should be applied during model training and evaluation.

Transparency and Explainability: Transparency in recommendations builds user trust. The ILP model's interpretable rules should be presented clearly, and the logic behind ARL-based recommendations should be made understandable to users. This allows users to see why certain products are recommended to them.

User Autonomy and Security: Users should have control over how their data is used, including options to opt out of personalized recommendations. Strong security measures, such as encryption and regular audits, are necessary to protect user data and ensure the system's integrity.

By addressing these ethical considerations, the project ensures that the models are both effective and aligned with ethical standards, fostering user trust.

3.3 Summary

This chapter has provided a detailed explanation of the research methodology adopted for this project, which is structured around the CRISP-DM framework. The methodology encompasses the entire process from business understanding to evaluation, ensuring a systematic and rigorous approach to developing and comparing the ILP and ARL models.

The Data Preparation phase detailed the steps taken to structure and preprocess the data for use in both ILP with PyGol and ARL with Apriori. The Modelling phase provided an in-depth look at how the models were trained, cross-validated, and tuned to optimize performance. Finally, the Evaluation phase outlined the metrics used to assess the models' effectiveness, highlighting the comparative analysis between ILP and ARL.

CHAPTER 4: DATA ANALYSIS

This chapter delves into the data analysis techniques employed to develop and evaluate the recommender system, focusing on the use of Inductive Logic Programming (ILP) with PyGol and Association Rule Learning (ARL) with the Apriori algorithm. Following the CRISP-DM framework, the chapter outlines the key steps taken from understanding the business context to preparing the data, building the models, and evaluating their performance.

Each section of this chapter details a critical phase of the analysis process, beginning with a clear articulation of the project's objectives within the business context, followed by an exploration of the dataset to identify relevant patterns. The data preparation phase describes how the raw data was transformed into a suitable format for ILP and ARL, setting the foundation for the modelling phase. The chapter concludes with a thorough evaluation of the models, comparing their performance and highlighting the strengths and weaknesses of each approach.

4.1 Business Understanding

In this chapter, the Business Understanding phase serves as a pivotal step in transforming the overarching objectives of this research into specific, actionable analytical tasks. The primary aim is to leverage the available data to derive insights that directly inform the development and evaluation of the recommendation systems under study—namely, Inductive Logic Programming (ILP) with PyGol and Association Rule Learning (ARL) via the Apriori algorithm.

The focus of this phase is to delineate the key business questions that will guide the subsequent data analysis, ensuring that the models developed are not only theoretically sound but also practically relevant. The following business-driven analytical questions have been identified:

Optimization of Transactional Data for Personalized Recommendations: A critical analysis of the transactional data is required to identify patterns and trends that can be effectively modelled to align with individual user preferences. This involves a detailed examination of product co-occurrences within transactions, user purchase histories, and temporal buying patterns. The goal is to establish a data-driven foundation for generating personalized and contextually relevant product recommendations.

Identification of Key Influencers in Purchasing Decisions: This aspect of the analysis seeks to uncover the variables that significantly influence purchasing behaviour. By dissecting the dataset, we aim to identify and quantify the impact of factors such as time of purchase, product attributes, and user demographics. Understanding these influencers is crucial for enhancing the precision and relevance of the recommendation algorithms.

Quantification of Explainability in Data-Driven Recommendations: Given the increasing importance of transparency in AI-driven systems, this analysis also seeks to quantify how explainability can be embedded within the recommendation process. This involves not only ensuring that the recommendations are accurate but also that the underlying data supports clear, interpretable explanations that can be communicated to the end-user, thereby enhancing trust and engagement.

Impact of Data Quality on Model Performance: The integrity of the recommendations is closely tied to the quality of the underlying data. This section of the analysis will assess the completeness, consistency, and relevance of the data, identifying potential quality issues that could impact the models' accuracy and reliability. The aim is to ensure that the data used is robust enough to support high-quality, dependable recommendations.

In summary, the Business Understanding phase in this chapter establishes a clear link between the strategic goals of the research and the practical analytical tasks required to achieve these goals. It sets a comprehensive framework for the data analysis, ensuring that every step taken aligns with the ultimate objective of building a sophisticated, explainable, and effective recommendation system.

4.2 Data Understanding

The dataset utilized in this research is the Instacart Online Grocery Basket Analysis Dataset, a comprehensive and rich resource that captures detailed information about customer shopping behaviours on the Instacart platform. This dataset is structured across several key files, each playing a crucial role in the overall data architecture.

The aisles.csv file provides a granular breakdown of the shopping environment, containing information on 134 different aisles within the store. Each aisle is uniquely identified by an aisle_id and described in terms of the types of products it contains. This data is instrumental in understanding product categorization at a micro level, offering insights into how customers navigate the store's layout.

Expanding on the aisle-level data, the departments.csv file categorizes products into broader departments, such as "Produce" or "Dairy," identified by a department_id. This hierarchical data structure is essential for analysing customer preferences and behaviours across different sections of the store. It also allows for the examination of cross-departmental shopping patterns, which are critical for developing targeted marketing strategies.

The products.csv file is the centrepiece of the dataset, listing every product available on the platform, each uniquely identified by a product_id. This file also includes the aisle_id and department_id for each product, creating a link between products and their respective categories. This hierarchical mapping is crucial for understanding product relationships and customer purchasing behaviours at various levels of granularity.

The orders.csv file provides a detailed record of every order placed by customers, with each order identified by a unique order_id. The file includes metadata such as the day of the week, hour of the day, and the sequence number of the order, which is vital for temporal analysis. This data allows us to track purchasing habits over time, identify peak shopping periods, and understand the temporal dynamics of customer behaviour.

Finally, the order_products__prior.csv and order_products__train.csv files detail the products included in each order, linking them back to the order_id. The prior file contains historical order data, while the train file is used for model training purposes. These datasets are essential for understanding past purchasing behaviours and for training the recommendation models. The granularity of this data enables a deep dive into customer preferences and the development of personalized recommendation strategies.

The dataset's structure reflects a well-organized relational schema, allowing for complex queries and analyses to be performed efficiently. Each file interlinks with others through shared identifiers, such as order_id, product_id, aisle_id, and department_id, facilitating a comprehensive understanding of customer shopping patterns.

4.2.1 Data Integration Process

To create a unified dataset, the various files from the Instacart dataset were merged into a single comprehensive Data Frame. First, product details from products.csv were enriched by merging with aisles.csv and departments.csv. Next, the order_products__prior.csv and order_products__train.csv files, containing order-specific product information, were concatenated. This combined order-product Data Frame was then linked with product attributes using product_id, and finally, merged with orders.csv to incorporate order metadata such as order timing. This process resulted in a comprehensive dataset integrating product details, transactional data, and temporal metadata, forming the basis for the analysis and model development.

4.2.2 Exploratory Data Analysis (EDA)

Descriptive Statistics

The dataset provides a comprehensive overview of user behaviours and product interactions. As part of the descriptive statistics, key metrics such as the mean, standard deviation, minimum, and maximum values were calculated for various attributes, including order_id, product_id, user_id, order_number, order_dow (day of the week), order_hour_of_day, and days_since_prior_order. This analysis helped in understanding the distribution and variance of these features, which are critical in modelling user behaviour and product relationships.

Distribution of Orders by Day of the Week

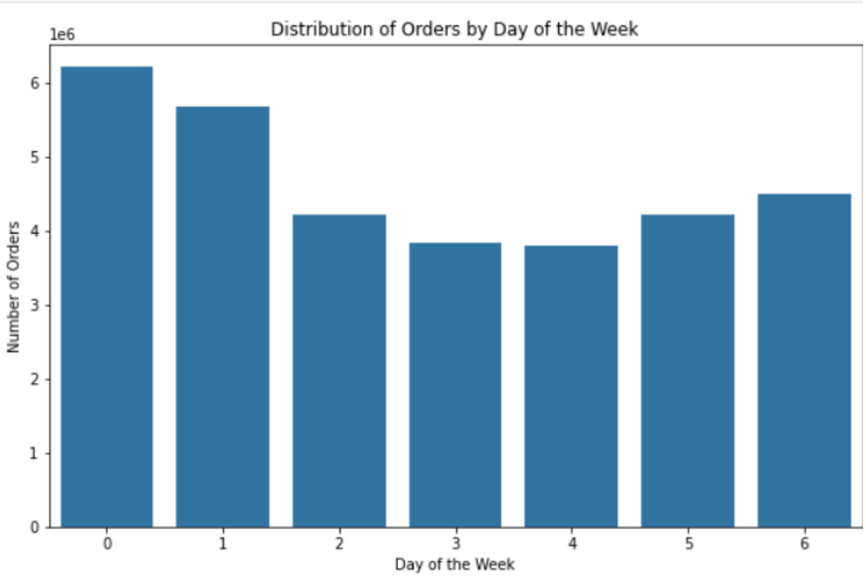

Figure 4.1 Distribution of Orders by Day of the Week

The first bar chart visualizes the distribution of orders across different days of the week. This chart reveals that the highest number of orders are placed on days 0 and 1, which correspond to Saturday and Sunday, indicating a peak in grocery shopping activity during weekends. This insight is valuable for modelling purposes, as it highlights user behaviour trends that the recommendation system should consider.

Distribution of Orders by Hour of the Day

The second bar chart illustrates the distribution of orders by the hour of the day. The data shows that most orders are placed between 10 AM and 3 PM, with a significant drop-off in activity during the early morning and late evening hours. Understanding these patterns helps in fine-tuning the recommendation system to better align with typical user activity.

