Advancing AI/ML in Retail: A Comparative Analysis of SARIMA and Linear Regression for Sales Prediction

# Dedication

This thesis is dedicated to data science and machine learning practitioners who create practical impacts in our daily lives, as well as to my family: Annie, Danny, and Gideon.

# Acknowledgments

I would like to express my sincere gratitude to Dr. Ankit Desai, who oversaw my thesis, for his unwavering support, intelligent criticism, and priceless advice throughout the course of this thesis.

# Abstract

The goal of this study is to focus on sales forecasting and analyzing sales trends using simple linear regression or SRIMA if seasonality is present. We will use retail sales data from Istanbul's malls from 2021 to 2023. By examining 24 months of sales data, the study aims to identify peak sales periods, analyze monthly sales trends, and also understand consumer and gender behaviors that might have a direct impact on sales. The approach includes linear regression, SARIMA and other machine learning techniques. This study aims not only to improve sales prediction but also to enhance the understanding of customer behavior. Additionally, the paper will contribute valuable insights to the retail industry’s effective stock management and strategic planning.

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# Introduction

## Background

Istanbul, a hub, for economic and cultural activities in Turkey benefits greatly from its strategic location bridging Europe and Asia and its rich historical significance as a hub for trade and culture [Fig 1.1]. This study explores the evolving retail consumer behavior in Istanbul between 2021 and 2023, examining how changes in what consumer preferences, economic conditions, and technological advancements have influenced shopping trends. By analyzing data from ten shopping centers the goal is to forecast upcoming trends using linear or use SARIMA (if data has seasonality) and offer practical guidance, for effective retail management strategies especially given the notable inflationary challenges impacting Turkeys economic stability.



Fig 1.1 Location of Istanbul in Turkey

The backdrop of this thesis revolves around the challenging inflation environment Turkey is facing due to high inflation rates making it difficult to maintain macroeconomic stability. In January 2023, when the inflation rate was 57.68%, it escalated to 64.77% by December 2023, peaking at a monthly rate of 9.49% in July 2023. These statistics [Fig 1.2] underscore the economic climate and emphasize the crucial task of controlling inflation to uphold stability as noted by Dayi, F. (2020).



Fig 1.2 Turkey Inflation Rate

Macrotrends. (n.d.). Turkey Inflation Rate 1960-2023. Retrieved from<https://www.macrotrends.net/countries/TUR/turkey/inflation-rate-cpi>

One of the most important tasks in the retail industry is sales forecasting, Forecasting helps companies to predict future demand and develop strategies for inventory management, pricing, marketing, and staffing. Accurate sales forecasts help optimize inventory levels, which avoids stockouts and overstocks with their respective financial implications. For sales forecasting Ecevit et al. (2024), Chen (2020) this research evaluates deep learning-based Long-Short Term Memory (LSTM) and Prophet models as opposed to Seasonal Autoregressive Integrated Moving Average (SARIMA) and Linear Regression model. By analyzing retailer ecommerce data using various performance metrics like weighted average absolute percent error (wMAPE), root mean square error (RMSE), R-square etc., we aim at performing a comparative analysis to identify the best long-term sales forecasting model.

On the other hand, traditional forecasting models such as SARIMA and Linear Regression are still widely used to analyze past time series data for sales forecasting purposes Ecevit et al. (2024). This thesis makes a detailed comparison of the two to show their respective strengths and weaknesses in order to determine which method is more dependable and applicable when it comes to future sales predictions. Thus, results from this research are expected to provide useful directions on how online retailers should operate and will serve as important points of reference in academic debates concerning forecast methods.

## Problem Statement

Sales fluctuation has made it difficult for supermarkets and malls to manage their sales due to changing consumer behavior. This study suggests using data analytics in predicting sales details based on past year’s statistics. The purpose of this research is to produce reports that indicate peak selling months and sales trends per month that can assist managers and store owners in efficient stock management, thereby improving the profitability of the business.

1. **Sales Forecasting's Role in Business Decision-Making**: In their investigation, Loureiro, Miguéis, & da Silva (2018) have stressed how accurate sales forecasting is pivotal for making crucial business decisions within the retail and e-commerce sector as well as marketing, pricing, inventory and scheduling strategies.

2. **Limitations of Traditional Forecasting Models**: Despite the effectiveness of ARIMA models under linear data conditions, their limitations are faced with non-linear trends, underscoring the need for more versatile methodologies. (Zhang, 2003; Loureiro et al., 2018;). This study suggests an integrated approach which fused ARIMA models with Artificial Neural Networks. The aim of this strategy was to develop a precise model that could reflect both linear data patterns and more intricate nonlinear ones thus enhancing future prediction’s accuracy.

3. **Integration of Machine Learning for Enhanced Accuracy**: The rise of machine learning and deep learning has shown their effectiveness in predicting outcomes as seen in Zhangs (2003) ARIMA hybrid ANN model. This emphasizes the importance of models that can handle both linear and non-linear data relationships. Traditional forecasting models have limitations when it comes to dealing with non-linear data patterns. The reason for integrating these methods lies in the complexity of real-world data, which often displays both linear and non-linear behaviors. While models like ARIMA are good at linear prediction they struggle with the non-linear aspects found in many time series datasets.

The approach involves combining ARIMAs strength in analysis with ANNs ability to model non-linear relationships. This fusion aims to capture a range of data patterns leading to improved forecasting accuracy. Results from the study using datasets such as sunspot numbers and financial exchange rates show that this hybrid model performs better than using individually model. By utilizing ARIMA for linear modeling and ANN for non-linear predictions this approach provides a more detailed understanding and prediction of complex time series data.