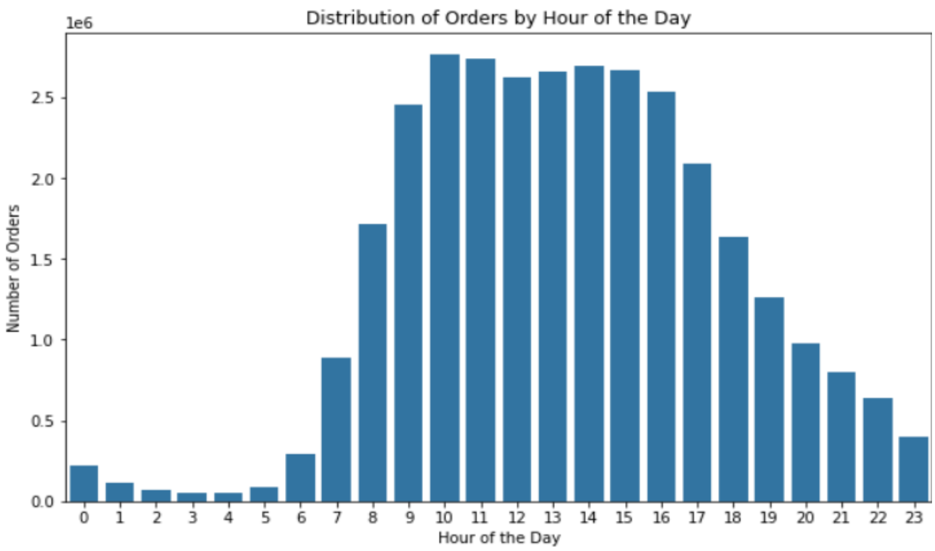

Figure 4.2 Distribution of Orders by Hour of the Day

Top 10 Most Ordered Products

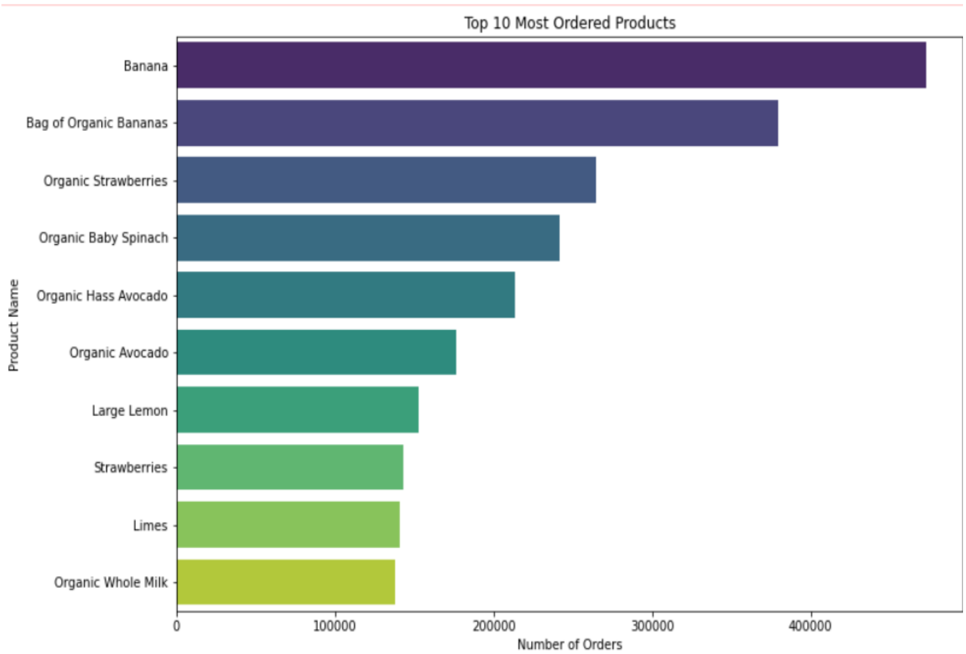

Figure 4.3 Top 10 Most Ordered Products

A bar chart was generated to show the top 10 most ordered products. Bananas, Bag of Organic Bananas, and Organic Strawberries are among the top items, highlighting user preferences for fresh produce. These popular products serve as a baseline for the recommendation system, providing a starting point for generating suggestions.

Top 10 Products by Reorder Rate

Another bar chart focuses on the top 10 products by reorder rate, showing products that customers frequently repurchase. High reorder rates indicate strong customer loyalty to specific items, which can be leveraged to enhance the recommendation system's predictive accuracy.

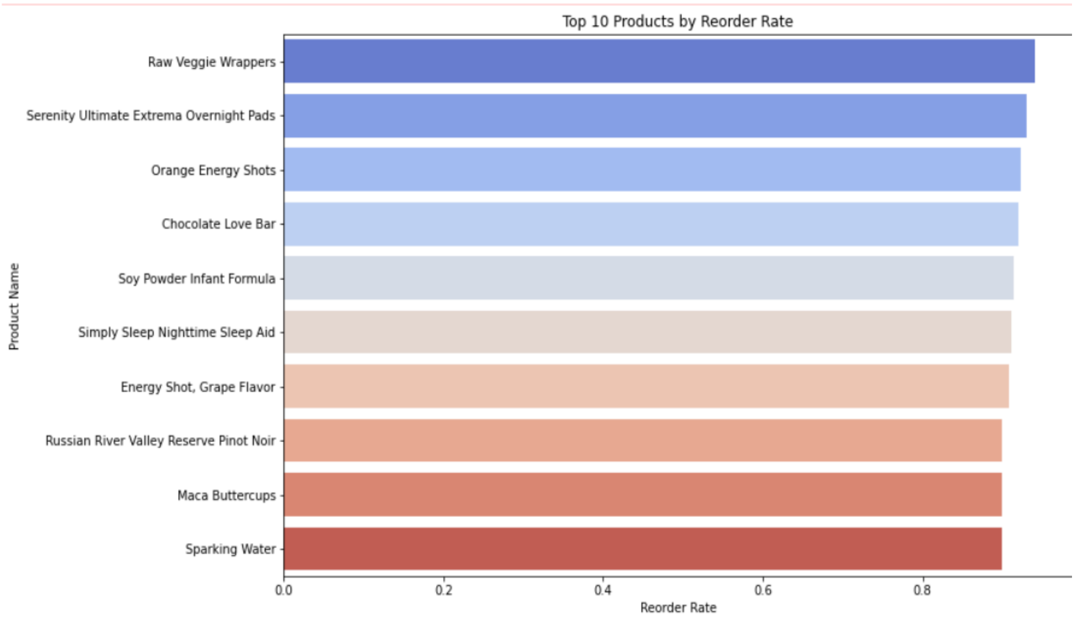

Figure 4.4 Top 10 Products by Reorder Rate

Correlation Matrix Heatmap

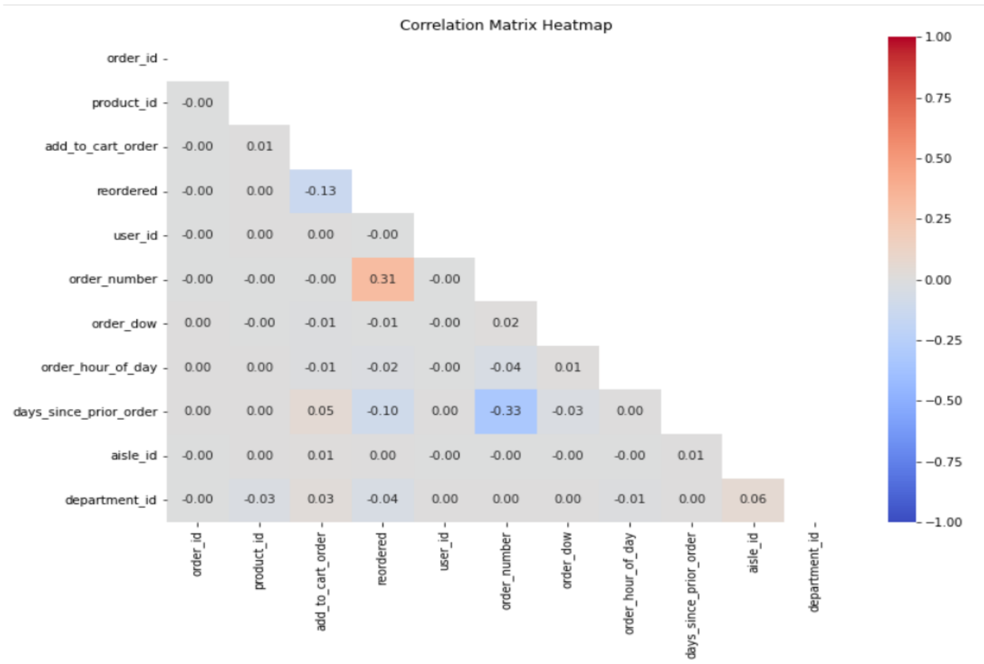

Figure 4.5 Correlation Matrix Heatmap

A correlation matrix was created to examine the relationships between different variables in the dataset. The heatmap visualizes the strength of correlations, with certain attributes like order_number and days_since_prior_order showing notable relationships. This information is crucial for feature selection and engineering, as it highlights which variables are most likely to influence user purchasing decisions.

Box Plot: Distribution of Orders by Hour of the Day

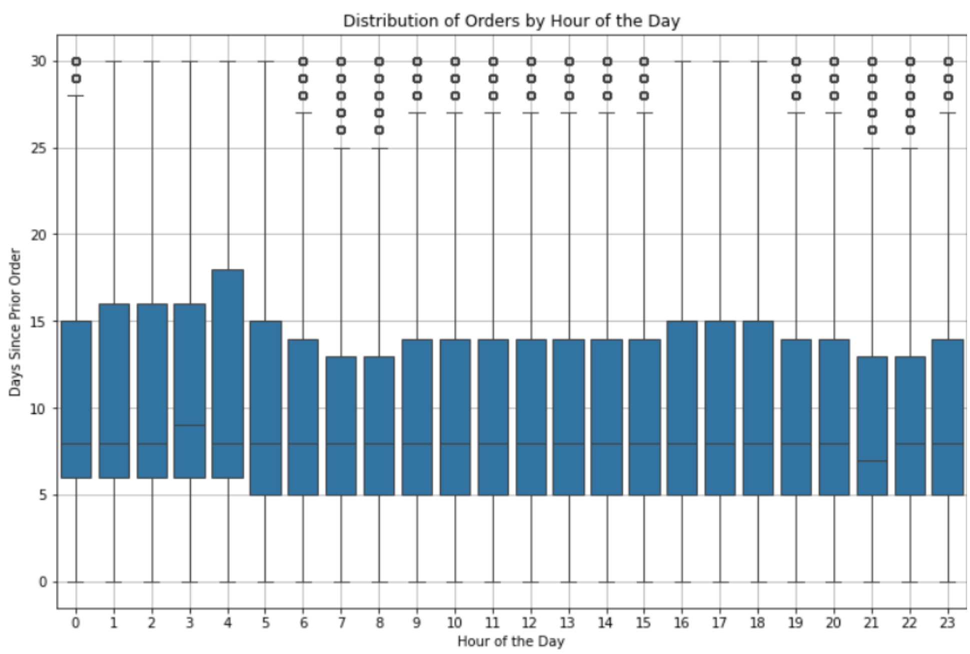

Figure 4.6 Box Plot: Distribution of Orders by Hour of the Day

A box plot was used to analyse the distribution of orders by the hour of the day, in relation to the number of days since the prior order. This visualization helps identify outliers and the variability in ordering patterns, offering deeper insights into user behaviour over time.

Pairplot of Order Timing Features

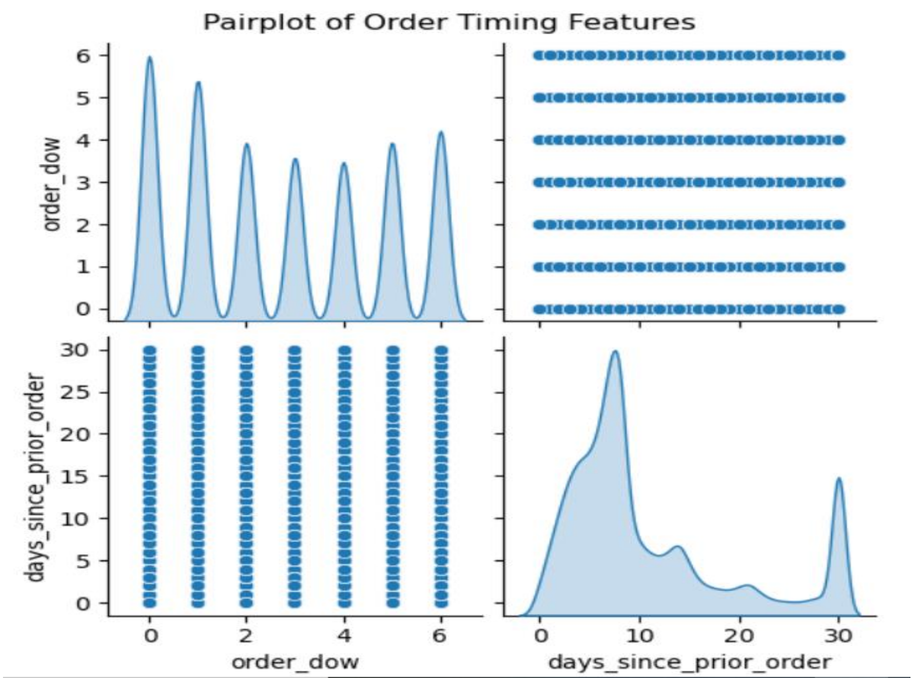

Figure 4.7 Pairplot of Order Timing Features

This pairplot visualizes order_dow (day of the week) and days_since_prior_order. The diagonal plots show that orders are spread across the week, with noticeable peaks at 7 and 30 days, indicating common reorder intervals. The scatterplots highlight the structured, cyclical nature of customer ordering behaviour.

Feature Importance using Random Forest

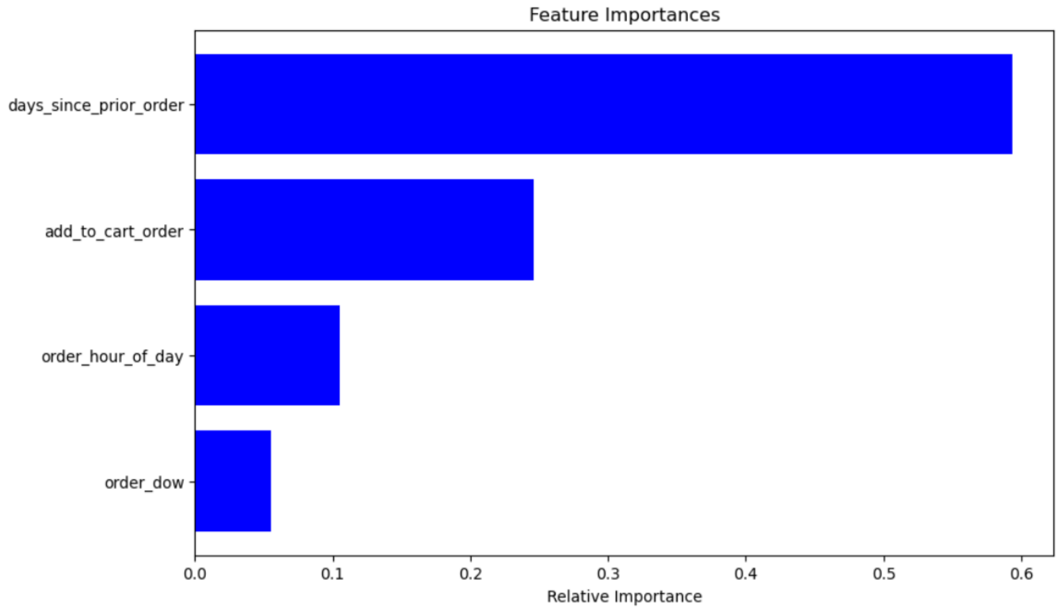

Figure 4.8 Feature Importance using Random Forest

This feature importance plot shows that days_since_prior_order is the most influential factor in predicting reorder behaviour, followed by add_to_cart_order. Order_hour_of_day and order_dow have less impact, indicating that the timing and sequence of orders play a more crucial role in customer purchase patterns**.**

Customer Segmentation Analysis

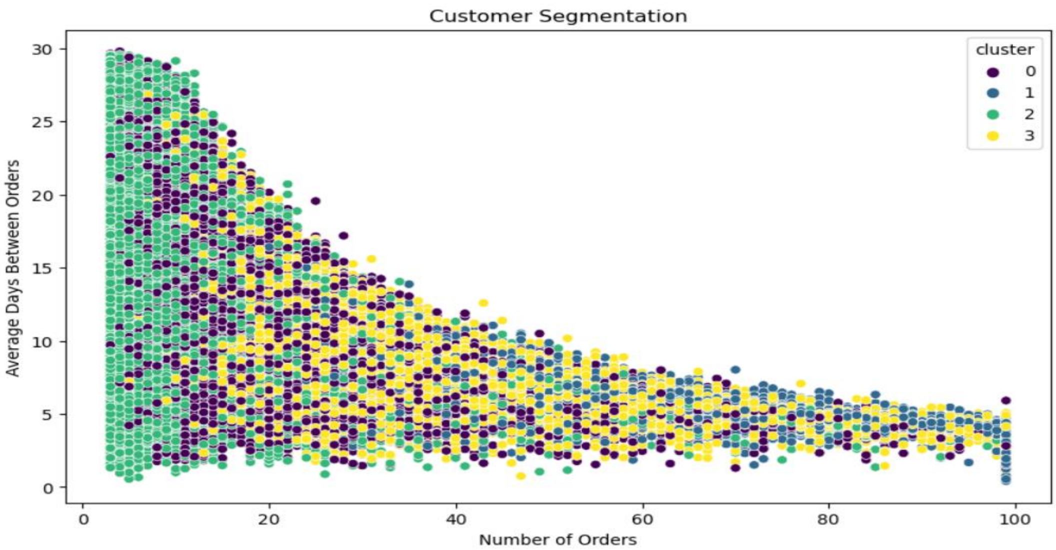

Figure 4.9 Customer Segmentation Analysis

This scatter plot illustrates customer segmentation based on the number of orders and the average days between orders. The clustering reveals distinct customer groups, where those with fewer orders tend to have longer intervals between purchases, while frequent shoppers typically reorder more quickly. The color-coded clusters highlight the different purchasing behaviours within the dataset, providing insights into customer engagement and shopping patterns.

3D Visualization of Customer Segmentation Based on Purchasing Behaviour Using K-Means Clustering