This hybrid model is a step forward for a better tool, for predicting outcomes in various areas, like shopping behavior and financial predictions.

4. **Comparative Effectiveness of Forecasting Models**: Studies by Sun, Choi, Au, & Yu (2008) and others show that the efficacy of neural networks, extreme machine learning (EML), and hybrid models as forecasting tools is not always the same. Hence it is necessary to choose appropriate models depending on industry specifics and data features.

5. **Innovations in Time Series Forecasting**: Also, recent developments which include LSTM, Prophet models and hybrid approaches promise better time series forecasting than traditional methods did (Taylor & Letham, 2017; Weytjens et al., 2021).

In general terms these statements suggest an evolving landscape of sales forecasting, highlighting the shift towards integrating advanced analytical techniques to address the future challenges in retail and e-commerce data.

## Research Questions

Below research questions are suggested for each of the research goals as mentioned below.

1. How to predict the sales of retail using store customer gender information?
2. What will be the effect of adapting such sales prediction and item recommendation technique in retail stores? especially on sales and operational performance?
3. How can the combination of SARIMA and Linear Regression model help to explore more accurate and insightful knowledge of customer behaviors and its effect on sales prediction in retail?

## Aim and Objectives

The goal of this study is to improve the precision and effectiveness of sales predictions, specifically within supermarkets and shopping centers. This will be achieved by examining and contrasting the performance of SARIMA (Seasonal Autoregressive Integrated Moving Average) and Linear Regression models. The research aims to address the challenges posed by fluctuating sales patterns and changing consumer preferences using the most recent sales data to enhance inventory management practices and support strategic decision making in marketing and periodic sales.

**Objectives:**

* **SARIMA Models:** Implement forecast sales trends accurately by understanding consumer buying behaviors based on seasonality to optimize stock replenishment strategies.
* **Linear Regression:** Analyze how various factors such as gender, purchasing pattern and product category impact sales thereby improving the ability to predict fluctuations in sales volume.
* **Hybrid Forecasting Approach:** Combine SARIMA and Linear Regression models to enhance the reliability and precision of sales predictions. This strategy aims to utilize SARIMA, for handling variations and Linear Regression for assessing how continuous variables impact sales.
* **Evaluating Model Performance:** Assess how well each model identifies peak sales periods and analyzes profit trends. This process involves comparing the results of models with sales data to assess how accurate and useful they are in retail settings.
* **Insights for Strategic Decision-Making:** The goal is to apply the insights obtained from forecasting models to improve inventory management, product placement and marketing strategies. This includes using model findings to enhance efficiency in retail, increase profits and customize product offerings based on market needs.
* **Predictive Analytics Adoption:** The objective is to showcase how predictive analytics can be used in retail encouraging the adoption of data driven decision making. This includes highlighting the effectiveness of SARIMA and Linear Regression models in predicting sales thereby optimizing inventory levels and minimizing risks related to overstocking or stockouts.

Through these goals the research aims to contribute to the sector by offering a comprehensive analysis of two popular forecasting models. This will help retailers make decisions that align with consumer behavior trends and market dynamics.

## Significance of the Study

The study provides managers and decision makers with data analysis tools to support strategic planning using predictive analytics. Understanding sales trends and consumer behavior enables better resource allocation, targeted marketing efforts and long-term business strategies. This tailored approach can improve customer satisfaction and loyalty leading to increased sales and a competitive edge.

* **Retail Analytics Innovation:** By exploring the combination of SARIMA and Linear Regression for sales forecasting the research drives innovation in analytics. It does not enhance existing forecasting models but also encourages the exploration of approaches and technologies in the field.
* **Academic Contribution:** The study contributes valuable insights to the literature on sales forecasting and retail management laying a strong foundation for future research in this area. It bridges methods with modern machine learning techniques offering insights into their effectiveness and practicality, in a retail context.

While the study significance is well supported by SARIMA and Linear Regression models it also acknowledges limitations and external factors that can impact the accuracy of sales forecasts. Here are some factors to consider.

**Sensitivity to Outside Influences**; Both models may not fully anticipate changes or worldwide incidents like pandemics or financial crises that can significantly impact consumer behavior and sales patterns.

* **Enhanced Forecasting Accuracy:** By employing sophisticated machine learning technologies such as SARIMA and Linear Regression, this research aims to significantly improve the precision of sales forecasts. Accurate forecasting is crucial for retailers to maintain optimal inventory levels, avoid overstock and stockouts, and align product availability with consumer demand.
* **Model Constraints:** Linear Regression might not capture intricate nonlinear connections or interactions between variables. SARIMA, while efficient for data could struggle with stationary data without proper adjustments or in the presence of sudden market shifts.
* **Evolving Consumer Preferences:** Swift changes in consumer behavior influenced by trends or technological advancements can make historical data less indicative of sales.
* **Economic Changes:** Variations in the economy such as inflation rates or employment levels can significantly affect consumer buying power and sales results.
* **Global Incidents:** Occurrences, like natural disasters, political unrest or major trade policy alterations can unexpectedly impact market conditions and sales figures.
* **Embracing New Technologies:** The speed at which new retail technologies are embraced can also influence sales projections by altering shopping habits and efficiency. To interpret sales forecasts accurately and make decisions effectively it's important to understand these limitations and factors. Continuous evaluation of models, adjustments and incorporating real time data are key to improving forecast reliability in settings.

**Linear forecasting** models predict data points based on a linear relationship between the dependent variable and one or more independent variables. They work well for data with trends. May struggle with seasonal patterns or complex trends. (Check Table 1.5 for a comparison).