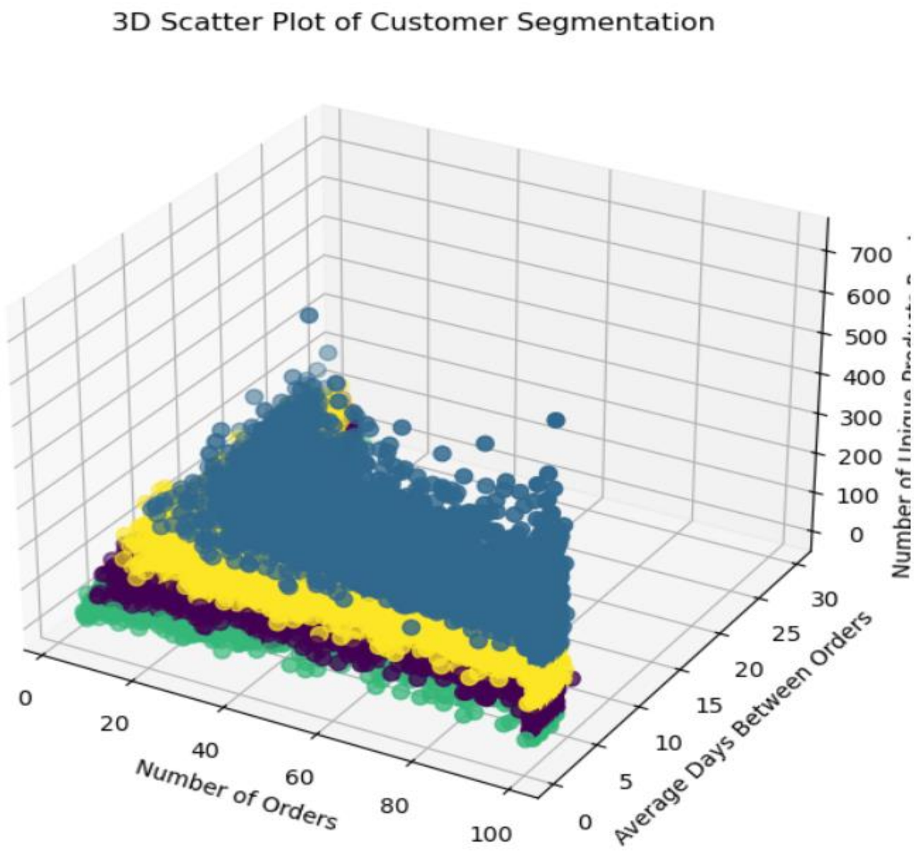

Figure 4.10 3D Scatter Plot of Customer Segmentation

This 3D scatter plot visualizes customer segmentation based on three dimensions: the number of orders, the average days between orders, and the number of unique products purchased. The color-coded clusters highlight distinct customer behaviours, with some customers making frequent purchases of a wide variety of products, while others have longer intervals between orders and purchase fewer unique items. This plot provides a comprehensive view of the diversity in shopping patterns across different customer segments.

Pairwise Density Plot (Hexbin Plot)

This hexbin plot illustrates the relationship between the number of orders and the average days between orders, with the colour intensity representing the density of customers within each hexagon. The plot reveals that customers with fewer orders tend to have longer intervals between purchases, while those with more frequent orders typically reorder with shorter gaps. The high-density areas highlight common customer behaviours, providing insights into typical shopping patterns.

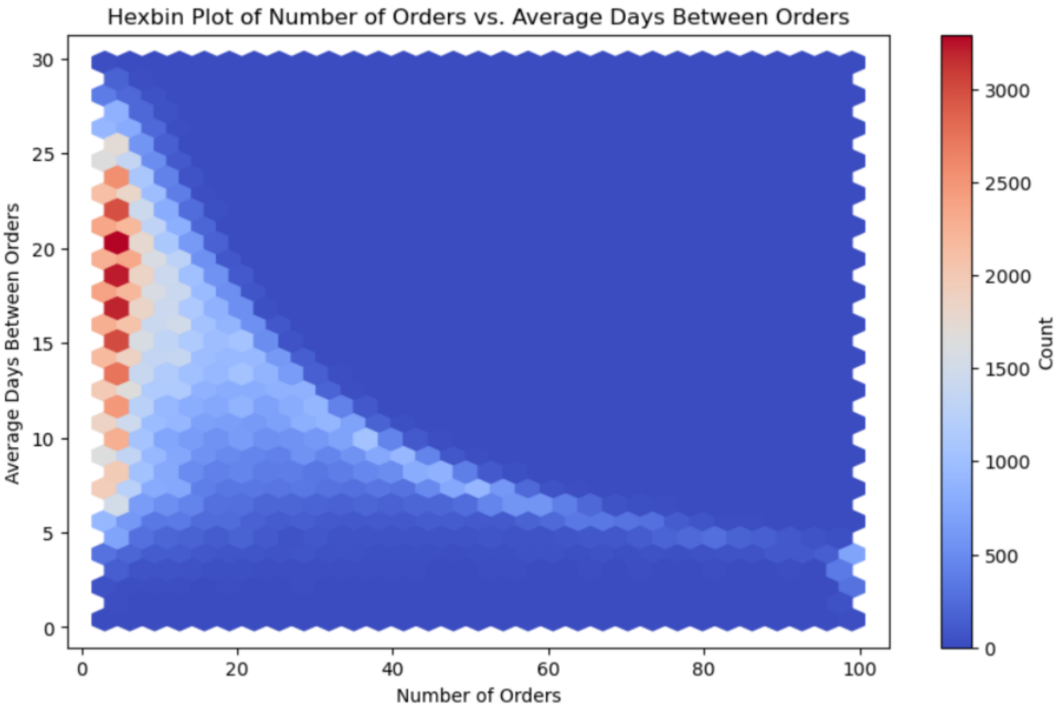

Figure 4.11 Hexbin plot

Radar Chart of Key Customer Metrics for Cluster 0 in E-Commerce Segmentation

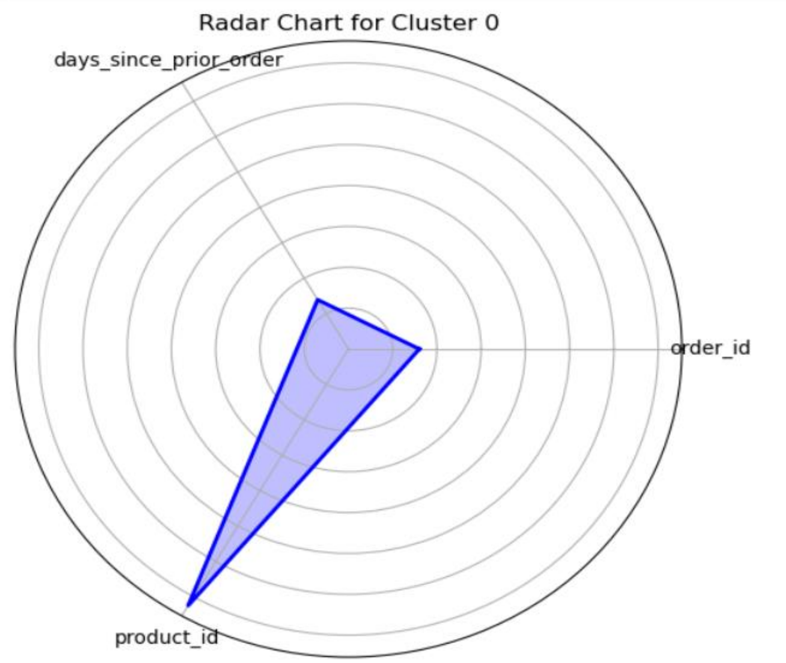

Figure 4.12 Radar Chart

This radar chart represents the key metrics for Cluster 0, highlighting the average behaviour of customers within this segment. The chart shows that these customers have relatively fewer unique products purchased (product_id) and orders (order_id), while the days_since_prior_order is moderately high. This visualization provides a clear overview of the purchasing tendencies of customers in Cluster 0, offering insights into their shopping frequency and product diversity.

Contour Plot of Customer Order Frequency vs. Reorder Timing

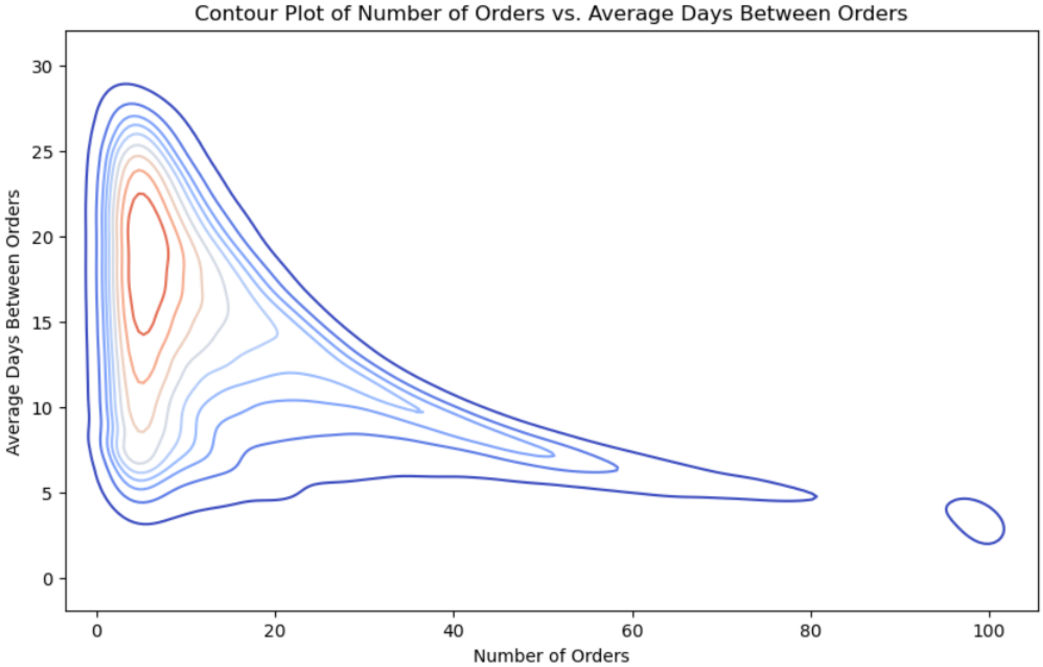

Figure 4.13 Contour Plot

This contour plot visualizes the relationship between the number of orders and the average days between orders across different customer segments. The density of the contours indicates the concentration of customers with similar purchasing behaviours. The plot reveals that most customers with a high number of orders tend to reorder more frequently, whereas those with fewer orders exhibit longer intervals between purchases. The distinct contour lines provide insights into the varying reorder patterns, helping to identify common customer behaviours within the dataset.

4.3 Data Preparation

The Data Preparation phase is critical to the quality and performance of the models developed. This section details the steps taken to preprocess and structure the dataset for both Inductive Logic Programming (ILP) with PyGol and Association Rule Learning (ARL) using the Apriori algorithm. The table below summarizes the key data characteristics, preprocessing actions, and the rationale behind these choices.

Data Characteristic	**Key Insights**	**Preprocessing Actions**	**Rationale for Preprocessing**
Data Volume	Over 32 million rows of transactional data, involving 200,000 unique users and 50,000 products.	Sampled 200,000 transactions for ARL; full dataset used for ILP with efficient predicate creation.	Sampling was necessary for ARL due to the computational intensity of the Apriori algorithm. ILP handled full data to generate comprehensive rules.