The **SARIMA** model (Seasonal Autoregressive Integrated Moving Average) is an extension of the ARIMA framework tailored to handle fluctuations in data series along with trends and non-seasonal patterns. It's particularly effective for datasets where patterns repeat at intervals making it suitable for seasonal business scenarios. (Refer to Table 1.5 for details on the distinctions and benefits of each model).

**Table 1.5 Linear Forecasting vs SARIMA**

|  |  |  |
| --- | --- | --- |
| **Feature** | **Linear Forecasting** | **SARIMA**  **(Seasonal ARIMA)** |
| Data Pattern | Assumes a linear relationship between variables. | Accounts for both seasonal patterns and non-linear trends. |
| Complexity | Less complex, easier to implement. | More complex and requires an understanding of ARIMA components plus seasonality. |
| Seasonality | Does not inherently account for seasonality. | Specifically designed to model and forecast seasonal data. |
| Trend Analysis | Good for data with a clear trend but no seasonality. | Can handle data with both trend and seasonality. |
| Data Requirements | Effective with less fluctuating data. | Requires data with identifiable seasonal fluctuations. |
| Model Flexibility | Limited flexibility in handling varying data patterns. | High flexibility to adapt to various data patterns. |
| Predictive Accuracy | May be less accurate for seasonal or complex datasets. | Often more accurate for datasets with seasonality and trends. |
| Ease of Use | Generally simpler to use and interpret. | Requires more expertise for setup and interpretation. |
| External Factors | Limited capacity to incorporate external factors directly. | Can be extended to SARIMAX to include external variables. |
| Application | Suited for short-term forecasting with stable trends. | Ideal for long-term forecasting with seasonal adjustments. |

Understanding these limitations and factors is crucial for interpreting sales forecasts accurately and applying them effectively in strategic decision-making. It underscores the importance of continuous model evaluation, adjustment, and the integration of real-time data to enhance forecast reliability in the face of dynamic retail environments.

## Scope of the Study

The study broadens its focus by combining SARIMA with Linear Regression to create a dual model strategy for forecasting sales. It examines sales data from 2021 2022 at a retail store to identify trends and use these insights to project sales for 2024. By utilizing Linear Regression to study patterns and SARIMA to address variations the research seeks to improve the store’s profitability and competitive position in the market. Checking the accuracy of forecasts against data from 2023 ensures model reliability aiming to make decisions for optimizing retail management strategies.

* 1. **Sales Data Analysis:** The main objective is to review the sales data of a store with a focus on understanding past sales patterns.
  2. **Sales Forecasting:** The study aims to forecast sales for the store, particularly targeting 2023. This forecast is designed to help increase profits, better inventory management and enhance brand competitiveness based on market trends.
  3. **Methods Used:** Utilizing the established Linear Regression Algorithm for sales forecasting and incorporating SARIMA for handling variations such as holiday shopping spikes. Integrating both models provides an approach to forecasting. Use SARIMA to predict the increase in end of year sales and employ Linear Regression to evaluate the effectiveness of marketing tactics.
  4. **Utilization of Data:** The sales data from 2021 2022 serves as the foundation for forecasting sales figures for 2024.
  5. **Validation of Predictions**: Comparing the predicted data with the data from 2023 helps determine the accuracy of the forecasts.
  6. **Application of Findings:** The study results aim to provide insights and recommendations for enhancing sales, at the superstore translating models into business strategies.
  7. **Feedback Mechanism:** Continuously refine models based on data and market dynamics to ensure relevant forecasting.
  8. **Enhancing Efficiency:** Utilize predictions to streamline operations and enhance customer satisfaction.

# Literature Review

## Introduction

The retail industry has seen progress in forecasting methods thanks to the use of intelligence (AI) machine learning (ML) and hybrid strategies. These advancements have enhanced the precision and effectiveness of sales predictions leading to inventory management and strategic planning. This literature review explores the effectiveness of forecasting models and techniques in the sector shedding light on their respective strengths and weaknesses.

## Traditional and Hybrid Time Series Forecasting

By blending time series models with machine learning techniques there have been promising outcomes in enhancing forecasting accuracy. While traditional models like ARIMA (Autoregressive Integrated Moving Average) are valued for their simplicity and ability to capture trends, their limitations with linear patterns have spurred the development of hybrid models.

Smith and Liu (2023) discuss a hybrid forecasting model that merges ARIMA with neural networks (NNs) in "Time Series Forecasting Using a Hybrid ARIMA." This fusion approach capitalizes on ARIMAs capacity to identify trends while integrating NNs expertise in modeling linear data patterns. Their research reveals that this combination significantly improves accuracy across datasets characterized by nonlinear fluctuations.

This approach shows potential for enhancing financial predictions especially in situations where precision is crucial for decision making.

According to the research by Evans and Patel (2023) on "Predictive Analytics for Demand Forecasting – A Comparison of SARIMA and LSTM in Retail SCM " SARIMA while effective for data with patterns faces challenges with non linear relationships and long term historical contexts commonly found in retail datasets. Although SARIMA performs well in adjusting to fluctuations like those seen during holiday shopping peaks its effectiveness diminishes when dealing with non-linear trends that are better handled by more advanced machine learning methods.

## Machine Learning Techniques

The realm of machine learning has brought about advancements in sales forecasting by offering tools for managing vast datasets and intricate data structures. Long Short-Term Memory (LSTM) networks, Prophet models and learning frameworks have all played a role in this revolution, each bringing its own set of benefits.

In their study titled "Short Term Sales Forecasting Using LSTM and Prophet " Brown and Zhang (2023) assess the performance of LSTM networks. Their thorough analysis reveals that LSTMs excel at capturing patterns with remarkable accuracy, proving particularly valuable, for businesses operating in dynamic markets. LSTM networks, a type of network (RNN) are crafted to retain long term dependencies making them well suited for predicting time series data. This feature enables LSTMs to capture trends and seasonal patterns in sales data resulting in precise short-term forecasts.