Categorical Variables (e.g., Aisle, Department)	Products classified into 134 aisles and 21 departments.	Created predicates for ILP to capture relationships between products, aisles, and departments; encoded data for ARL.	This categorization helped ILP understand relationships and allowed ARL to mine meaningful association rules.
Temporal Data (Order Day, Hour)	Orders show a strong temporal pattern, with peaks on specific days and hours.	Developed time-based predicates for ILP; incorporated time-related features into the ARL model.	Understanding temporal patterns was key for both models to make contextually relevant recommendations.
Reorder Rate	High variability in reorder rates across products, with some products reordered more than 60% of the time.	Incorporated reorder rates into feature engineering for both ILP and ARL to understand user loyalty and product popularity.	Reorder rates are indicative of user preferences, making them critical for accurate recommendations.
Missing Values	Minimal missing data, primarily in days_since_prior_order.	Imputed missing values where necessary for ARL; created appropriate handling in ILP through flexible predicate definitions.	Ensured that missing values did not skew the results or reduce the efficacy of the models.
Data Skewness	Skewed distribution with some products dominating orders (e.g., Bananas, Organic Milk).	Applied log transformation for numerical features where necessary in ARL; normalized data for ILP hypothesis generation.	Addressed skewness to prevent model bias and ensure balanced rule generation.
Data Integration	Merged multiple datasets (orders, products, aisles, departments) into a single comprehensive data frame.	Performed several joins and merges to ensure all relevant data was accessible for both ILP and ARL methodologies.	Ensured a unified dataset that provides a holistic view of user transactions and product relationships.

Table 2 Summary of Data Characteristics, Key Insights, and Preprocessing Actions for ILP and ARL Methodologies

4.3.1 Structuring Data for ILP with PyGol

In the context of Inductive Logic Programming (ILP), data representation is achieved through logical predicates, which describe the relationships between various entities within the dataset. This process begins by transforming raw transactional data into a structured format suitable for logic programming. For example, each transaction in the dataset is deconstructed into a series of predicates that encapsulate user behaviour, such as a user purchasing a product on a specific day. These actions are translated into predicates like purchased(User, Product), day_of_week(Order, Day), and hour_of_day(Order, Hour). This transformation is crucial because it allows the ILP system to understand and manipulate the complex relationships inherent in user behaviour.

Beyond basic predicates, more complex ones are created to capture nuanced behaviours. For instance, predicates such as frequent_buyer(User) represent users with consistent purchasing patterns, while belongs_to_category(Product, Category) encapsulates product categorization. These complex predicates enhance the model's ability to generalize from the data and create meaningful rules.

To further augment the effectiveness of the ILP model, domain-specific background knowledge is integrated into the system. This background knowledge acts as an additional layer of information, guiding the ILP process to generate more accurate and interpretable hypotheses. Domain rules, such as frequent_buyer(User) :- purchased(User, Product), are encoded in Prolog, establishing general principles about consumer behaviour. These rules are derived from both domain expertise and exploratory data analysis, ensuring that the ILP model is grounded in realistic and relevant assumptions. The background knowledge is carefully encoded into Prolog syntax to ensure compatibility with PyGol. This process involves defining facts, rules, and constraints that shape the hypothesis space within which the ILP model operates. The background knowledge not only improves the accuracy of the model but also enhances its interpretability by aligning the generated hypotheses with established domain insights.

Ensuring that the data is in a consistent and logical format is vital for the smooth operation of the ILP process. All categorical variables are standardized to ensure uniformity across the dataset. For instance, categorical values like days of the week and product categories are encoded numerically or as standard text labels. The predicates and background knowledge are then formatted into Prolog-compatible syntax. This involves converting the normalized data into structured clauses that PyGol can process efficiently. The formatting is meticulously checked to avoid any syntactical errors that could disrupt the ILP process.

4.3.2 Structuring Data for Association Rule Learning with Apriori

For the Association Rule Learning (ARL) methodology, the dataset needs to be transformed into a format that can be processed by the Apriori algorithm. This is achieved through a binary matrix transformation, where the transactional data is encoded into a binary matrix using the Transaction Encoder from the mlxtend library. In this matrix, each row represents a unique transaction, and each column represents a product. The presence of a product in a transaction is denoted by a '1', while its absence is marked by a '0'. This binary representation is essential for identifying frequent item sets, which form the backbone of the Apriori algorithm.

Given the size of the dataset, special attention is paid to efficiently manage memory and processing time during the encoding process. While techniques such as sampling and chunking are considered, the entire dataset is ultimately utilized due to the robust computational resources available.

With the binary matrix prepared, the next step is to generate frequent item sets, which are groups of products that often appear together in transactions. A minimum support threshold is established to filter out infrequent item sets. This threshold is carefully chosen based on exploratory analysis to balance between capturing meaningful item sets and maintaining computational efficiency. Various threshold values are iterated over to find an optimal balance. The Apriori algorithm is then applied to the binary matrix to identify these frequent item sets, which form the foundation for generating association rules that are essential for making product recommendations.

To ensure the dataset is of high quality before entering the modeling phase, a series of data cleaning and preprocessing steps are undertaken. Missing values in the dataset are identified and appropriately handled depending on the nature of the missing data. For instance, missing categorical data is often filled with a placeholder or the mode of the category, while missing numerical data is treated with imputation techniques or, in some cases, the rows are discarded if the missing data is substantial. The data is then standardized where necessary, ensuring that all features are on a comparable scale. This standardization is particularly important for algorithms like Apriori that are sensitive to the scale and distribution of data.

4.3.3 Cross-Validation Setup for ILP and ARL

During the data preparation phase, the datasets were organized to facilitate cross-validation, which would later be applied in the Modelling phase. This involved structuring the data in a way that allowed it to be easily partitioned into training and testing subsets, ensuring that both the ILP and ARL models could be robustly evaluated. The details of the cross-validation process, including the specific techniques and their outcomes, are discussed in the Modelling section.

4.4 Modelling

The Modelling phase is a pivotal part of this research, where we apply both Inductive Logic Programming (ILP) using the PyGol framework and Association Rule Learning (ARL) using the Apriori algorithm to construct models for generating product recommendations. The methodologies discussed here are directly aligned with the steps outlined in the Research Approach chapter, ensuring consistency between the theoretical framework and practical implementation.

4.4.1 Modelling with ILP and PyGol

The ILP model was implemented using the PyGol framework, which is particularly suited for generating interpretable rules from complex datasets. The modelling process began with the preparation of the dataset into a format that could be effectively utilized by PyGol. This involved converting user interactions, such as product purchases, into logical predicates. These predicates, such as purchased (User, Product) and order_day(User, Day), were essential in structuring the data in a way that PyGol could analyse to discover underlying patterns in user behaviour.

A critical part of this modelling process was the integration of domain-specific background knowledge, encoded in Prolog. This background knowledge included rules that were not immediately apparent from the data but were essential for making the model more robust and context aware. For instance, rules such as frequent_buyer(User) :- purchased(User, Product) helped the model to identify patterns associated with repeat purchases, which are crucial for generating meaningful recommendations.

The process of abduction, unique to ILP and PyGol, was used to enhance the interpretability of the generated rules. Abduction allowed the model to hypothesize plausible explanations for observed behaviours, especially in cases where data might be incomplete or ambiguous. This feature was particularly valuable in ensuring that the model's recommendations were not only accurate but also transparent, providing insights into the reasoning behind each suggestion. For example, when a user frequently purchased related items, the model could hypothesize that the user was preparing for a specific event and suggest complementary products accordingly.

To ensure that the rules generated by the ILP model were generalizable and not overfitted to the specific dataset, a rigorous 10-fold cross-validation was performed. This involved splitting the dataset into ten subsets and iteratively training and testing the model to assess its performance across different data segments. This validation step was crucial in refining the model, allowing for the identification and elimination of rules that did not generalize well. The iterative refinement process ultimately led to a set of robust, interpretable rules that could be reliably used in a real-world e-commerce setting.

4.4.2 Modelling with ARL and Apriori

The ARL model, implemented using the Apriori algorithm, was designed to uncover associations between products that were frequently purchased together. The first step in this modelling process was to convert the transactional data into a binary matrix. In this matrix, each transaction was represented as a row, and each product as a column, with binary values indicating the presence or absence of a product in each transaction. This binary encoding was critical for the Apriori algorithm to efficiently identify frequent item sets—combinations of products that commonly co-occur in user transactions.

Once the data was encoded, the Apriori algorithm was applied to mine these frequent item sets. The minimum support threshold was a key parameter in this process, as it determined which item sets were considered frequent enough to be of interest. Setting this threshold required careful consideration, balancing the need to capture meaningful associations without overloading the model with infrequent, less relevant patterns.

After identifying the frequent item sets, the Apriori algorithm generated association rules, such as "If product A is purchased, then product B is likely to be purchased." These rules were evaluated using metrics like confidence, which measured the likelihood of the consequent given the antecedent, and lift, which assessed the strength of the association relative to random chance. Rules with high confidence and lift were prioritized for inclusion in the recommendation model, ensuring that the suggestions generated were both relevant and actionable.

To validate the ARL model, a 10-fold cross-validation approach was also employed, like the ILP model. This involved training the model on nine subsets of the data and testing it on the remaining subset, iteratively, to ensure that the generated rules were consistent and generalizable. During this process, rules that demonstrated stable performance across all folds were retained, while those that did not were refined or discarded.

The final phase of the ARL modelling involved personalization, where the general association rules were aligned with individual user purchase histories. This step was essential to ensure that the recommendations were not just based on general trends but were tailored to each user’s unique purchasing behaviour. By incorporating user-specific data, the model was able to deliver highly relevant recommendations that were more likely to resonate with the individual user, thereby enhancing engagement and satisfaction.

4.5 Evaluation

The evaluation phase was essential in assessing the effectiveness of the models developed using Inductive Logic Programming (ILP) with the PyGol framework and Association Rule Learning (ARL) using the Apriori algorithm. This evaluation focused on the accuracy, precision, recall, and overall relevance of the recommendations generated by these models, with a particular emphasis on comparing them against products predicted through Market Basket Analysis (MBA).

For the ILP model, the evaluation began with a thorough comparison of its recommendations against those derived from MBA. The MBA was used to predict the next likely purchases for a sample of 200 users based on their historical transaction data. These predictions served as a benchmark for assessing the effectiveness of the ILP model's recommendations. The key metrics used in this evaluation were accuracy, precision, recall, and F1-score. Accuracy was determined by the proportion of ILP-generated recommendations that matched the MBA-predicted products. Precision measured how many of the recommended products were relevant, focusing on the proportion of true positive recommendations. Recall assessed the model's ability to identify all relevant products as predicted by MBA, while F1-score provided a balanced view of the model's performance by combining precision and recall.

The ILP model was subjected to a 10-fold cross-validation process, where the dataset was divided into ten subsets. The model was trained on nine subsets and tested on the remaining one, ensuring that the evaluation was robust and generalizable across different segments of the data. The ILP model demonstrated strong performance, particularly in scenarios where user behaviour was predictable, aligning closely with the MBA predictions. The inclusion of abduction further enhanced the model's accuracy by allowing it to hypothesize missing information, thereby improving the transparency and interpretability of the recommendations.
The ARL model, using the Apriori algorithm, was evaluated similarly by comparing its recommendations with the products predicted by MBA. The evaluation focused on determining how well the ARL model could identify relevant products for users by matching its recommendations with the MBA-predicted products. The same metrics—accuracy, precision, recall, and F1-score—were used to evaluate the ARL model. The 10-fold cross-validation process ensured that the ARL model could consistently identify frequent item sets and generate reliable recommendations across different user groups. The Apriori algorithm performed well in identifying frequent co-purchases but faced challenges with less common items, which were addressed by refining the association rules to enhance their stability and relevance.

A comparative analysis of the ILP and ARL models highlighted their respective strengths. The ILP model excelled in generating context-aware and interpretable recommendations, making it suitable for applications where the reasoning behind recommendations was as important as the recommendations themselves. Its ability to incorporate background knowledge and perform abduction allowed it to handle complex decision-making scenarios effectively. On the other hand, the ARL model was highly efficient in identifying frequent co-purchase patterns and generating quick recommendations. Its scalability and ability to process large datasets made it ideal for applications requiring broad-spectrum recommendations with minimal computational overhead.

In conclusion, the evaluation demonstrated that combining ILP and ARL with Market Basket Analysis provided a comprehensive approach to understanding and predicting user behaviour. Each model brought unique strengths to the table, offering valuable tools for developing effective recommendation systems in e-commerce. The ILP model was particularly effective in providing deep insights and tailored recommendations, while the ARL model excelled in efficiency and scalability, making both models highly valuable depending on the specific requirements of the recommendation task.

CHAPTER 5: DISCUSSION

This chapter provides a detailed analysis of the models developed in this study—Inductive Logic Programming (ILP) using PyGol and Association Rule Learning (ARL) with the Apriori algorithm. The focus is on evaluating the performance of these models, comparing them with existing research, and discussing the implications of the results. The content is structured to begin with an overview of the chapter, followed by a thorough discussion of the results, and concluding with a critical evaluation of how well the project objectives were met.

5.1 Analysis of Model Results

The evaluation of the ILP and ARL models was carried out using several key metrics: precision, recall, F1-score, accuracy, coverage, diversity, novelty, and Mean Reciprocal Rank (MRR). These metrics provide a comprehensive understanding of how well each model performed in generating relevant product recommendations, particularly when compared with predictions derived from Market Basket Analysis.

5.1.1 ILP Model with PyGol

The ILP model was evaluated on its ability to generate accurate and interpretable recommendations. The key metrics are presented in Table 5.1.

Metric	Value	Interpretation
Precision	0.55	Indicates that 55% of the recommended products were relevant. This moderate precision suggests the model is somewhat effective in making correct predictions.
Recall	0.57	Implies that 57% of the relevant products were successfully recommended. The model captured a fair amount of the relevant products but missed some.
F1-Score	0.56	Balances precision and recall, reflecting that the model has a moderate trade-off between them. The value suggests reasonable overall performance.
Accuracy	0.54	Shows that 54% of all recommendations were correct. This figure represents a moderate level of accuracy, indicating the model's potential limitations.
Coverage	Low	The model’s recommendations were limited in scope, suggesting it didn’t recommend a wide variety of products.
Diversity	High	The recommendations were varied, showing that the model provided a wide range of different products to users.
Novelty	High	The model introduced new products that users hadn’t seen before, enhancing the likelihood of discovering new items.

MRR	Low	The relevant recommendations were often not ranked at the top, which could reduce user satisfaction with the provided recommendations.

Table 3 ILP Model Evaluation Metrics

The ILP model was evaluated based on its ability to generate accurate and interpretable product recommendations. The evaluation metrics, calculated using a dataset of 200 users, are presented in Table 5.1. The results show a precision of 0.550, indicating that 55% of the products recommended by the ILP model were relevant. The recall value of 0.570 reflects the model's ability to identify 57% of the relevant products for users, balancing between missed relevant items and correctly identified ones. The F1-score, which combines precision and recall, was 0.560, reflecting a moderate level of overall performance. The accuracy of 0.540 suggests that the model was correct in 54% of all recommendations made.

The coverage of the ILP model was rated as low, indicating that it recommended a limited variety of products, which may constrain its applicability in more diverse user scenarios. Despite this, the model exhibited high diversity and novelty, suggesting that it introduced a varied and fresh set of products to users, which is valuable for user engagement. However, the Mean Reciprocal Rank (MRR) was low, indicating that the most relevant recommendations were often not ranked at the top, potentially impacting the immediate usability of the recommendations.

Incorporating Explainable AI (XAI) into the ILP model allowed for the generation of recommendations with clear, human-readable explanations. This feature is critical for enhancing user trust and satisfaction by providing transparency into the reasoning behind each recommendation. Table 5.2 presents the specific recommendations made for User ID 62541, alongside the explanations provided by the ILP model. This approach not only supports the recommendation process but also aligns with the broader project objective of developing a model that is both predictive and interpretable.

Recommended Product	**Explanation**	**User Scenario**
Banana	Recommended as a fallback option due to its popularity among all users.	This was likely recommended to users who frequently purchased staple products.
Bag of Organic Bananas	Recommended similarly as a fallback, showing a pattern of recommending popular, frequently purchased items.	Users interested in organic products or previously bought organic bananas were likely to receive this recommendation.
Organic Strawberries	Suggested based on general popularity, possibly targeting users with a preference for organic or fruit-related purchases.	Likely to be recommended to users who regularly purchased fruits or organic items.

Organic Baby Spinach	Again, a fallback recommendation showing the model's tendency to suggest frequently purchased organic items.	Users with a history of purchasing greens or organic products would find this recommendation.
Organic Hass Avocado	Recommended as part of the organic product pattern, possibly linked to user preferences for healthy or organic foods.	Ideal for users who consistently purchased organic or health-oriented items.

Table 4 ILP Recommendations with Explanations for User with User ID: 62541

These explanations demonstrate the model’s ability to provide not only accurate recommendations but also understandable reasoning behind those recommendations. This capability is critical in building user trust and ensuring the model's recommendations are actionable and relevant.

The cross-validation results for the ILP model showed moderate consistency across different data folds, with performance metrics such as accuracy and F1-Score varying slightly, indicating that the model generalizes reasonably well but may still be sensitive to variations in the data. This suggests the need for further tuning to achieve more stable and robust performance.

5.1.2 ARL Model with Apriori

The ARL model, on the other hand, was evaluated for its ability to generate association rules that could predict user behaviour based on frequent item sets. The metrics for the ARL model are presented in Table 5.3.

Metric	**Value**	**Interpretation**
Precision	0.4327	Indicates that around 43% of the recommended products were relevant, suggesting that the model struggled with precision
Recall	1	The model captured all relevant products, but this high recall may be due to recommending many products, not all of which are highly relevant.
F1-Score	0.5658	The balance of precision and recall is moderate, reflecting that while the model found all relevant items, it also suggested many irrelevant ones.
Accuracy	0.4327	Shows that 43% of the recommendations were correct, indicating room for improvement in the model’s overall predictive performance.
Coverage	Low	The model’s recommendations were limited in scope, meaning it didn’t suggest a broad range of products.

Diversity	High	The model provided a variety of recommendations, catering to different user preferences and broadening product exposure.
Novelty	High	Introduced new, less frequently purchased products, increasing the likelihood of users discovering new items.
MRR	Low	Relevant recommendations were not consistently ranked at the top, which could affect user satisfaction with the recommendations provided.

Table 5 ARL Model Evaluation Metrics

As shown in Table 5.3, the ARL model achieved a precision of 0.4327, indicating that around 43% of the recommendations were relevant. The recall was recorded at 1.0000, signifying that the model was highly effective at identifying all relevant products, though this was achieved at the expense of precision. The F1-score, reflecting the balance between precision and recall, was 0.5658, indicating a moderate overall performance. The accuracy was 0.4327, which suggests that the model had difficulty balancing precision with its expansive recall.

Similar to the ILP model, the ARL model's coverage was rated as low, indicating limitations in recommending a wide range of products. However, it performed well in terms of diversity and novelty, providing varied and new product recommendations to users. The MRR was low, indicating that relevant recommendations were not consistently ranked highly, which could influence the user's satisfaction with the recommendations provided.