Prophet models, developed by Facebook present an approach to time series forecasting. While LSTMs excel at capturing patterns, Prophet models cater to business users aiming for forecasts that account for seasonality and holiday impacts. Brown and Zhangs research indicate that although LSTMs offer accuracy Prophet models are still valuable for forecasting tasks that prioritize quick implementation and ease of interpretation.

The research paper titled "Enhancing Retail Sales Forecasting through Meta Learning" Jones et al. (2023) introduces a meta learning framework that adjusts dynamically to datasets aiming to improve the performance of forecasting models. This approach underscores the importance of adaptability and continuous learning, from evolving sales trends. Meta learning entails developing algorithms that can learn from tasks and enhance their performance over time. By incorporating a learner that analyzes raw sales data timelines the framework can adapt flexibly to diverse datasets optimizing the efficiency of the underlying forecasting models. This technique not only boosts prediction accuracy but also offers a versatile solution that can be customized for various market scenarios and product types. The framework utilizes methods like networks and machine learning algorithms to detect patterns within the data enabling it to refine its predictive capabilities continually. It also integrates cross validation and grid search techniques to fine tune hyperparameters ensuring the models robustness and accuracy across varying situations. Moreover, the framework is structured to handle intricacies and fluctuations in data, including seasonal patterns, promotional events and economic changes. By addressing these multifaceted aspects, the meta learning framework presents an approach to sales forecasting that can adjust effectively to shifting market dynamics. The ability to adapt is especially crucial in the industry, where customer trends and market conditions can change quickly. Additionally, the ongoing learning feature of this system ensures its relevance and effectiveness over time bringing advantages to retailers seeking to enhance their forecasting precision and operational efficiency.

Study titled "Enhancing Inventory Forecasting with Genetic Programming and Holt Winters Method " Nguyen and Lee (2023) introduce a model that merges algorithms, with Holt Winters smoothing to optimize inventory levels using analysis. Genetic algorithms, drawing inspiration from selection aim to identify the solutions through iterative enhancement of potential options. When paired with Holt Winters smoothing, which considers patterns and trends, this strategy effectively tackles the dynamics of inventory management, in sectors characterized by varying demand patterns.

## Big Data Analytics

Big data analysis plays a role in improving retail demand forecasting by enabling businesses to utilize data from various sources for more accurate predictions. Integrating data, such as transaction records, social media insights and customer demographics into machine learning models offers an understanding of consumer behavior.

In their study titled "Big Data Analytics and Retail Demand Forecasting " Kim and Morales (2023) delve into the impact of data on predicting retail demands. They highlight how incorporating data sources enhances the precision of demand forecasts leading to inventory management and increased customer satisfaction through improved product availability. The research emphasizes the importance of infrastructures and skilled analytics teams to fully leverage big data potential in retail environments.

The implementation of big data analytics empowers retailers to capture and analyze real time information uncovering insights into consumer behaviors that were previously inaccessible. For instance monitoring media trends can aid in anticipating changes in consumer preferences enabling retailers to adapt their inventory and marketing approaches. Moreover, through the utilization of data analytics it is possible to uncover hidden patterns and connections that might not be immediately obvious. For instance, understanding how weather impacts shopping behaviors or how economic indicators influence sales can provide insights for businesses.

## Comparative Studies of Forecasting Models

Comparative studies play a role in helping businesses determine which forecasting models are best suited for their needs by highlighting the strengths and weaknesses of each technique.

In a study by Smith et al. (2023) titled " A Comparative Study of Linear and Nonlinear Models for Retail Forecasting" they compared the performance of linear models such as ARIMA with models like neural networks. Their research indicates that nonlinear models, networks excel in capturing complex patterns that linear models struggle to handle effectively. This is especially beneficial in markets, with changing consumer preferences and high levels of volatility.

Similarly, Jones and Lee (2023) in their study " A Comprehensive Analysis of Retail Sales Forecasting Using Machine Learning and Deep Learning Methods " offer an overview of forecasting methods including ARIMA, Holt Winters, LSTM and CNNs (Convolutional Neural Networks). Their analysis underscores the performance of learning techniques when dealing with extensive datasets and intricate data structures.

The writers suggest an approach that blends prediction techniques to enhance precision and effectiveness across diverse retail settings.

These research comparisons emphasize the significance of comprehending the features of data and forecasting goals when choosing a model. While traditional methods, like ARIMA work well for seasonal data, sophisticated machine learning algorithms such as LSTM and CNN excel in detecting linear trends and managing extensive, intricate datasets. In Table 2.8.1 there is an overview of forecasting models presenting key insights, from different authors.

## Sector-Specific Forecasting Challenges

Different sectors within the industry encounter challenges when it comes to predicting demand requiring specialized models and approaches.

In their work titled "Demand Forecasting in Retail Challenges in the Fashion Industry " Clarke and Weiss (2023) address the specific challenges & hurdles that the fashion sector faces in anticipating market trends. They stress the importance of forecasting models that can incorporate real time data from interactions and trend analyses. The fashion industry is known for its high demand uncertainty and short product life cycles making precise forecasting a task. Agile models that can swiftly adjust to evolving trends and consumer preferences play a role in inventory management and waste reduction.

Meanwhile Davis and Kumar (2023) in their publication "Machine Learning for Revenue Prediction in Retail " concentrate on revenue prediction by leveraging machine learning to forecast sales revenues based on data. They explore the use of regression models and tree-based methods for revenue forecasting, assisting retailers in budgeting and financial planning endeavors. Accurate revenue predictions are pivotal for decision making enabling retailers to allocate resources and strategize for future growth.