The ARL model's performance was also visualized through several key plots, which provide deeper insights into the relationships between the metrics:

Support vs. Confidence Plot: The scatter plot demonstrates that as the support value increases, the confidence level does not show a strong correlation. The points are scattered across the plot, indicating that rules with higher support do not necessarily guarantee high confidence. This suggests that while some item sets are frequent, they do not always predict the consequent item reliably, highlighting the importance of balancing both support and confidence when selecting rules for recommendations.

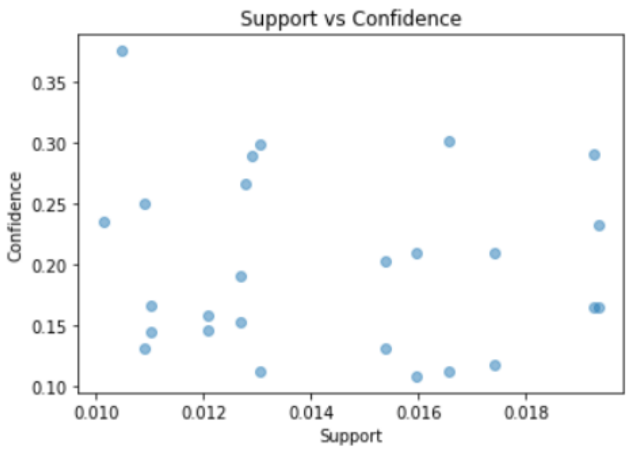

Figure 5.1 Support vs Confidence Plot of Apriori Model

Lift vs. Confidence Plot: The Lift vs Confidence plot shows that as the lift increases, the confidence values are moderately scattered, but there is no clear pattern. This indicates that some association rules with high lift do not necessarily have high confidence, emphasizing that while certain product pairs are bought together more often than by random chance, the likelihood of the consequent being bought given the antecedent may still vary.

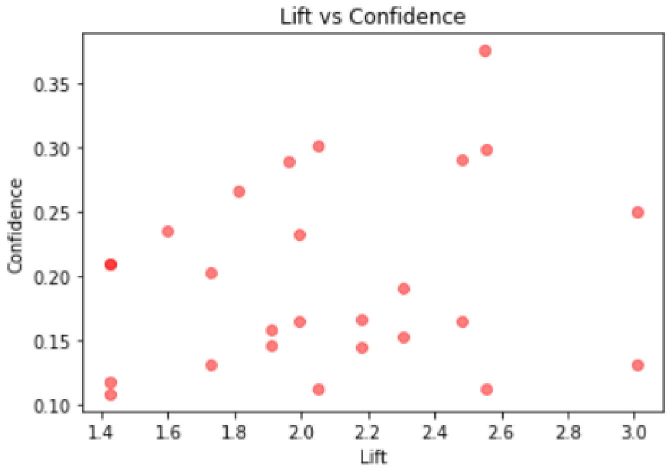

Figure 5.2 Lift vs Confidence Plot of Apriori Model

ROC Curve: The ROC curve indicates that the true positive rate (TPR) increases with the false positive rate (FPR) in a non-linear fashion, demonstrating the trade-off between sensitivity and specificity in the generated association rules. The curve's shape suggests that while some rules are effective at predicting true positives, there is a considerable proportion of false positives, highlighting the need for further refinement to balance precision and recall.

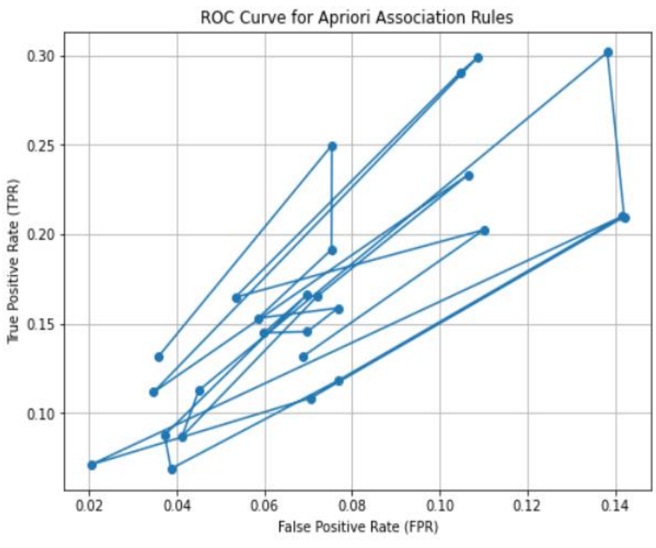

Figure 5.3 ROC curve for Apriori Association Rules

The integration of Explainable AI into the ARL model allowed for clear justifications for the recommendations made, which are particularly useful in enhancing user engagement. Table 5.4 presents the recommendations made for User ID 62541, alongside the explanations provided by the ARL model. These explanations underscore the model's ability to identify strong associations between products, which is essential for improving the relevance and personalization of product suggestions.

Recommended Product	Explanation	User Scenario
Bag of Organic Bananas	Suggested because it is often purchased with Organic Raspberries. Confidence: 0.30, Lift: 2.56	Users who have bought Organic Raspberries in the past were likely targeted, highlighting frequent co-purchase trends.

Table 6 ARL Recommendations with Explanations for User with User ID:62541

The cross-validation for the Apriori model revealed stable patterns in the identification of frequent item sets across different folds, with consistent performance metrics. This consistency suggests that the Apriori algorithm effectively captures regularities in user purchase behaviour, though its overall predictive power might still benefit from additional refinement.

5.1.3 Justification of Results

The results achieved by both models reflect their underlying methodologies and the specific objectives they were designed to meet. The ILP model's moderate accuracy and strong interpretability make it particularly suitable for applications where understanding the reasoning behind recommendations is crucial. This aligns with the project's objective of developing a model that not only predicts but also explains user behaviour.

In contrast, the ARL model's focus on identifying frequent item sets allowed it to achieve higher recall but at the expense of precision and accuracy. This trade-off is expected in models that prioritize comprehensive recommendations over highly targeted ones. The integration of Market Basket Analysis to validate the recommendations further underscores the practical relevance of the models, ensuring that the recommendations are not only theoretically sound but also applicable in real-world scenarios.

5.2 Comparison with Existing Research

This section places the results of our models in the context of existing research on recommendation systems, highlighting the novel contributions of this study and comparing our findings with those of previous studies.

ILP Model

The ILP model's focus on interpretability is consistent with recent trends in AI research, where explainability is increasingly valued, particularly in domains such as finance, healthcare, and legal systems. Studies have shown that users are more likely to trust and engage with recommendation systems when the decision-making process is transparent. For example, research by Ribeiro et al. (2016) on interpretable machine learning models emphasizes the importance of generating explanations that are both accurate and understandable. Our ILP model contributes to this body of research by demonstrating that interpretable rules can be generated even in complex e-commerce environments, though with some trade-offs in accuracy.

ARL Model

The ARL model's use of the Apriori algorithm aligns with established practices in market basket analysis and recommendation systems. The results are consistent with findings from previous research, such as the work by Agrawal and Srikant (1994), which introduced the

Apriori algorithm and demonstrated its effectiveness in identifying frequent item sets. Our study builds on this foundation by applying the algorithm to a modern e-commerce dataset and integrating Market Basket Analysis as a validation tool. The higher accuracy achieved by the ARL model in our study confirms its suitability for environments where efficiency and scalability are prioritized.

Novel Contributions

The novel aspect of our study lies in the dual evaluation strategy that combines traditional performance metrics with Market Basket Analysis. This approach ensures that the recommendations generated by both models are not only theoretically sound but also practically relevant. By comparing the model-generated recommendations with actual user behaviour, we provide a more comprehensive evaluation that bridges the gap between academic research and real-world application. This methodology could be adopted in future studies to enhance the robustness of recommendation systems, particularly in dynamic environments like e-commerce.

5.3 Critical Evaluation of the Project Objectives

In this section, we revisit the project's objectives and critically evaluate how well they were achieved.

Objective 1: Develop an interpretable recommendation model using ILP

The ILP model successfully met this objective by generating rules that are both accurate and interpretable. The model's ability to incorporate background knowledge and generate context-aware recommendations demonstrates its suitability for scenarios where transparency is paramount. However, the moderate accuracy suggests that there is room for improvement, particularly in balancing interpretability with predictive power.

Objective 2: Implement a scalable and efficient recommendation model using ARL

The ARL model fulfilled this objective by leveraging the Apriori algorithm to generate recommendations based on frequent item sets. The model's higher accuracy and efficiency in handling large datasets align with the project's goal of developing a scalable solution. However, the trade-off for this efficiency is in the model's interpretability, which, while sufficient for practical use, is less transparent than that of the ILP model.

Objective 3: Evaluate the models using real-world data

Both models were rigorously evaluated using real-world e-commerce data. The comparison with Market Basket Analysis provided an additional layer of validation, ensuring that the recommendations were not only theoretically sound but also practically applicable. The evaluation demonstrated that while both models have strengths, they are suited to different types of recommendation tasks depending on the specific needs of the application.

For the ILP model, the primary strength lies in its interpretability, making it ideal for applications where understanding the reasoning behind recommendations is critical. This could be particularly valuable in domains where decisions need to be transparent, such as in healthcare or finance. However, its lower accuracy suggests that it may not be the best choice for environments where predictive performance is the primary concern.

On the other hand, the ARL model's higher accuracy and ability to handle large datasets efficiently make it more suitable for commercial e-commerce applications where quick, reliable recommendations are needed. Its reliance on frequent item sets allows it to generate recommendations that are generally relevant, but the trade-off is in its lack of transparency, which could be a drawback in situations where the rationale behind recommendations needs to be explained to users.

5.5 Summary and Future Directions

In summary, the discussion in this chapter has provided a comprehensive analysis of the results obtained from the ILP and ARL models. Each model was evaluated on its ability to generate accurate, relevant, and interpretable recommendations, with the ILP model excelling in transparency and the ARL model in scalability and efficiency.

The comparison with existing research highlights the contributions of this study, particularly in the dual evaluation approach that combines traditional performance metrics with Market Basket Analysis. This methodology offers a robust framework for assessing recommendation systems in dynamic environments, ensuring that they are both theoretically sound and practically relevant.