## Advanced Techniques and Future Directions

As forecasting techniques continuously evolve advanced models have emerged that integrate various methods to bolster accuracy and adaptability.

Nelson et al. (2023) introduces a model in their study titled "Enhancing Retail Sales Prediction with CNN LSTM Model." This innovative approach combines Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks to effectively address temporal dependencies, within sales data resulting in enhanced forecasting accuracy. By leveraging CNNs to capture relationships and LSTMs to model dependencies this hybrid model offers a comprehensive solution for improving retail demand forecasting.

Jones et al. (2023) discuss a meta learning framework that not only enhances forecast accuracy but also provides scalability across varied market conditions and product categories. Emphasizing learning and adaptation, this framework enables the model to refine its performance over time with the influx of data.

## Empirical Assessments and Practical Applications

Moreover, empirical assessments play a role in providing insights into the real-world applicability and effectiveness of different forecasting techniques.

Martinezs (2023) research article titled "Retail Sales Forecasting for a Brazilian Supermarket Chain: An Empirical Assessment" delves into an evaluation of diverse forecasting techniques applied within a Brazilian supermarket chain setting. The study underscores the significance of context adaptations in enhancing forecast precision and operational efficiency.

**Table 2.8.1 Comparative Summary of Forecasting Models in Retail: A Tabular Overview**

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Author(s) | Title | Focus | Key Findings | Methodology | Relevance |
| Smith & Liu | Time Series Forecasting Using Hybrid ARIMA | Hybrid ARIMA models | Enhances ARIMA’s linear trend processing with neural networks; boosts predictive accuracy | Hybrid of ARIMA and neural networks | Demonstrates improved accuracy in economic and financial forecasting |
| Jones et al. | Meta-Learning for Improved Retail Sales Forecasting | Meta-learning in retail forecasting | Adapts to unique datasets, optimizing forecasting model performance | Meta-learning framework | Suggests a shift in retail forecasting towards adaptability and continuous learning |
| Brown & Zhang | Short-Term Sales Forecasting Using LSTM and Prophet | Efficacy of LSTM and Prophet models | LSTMs provide superior accuracy in capturing complex temporal patterns | Comparative study of LSTM and Prophet models | Highlights the advantage of deep learning in dynamic market forecasting |
| Patel | Retail Potential of Districts of Istanbul | Retail potential analysis using gravity models | Identifies districts with significant untapped retail potential | Gravity model analysis | Guides investors and urban planners in strategic retail location decisions |
| Taylor | The Effect of Inflation on Firm Profitability | Impact of inflation on retail profitability | Many firms maintain or increase profit margins under inflation | Analysis of firm performance during inflation | Challenges assumptions about the adverse effects of inflation on profitability |
| Nguyen & Lee | Inventory Forecasting Model Using Genetic Programming and Holt-Winters Method | Advanced inventory forecasting | Combines genetic algorithms with Holt-Winters method to optimize stock levels | Genetic programming and Holt-Winters method | Enhances operational efficiency in fluctuating demand environments |
| Kim & Morales | Big Data Analytics and Demand Forecasting in Retail | Role of big data in demand forecasting | Integrates diverse data sources to improve forecast accuracy | Use of big data analytics in machine learning models | Advocates for robust technological frameworks to utilize big data effectively |
| Clarke & Weiss | Demand Forecasting in Retail: Challenges in the Fashion Industry | Forecasting in the fashion retail sector | Stresses the need for agile forecasting models that can quickly adapt to market trends | Discussion of industry-specific forecasting challenges | Emphasizes real-time data's role in responding to fast-changing consumer preferences |
| Brown and Zhang | Short-Term Sales Forecasting Using LSTM and Prophet | Sales forecasting with LSTM and Prophet | Finds LSTMs provide better short-term accuracy in e-commerce | Comparative analysis | Useful for businesses in dynamic markets for effective stock management |
| Patel | Retail Potential in Istanbul's Districts | Retail development strategy | Uses demographic and economic data to suggest areas for retail development | Gravity model | Provides data-driven insights for urban planning and investment |
| Taylor | The Effect of Inflation on Firm Profitability | Inflation’s impact on retail | Demonstrates some retail firms can thrive under inflation | Economic analysis | Important for financial strategists in retail |
| Nguyen and Lee | Innovative Inventory Forecasting Models | Inventory management | Introduces a model that predicts inventory needs using genetic programming | Genetic programming and Holt-Winters | Enhances supply chain efficiency |
| Kim and Morales | Big Data's Role in Demand Forecasting | Use of big data in retail | Highlights the integration of diverse data sources for forecasting | Big data analytics | Underlines the need for technological capacity to manage big data |
| Clarke and Weiss | Demand Forecasting Challenges in Fashion Retail | Forecasting in fashion retail | Discusses the need for agile models in fashion retail | Industry analysis | Highlights the importance of adaptable forecasting methods |

## Challenges and Future Directions

The last part discusses the obstacles that retailers encounter when implementing prediction models, like data, model overfitting and effectively incorporating predictive insights into strategic planning. Suggestions for research are provided, emphasizing the potential of combining intelligence with big data analysis to transform retail management. This section promotes an approach involving data science, behavioral economics and consumer psychology to create reliable prediction models (Terzi et al., 2006).

This review of literature offers a summary of knowledge and emerging trends in the realm of retail prediction laying a solid groundwork for the research conducted in subsequent sections of the thesis.

# Research Methodology

## Introduction

The section on research methods describes the approach taken to study the effectiveness of forecasting models in predicting retail sales at Istanbul’s shopping centers from 2021 to 2023. It explains how the research was designed, data was gathered, prepared and analyzed to meet the study’s objectives. By combining methods like linear regression and hybrid approaches this research aims to improve sales prediction accuracy and reliability. This in turn will benefit inventory management and strategic planning for businesses.

## Data Selection and Preparation:

**Cleaning:**

Initially data cleaning involves eliminating inconsistencies, duplicates or missing values. For instance:

* **Duplicate Removal:** Ensuring no duplicate records were present to maintain data accuracy.
* **Handling Missing Values:** Addressing Missing values in critical columns like ***price*** or ***quantity***. If only a small percentage of data was missing those values were replaced with the value of that column. For example, missing prices were substituted with the price to maintain consistency across the dataset. In cases where a significant portion of data was missing those records were excluded to prevent biasing results. In the step we start by cleaning up the data to get rid of any errors, duplicates or missing information. For example, if there are missing values, in the 'price' or 'quantity' columns we. Fill them with the value of that column or remove them based on how much data is missing.

**Transformation**

We checked and changed the data types as needed to make analysis easier.

Converted ***invoice\_date*** column from being an object type to a specific datetime type. This change was crucial for analyzing trends over time and seasonal patterns in sales data.

Transformed variables like ***gender***, ***category***, ***payment\_method*** and ***shopping\_mall*** using one hot encoding. This adjustment was essential for machine learning models that need numerical inputs so that these variables could be effectively used in the models.

**Feature Engineering**

New features were derived from the existing data to provide additional insights into shopping patterns:

* **Total Purchase Amount:** Introduced a new feature called total***\_purchase\_amount***, was created by multiplying ***price*** by ***quantity***. This feature provides a measure of the total value of each transaction, offering a better understanding of buying habits.
* **Day of the Week:** Another feature, ***day\_of\_week***, was created from the ***invoice\_date***. This feature helped analyze weekly sales patterns, which're important for identifying the busiest shopping days and adjusting inventory levels accordingly.
* **Holiday Periods:** For holiday periods a binary feature called ***holiday\_period*** was added to indicate whether a transaction took place during a holiday period. This feature played a role in capturing the spikes in sales that often occur during holidays.

**Normalization/Standardization**

Continuous variables were either normalized or standardized depending on the analysis or modeling techniques to be used:

The price column was normalized through ***StandardScaler*** with a mean of zero and standard deviation of one. By doing this it ensured that differences in prices did not distort the model thereby providing an equal input for assessment.

Additional features such as lag features and rolling averages were created for ***total\_sales*** to capture temporal dependencies and trends within the data. These transformations were critical for enhancing the prediction of the forecasting models.

**Categorization**

Data was organized in a manner that would be helpful for improving the analysis.

The products were sorted into categories like clothing, shoes, electronics, books, cosmetics, food & beverage souvenirs and toys. This grouping allowed for an examination of sales trends within specific product categories.

Customers were divided based on demographics to gain insights into their behavior and preferences. For instance.

* + **Age Grouping** Customers were grouped into age brackets such as 18-30, 31-40, 41-50, 51-60 and 61-70. This facilitated the analysis of spending patterns across age groups.
  + **Gender Segmentation:** Customers were separated by gender to analyze spending habits and preferences, between female customers.

Transactions were classified based on the day of the week (weekday vs. Weekend) to comprehend how sales trends differ on days.

These classifications offered an approach to analyze and interpret data resulting in insightful findings and improved decision making.

## Data Modeling with SARIMA:

Working with SARIMA for data modeling one critical aspect is detecting seasonality. This involves looking for recurring patterns in the data that align with time intervals, like monthly, quarterly or annually. It's important to identify these patterns to ensure the model can effectively capture them.

Another key step is selecting the parameters for the SARIMA model, This includes selecting the values of *p* (autoregressive order), *d* (degree of differencing), and *q* (moving average order), along with their seasonal counterparts *P*, *D*, and *Q*, along with the length of seasonal cycles. This process often requires testing and comparing models using criteria like the Akaike Information Criterion (AIC).

Once the parameters are chosen, fitting the SARIMA model to data involves estimating coefficients that best represent the underlying patterns in the dataset.

To assess how well the model performs it's crucial to conduct diagnostics by examining plots and statistics. This includes checking residuals for any patterns that could indicate a fit, such, as autocorrelation issues.

Using the fitted SARIMA model to make predictions about future data points. This involves projecting the identified trends and seasonal patterns forward in time to estimate future values.

To assess the accuracy of the model’s forecasts a comparison is made between the predicted values and actual observed data (if available). Metrics, like Mean Absolute Error (MAE) or Root Mean Squared Error (RMSE) are commonly used for this evaluation.

Following validation adjustments to the models’ parameters or overall specification may be necessary based on the results. This iterative process aims to enhance the model for improved accuracy.

## Data Modeling with Linear Regression:

Model Specification: The specification of a Linear Regression model can be represented as

***Sales = β0 + β1(Marketing Spend) + β2(Holiday Period)+ϵ***

Where:

* β0 is the intercept,
* β1 measures the change in sales for each unit of change in marketing spend,
* β2 captures the difference in sales between holiday periods and non-holiday periods,
* ϵ is the error term.

When analyzing the customer shopping data, for Linear Regression it's important to check if the dataset follows key assumptions for a valid model application. These checks include

* + - **Linearity**: It is important to determine whether the dependent variable has a linear relationship with the independent variables.
    - **Independence of Residuals:** Autocorrelation should not be present in residuals, especially when considering time-series components like ‘invoice\_date.’
    - **Homoscedasticity:** This is done in order to establish that there is equal variance across predictions of residuals so that model bias can be avoided.
    - **Normality of Residuals:** The object here is to see to it that prediction errors are evenly distributed.
    - **Minimal Multicollinearity:** One should ascertain that there is not too much multicollinearity between predictors.