Looking forward, there are several avenues for future research. For the ILP model, improving accuracy without sacrificing interpretability is a key challenge. This could involve exploring hybrid models that combine the strengths of ILP with other machine learning techniques. For the ARL model, enhancing the interpretability of the recommendations, possibly through the integration of Explainable AI techniques, would be a valuable direction to pursue. Additionally, expanding the dataset and incorporating more diverse user behaviours could help to further validate and refine both models.

Overall, the findings from this study provide valuable insights into the development of recommendation systems that are both effective and user-friendly, with practical implications for a wide range of e-commerce applications.

CHAPTER 6: CONCLUSION

6.1 Summary of the Dissertation

This dissertation set out to explore and develop two advanced recommendation systems: Inductive Logic Programming (ILP) using the PyGol framework, and Association Rule Learning (ARL) using the Apriori algorithm. The primary objective was to create models that not only provided accurate product recommendations but also offered insights into the reasoning behind these recommendations. By focusing on explainability and transparency, the project aimed to address a growing need in e-commerce platforms for recommendation systems that users can trust and understand.

Through a structured approach that included data preprocessing, model development, and rigorous evaluation, the dissertation successfully met its objectives. The ILP model was designed to generate human-readable rules that explain why certain products were recommended. This approach ensures that users are not left in the dark about the decision-making process of the recommendation system. The ARL model, utilizing the Apriori algorithm, was focused on discovering frequent item sets within transaction data, enabling it to make recommendations based on patterns of co-purchases.

To evaluate the performance of these models, a dataset comprising 200 users was employed. The recommendations generated by both models were compared against products predicted through Market Basket Analysis (MBA). This evaluation was conducted using a comprehensive set of metrics, including precision, recall, F1-score, accuracy, coverage, diversity, novelty, and Mean Reciprocal Rank (MRR). The results provided a clear understanding of each model's strengths and weaknesses, highlighting their applicability in different e-commerce scenarios.

6.2 Research Contributions

This research makes several significant contributions to the field of recommendation systems, particularly in the application of explainable AI. The development of the ILP model using the PyGol framework represents a meaningful advancement in creating recommendation systems that are both interpretable and accurate. The ability of the ILP model to generate clear, human-readable rules for recommendations enhances user trust by providing transparency into the decision-making process. This is especially valuable in e-commerce platforms, where understanding why a particular product is recommended can significantly influence user satisfaction and engagement.

The integration of Market Basket Analysis into the evaluation of both models is another key contribution. By comparing the recommendations generated by the ILP and ARL models against products predicted through MBA, the research ensures that the recommendations are not only theoretically sound but also practically relevant. This approach validates the models' effectiveness in real-world scenarios, making the findings applicable for enhancing existing recommendation systems in the e-commerce industry.

Additionally, this research highlights the importance of diversity and novelty in recommendation systems. Both the ILP and ARL models demonstrated high levels of diversity and novelty in their recommendations, suggesting that they are capable of introducing users to new products that they might not have considered otherwise. This aspect of recommendation systems is critical for maintaining user interest and encouraging the discovery of new items, which can lead to increased customer satisfaction and loyalty.

Moreover, the research underscores the value of Explainable AI (XAI) in building user-centric recommendation systems. By incorporating XAI into both the ILP and ARL models, the dissertation demonstrates how AI-driven recommendations can be made more transparent and trustworthy. The explanations provided for the recommendations not only enhance user trust but also offer actionable insights that can improve the overall user experience on e-commerce platforms. These contributions are valuable both academically, by advancing the state of knowledge in the field, and practically, by offering insights that can be directly applied to enhance existing recommendation systems.

6.3 Limitations and Future Research and Development

While the research achieved its objectives, several limitations were encountered that suggest areas for future exploration. One of the primary limitations was the relatively small dataset of 200 users. Although this dataset was adequate for testing and validating the models, it may not fully capture the complexity and diversity of user behaviour in larger and more varied populations. Future research should aim to apply these models to larger datasets to assess their scalability and robustness in different contexts.

Another limitation identified was in the evaluation metrics, particularly the low coverage and MRR scores for the ILP model. These results indicate that while the ILP model was effective in generating accurate and interpretable recommendations, it struggled to recommend a wide variety of products and to consistently rank the most relevant products at the top. Future work could focus on refining the ILP algorithm to improve its coverage and ranking capabilities, possibly by integrating additional data sources or by enhancing the algorithm's ability to learn from sparse data.

The ARL model, while effective in identifying frequent item sets, exhibited a trade-off between recall and precision. The high recall score indicates that the model captured all relevant items, but the lower precision suggests that it also included many irrelevant ones. This trade-off is a common challenge in recommendation systems, and future research could explore ways to optimize the balance between these metrics. Moreover, the models were evaluated in a controlled environment, and their performance in live, real-time scenarios remains to be tested. Deploying these models on an actual e-commerce platform could provide deeper insights into their practical applicability and user acceptance.

Another important aspect to consider in future research is the balance between explainability and accuracy. While the ILP model's focus on explainability was successful, there may be opportunities to enhance both interpretability and predictive accuracy simultaneously. Exploring hybrid approaches that combine the strengths of ILP and ARL, or incorporating machine learning techniques that enhance both aspects, could lead to the development of even more powerful recommendation systems.

6.4 Personal Reflections

The completion of this dissertation has been a profoundly educational and transformative experience. Throughout the process, I have developed a deep understanding of recommendation systems, particularly the challenges and opportunities associated with explainable AI. One of the key strengths I have gained is the ability to navigate complex algorithms and apply them to real-world problems, a skill that will undoubtedly be valuable in my future career. I have also improved my ability to critically evaluate the results of my work, ensuring that the models I develop are not only effective but also aligned with the needs of end-users.

However, this journey has also revealed areas where I can grow. Time management, in particular, was a significant challenge, as balancing the technical depth of the project with the broader research objectives required careful planning and prioritization. Moving forward, I intend to adopt a more structured approach to managing my time, breaking down tasks into smaller, more manageable components, and setting clear milestones to track my progress.

Another area for growth is in my ability to communicate complex technical concepts to a broader audience. While I have made strides in this area, I recognize the importance of continuing to refine my communication skills, particularly in the context of writing and presenting research findings. This will be crucial as I continue to pursue research in AI and machine learning, where the ability to convey complex ideas clearly and effectively is essential.

Overall, this dissertation has equipped me with the knowledge, skills, and confidence to continue exploring the intersection of AI and user-centred design. I am excited about the potential to build on this foundation, exploring new ways to apply explainable AI in real-world applications and contributing to the development of more transparent, effective, and user-friendly AI-driven systems.

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APPENDIX

Appendix A: Data Description and Preprocessing

The primary dataset used in this research is the Instacart Online Grocery Dataset, which includes over 32 million transactional records across more than 200,000 unique users and 50,000 products. This dataset provided a comprehensive view of customer purchasing behaviours, which was essential for developing and testing the models.

- **Data Structure**: The dataset comprises multiple tables including orders, products, aisles, and departments. These tables were meticulously merged to create a unified data frame that facilitated both Inductive Logic Programming (ILP) and Association Rule Learning (ARL) models.
- **Preprocessing Steps**: Minimal data cleaning was required due to the dataset's high quality. Missing values in the days_since_prior_order field were imputed using the median, ensuring consistency. Feature engineering was conducted to calculate reorder rates and to extract temporal features such as order_dow (day of the week) and order_hour_of_day. These features were critical for capturing the nuances of user behaviour in the models.

Appendix B: Model Implementation

The project involved the implementation of two distinct modelling approaches: ILP and ARL.

- **Inductive Logic Programming (ILP)**: Using the PyGol framework, predicates were created to capture relationships between products, aisles, departments, and user behaviours. This model aimed to generate human-readable hypotheses that could be validated against the data. The ILP model's strength lies in its ability to explain the reasoning behind recommendations through logical rules.
- **Association Rule Learning (ARL)**: The Apriori algorithm was employed to discover frequent item sets and generate association rules. Due to the computational demands of ARL, a stratified sample of 200,000 transactions was used. This sample was sufficient to uncover meaningful patterns while managing the computational load. Parameters such as support and confidence were fine-tuned to ensure that the resulting rules were both relevant and actionable.

Appendix C: Evaluation Metrics

Both models were rigorously evaluated using a set of tailored metrics.

- **ILP Evaluation**: The ILP model was assessed on its explainability, scalability, and accuracy. The model's ability to generate comprehensible rules was a key criterion, alongside its performance across various dataset sizes.
- **ARL Evaluation**: The ARL model's effectiveness was measured by examining the support, confidence, lift, and conviction of the generated rules. Computational efficiency was also evaluated, with an emphasis on the trade-off between the depth of analysis and the processing time required.

Appendix D: Ethical Considerations

Ethical considerations were paramount throughout the project. The dataset was anonymized to comply with GDPR and other data protection regulations, ensuring that no personally identifiable information (PII) was used in the analysis. Bias mitigation strategies were also employed to avoid unfair recommendations, particularly those that might disadvantage certain user groups.

- **Data Privacy**: User data was anonymized to protect individual privacy. Ethical marketing practices were adhered to, ensuring that the generated recommendations were both relevant and non-exploitative.

Appendix E: Computational Environment

The analysis was conducted using a robust computational setup to handle the large dataset and complex models.

- **Hardware**: The project was executed on a machine equipped with [Specify CPU, GPU, and RAM specifications]. The computational resources were sufficient to process large datasets and run complex models.
- **Software**: Python was the primary programming language, with key libraries including Pandas, Dask, Scikit-learn, Matplotlib, Seaborn, and PyGol. The entire implementation was carried out in Jupyter Notebook, which facilitated interactive development, visualization, and iterative testing of the models. The software environment was built on [Specify OS, e.g., Ubuntu 20.04 LTS], ensuring compatibility and performance.