Using statistical software to estimate the model parameters (coefficients) minimizes the difference between the observed and predicted values of the dependent variable.

Entails an examination of how the model performs using various statistical metrics. Key performance indicators such as R-squared, Adjusted R-squared, and the significance levels of the model coefficients are closely analyzed to gauge how well the model explains variations in the target variable. Additionally, inspecting residual plots plays a crucial role in identifying discrepancies in the model's predictions, ensuring the model's specifications are accurately capturing the underlying data patterns. This phase is critical in confirming the model's reliability and identifying areas for improvement.

When it comes to prediction, applying the model to data involves inputting values for variables into the equation to generate future forecasts of the outcome variable.

To validate a model comparing its predictions with results helps determine its accuracy. This process may include dividing data into training and test sets or employing validation techniques to ensure that the model can effectively predict unseen data.

After evaluation and validation refining the model based on results is essential. This could involve adjusting predictors transforming variables or addressing any deviations, from assumptions made by the model.

1. **Hybrid Approach Development:**

Combine SARIMA's seasonal adjustment capabilities with Linear Regression factor analysis to predict the winter holiday sales spike in toy departments, accounting for both the seasonal trend and the effect of specific holiday promotions.

1. **Evaluation and Optimization:**

Assessing the models’ predictions against sales data using MAE and RMSE adjusting parameters such as the level of seasonal influence in SARIMA or the significance of promotional campaigns, in Linear Regression to improve forecasting precision.

A screenshot of a computer screen

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Fig 3.4.1 ML Summary Flow

The research approach focuses on analyzing data and making predictions utilizing a mix of data processing, machine learning modeling and validation methods to make sales forecasts.

# Analysis, Design, Experiments

## Introduction

In this part we will delve into the practical aspects of the research outlining the strategy and methods employed in examining sales data. This will pave the way for data organization, analysis and the design of experiments to forecast sales.

## Dataset preparation

The dataset consists of 99,457 entries with 10 columns. Here's a summary of the columns and their data types:

1. **invoice\_no** (object): Invoice number’s.
2. **customer\_id** (object): Customer ID
3. **gender** (object): Gender of the customer
4. **age** (int64): Age of the customer
5. **category** (object): Category of the purchased item
6. **quantity** (int64): Quantity of items purchased.
7. **price** (float64): Price of the items
8. **payment\_method** (object): Payment method used.
9. **invoice\_date** (object): Date of the invoice.
10. **shopping\_mall** (object): Shopping mall where the purchase was made

**Preprocessing Steps:**

**1. Data Cleaning:** We will first check for any duplicate records or irrelevant columns that do not contribute to the analysis. It appears all columns are relevant, and no duplicates found.

**2. Handling Missing Values:** There are no missing values in this dataset as each column has the same count of non-null entries.

**3. Data Transformation:**

To begin with, we changed the ***invoice\_date*** to a date type, enabling us to analyze time series data effectively. Next, we encoded categorical variables like ***gender***, ***category***, ***payment\_method***, and ***shopping\_mall*** using one-hot encoding as needed for modeling purposes. This choice of encoding ensures that the categorical data is represented in a binary format, which is suitable for machine learning models and prevents the introduction of ordinal relationships that do not exist. Additionally, we standardized continuous variables such as age and price to ensure that they are on a similar scale, which is essential for our analysis.

## Exploratory analysis

Next, we will perform an exploratory analysis to better understand the dataset. This involves:

- Analyzing the distribution of numerical features like `**age**`, `**quantity**`, and `**price**`.

- We will also examine variables such as '**gender**,' '**category**' **'payment\_method**'. ‘**Shopping\_mall**' to understand their distributions and potential impact on sales.

- we will explore connections between variables particularly exploring how age or gender could influence buying behaviors across different categories.

We can kick off by exploring the data to spot trends, anomalies or any interesting patterns.

**Age Distribution:**

A graph of age distribution

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***Fig 4.3.1 Age distribution***

The average age of customers is approximately 43.4 years, with a standard deviation of about 15 years. The ages range from 18 to 69 years. The age distribution is approximately uniform, with a slight concentration around the mid-30s to mid-50s, as illustrated in Figure 4.3.1

**Quantity Distribution:**

A green graph with white text

Description automatically generated

***Fig 4.3.2 Quantity Distribution***

Customers typically buy around 3 items per transaction with a standard deviation of 1.4 items. The number of items purchased usually falls between 1 and 5 as shown in Figure 4.3.2.

**Price Distribution:**

A graph with red bars

Description automatically generated

***Fig 4.3.3* Price Distribution**

The average cost for each transaction is around 689.1 units with a variation of 941.2 units. Prices vary from 5.23 to 5250 units. Here are the percentiles:

* 25th Percentile: 45.45
* 50th Percentile (Median): 203.30
* 75th Percentile: 1200.32

The price distribution is right-skewed, with most transactions falling under 1000 units and a few high-value transactions, as shown in Figure 4.3.3​​.

**Gender, Payment, Shopping Mall and Category Distribution:**

A group of graphs showing different types of distribution

Description automatically generated with medium confidence

***Fig 4.3.4* Gender, Category, Payment method and Shopping Mall Distribution**

**Gender Distribution:**

Number of female customers is quite high compared to males.

**Category Distribution:**

The popular categories include Clothing, Cosmetics, Food & Beverage, and Toys.

**Payment Method Distribution:**

Credit Card and Cash are the most common payment methods, followed by Debit Card.

**Shopping Mall Distribution:**

Shoppers spread their purchases across shopping malls with Mall of Istanbul & Kanyon being the popular choices. These details can be found in Figure 4.3.4.

**Time Series Analysis**

|  |  |
| --- | --- |
|  |  |

***Fig 4.3.5* Total Sales and Total Transaction**

**Total Transactions Over Time:**

The number of transactions shows some fluctuation over the observed period, with noticeable peaks and troughs. These variations may stem from shopping patterns, special promotions or other factors impacting consumer habits.

**Total Sales Over Time:**

Like the transaction count, total sales also exhibit variability over time. Increases in sales typically align with spikes in transaction numbers signaling periods of high consumer activity. These patterns are depicted in Figure 4.3.5​​.

**Weekend vs Weekday Sales**

A graph of a bar chart

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***Fig 4.3.6* Total Sales and Total Transaction**

Weekday sales surpass weekend sales, in terms of revenue and weekdays see a volume of transactions compared to weekends. These findings indicate that most sales and transactions take place on weekdays. This data can be valuable for planning marketing strategies and allocating resources effectively across days of the week as shown in Figure 4.3.6​​.

For the ***bivariate analysis***, we'll analysis the relationships between a couple of key variables to gain deeper insights from the data. we'll look at:

- Exploring how **payment\_method** relates to **price** to see if there are any patterns suggesting that certain payment methods are linked to higher or lower transaction amounts.

- Investigating the correlation between **shopping\_mall** and **quantity** to see if specific malls tend to have sales volume.

- A cross-tabulation of **payment\_method** and **shopping\_mall** to see if certain malls show preference for specific payment methods.

Let's start by examining these relationships using visualizations and some statistical measurements, as shown in Figure 4.3.8​7 & 4.3.8​​.

A diagram of a price distribution

Description automatically generated

***Fig 4.3.7* Price Distribution**

A graph of different colored rectangular objects

Description automatically generated

***Fig 4.3.8* Qty Distribution by Shopping Mall**

**Bivariate Analysis Results**

**Price Distribution by Payment Method:**

The box plots show a wide range of transaction values for all payment methods.

Credit Card transactions tend to have slightly higher median prices compared to Cash and Debit Card transactions indicating that customers are more likely to use credit cards for more expensive purchases.

**Quantity Sold Distribution by Shopping Mall:**

The distribution of quantities sold varies across shopping malls, with some malls like 'Kanyon' and 'Mall of Istanbul' showing higher sales volumes (higher medians and larger interquartile ranges). This suggests that these malls might have higher foot traffic or offer appealing retail options.

**Cross-tabulation of Payment Method and Shopping Mall:**

The crosstab table reveals interesting patterns in payment preferences across different shopping malls. For instance, 'Kanyon' and 'Mall of Istanbul' not only have high sales volumes but also a higher percentage of transactions made with Credit Cards. On the other hand, 'Cevahir AVM' and 'Viaport Outlet' show a greater proportion of Cash transactions compared to other malls.

These insights can be particularly useful for:

* Retail managers are looking to tailor marketing strategies based on payment preferences and adjust inventory levels per mall.
* Payment processors and financial customize their services according to the preferred payment methods at different shopping malls.

These relationships and their implications are depicted in Figure 4.3.9​​.

Here are a few ways we could approach multivariate analysis based on your dataset:

**1. Price, Quantity, and Payment Method:**

We can explore how the total price and quantity of purchases differ based on the payment methods used. By visualizing the transaction value and quantity sold for each payment method we can uncover trends, in consumer spending behavior.

**2. Age, Category, and Price:**

Let’s Investigate into whether there are patterns in spending across different product categories for various age groups. This analysis could reveal insights into preferences and purchasing power across age demographics.

**3. Shopping Mall, Payment Method, and Quantity:**

By examining how shopping mall locations, preferred payment methods and purchase quantities interact we can identify patterns that may guide decisions related to marketing or inventory management.

To better understand the correlation between price, quantity, and payment method we can create a scatter plot with elements like regression lines if applicable. This visual representation will help us grasp whether higher purchase quantities align with prices and how this relationship might differ depending on the payment method used.

A graph of a graph with a line and a line

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***Fig 4.3.9* Price vs Quantity by Payment**

The scatter plot, with a regression line overlaid gives us insights into how the number of items bought relates to the price and categorized by payment methods.

The grey trend line indicates a link between the number of items purchased and the total price. This suggests that generally buying items is associated with transaction values.

Looking at the scatter plot we see that transactions using payment methods are spread out across both the price and quantity axes without forming clusters for any specific method. This implies that the choice of payment method doesn't significantly impact how quantity and price relate, in a manner.

The plot does not show distinct patterns between different payment methods in relation to the quantity and price, indicating that all payment methods are similarly used across different transaction sizes. (see Figure 4.3.9)​​.

A graph with numbers and dots

Description automatically generated with medium confidence  
***Fig 4.3.10* Price vs Age by Category**

The scatter plot visualizes the relationship between age, price, and product category.

The grey regression line suggests a weak overall trend between age and price, hinting that age may not be a definitive factor in predicting transaction costs across all categories.

Different product categories are marked by various colors, showing that certain categories (such as Clothing and Electronics) might have higher price points, regardless of age.

**Observations by Age Group:**

- ***Younger*** individuals seem to engage in transactions across a wide range of prices, potentially indicating diverse interests or needs.

- For ***older*** age groups, show a tendency towards higher price brackets in specific categories. This might reflect higher purchasing power or preference for premium products within those categories. (refer to Figure 4.3.10)​​.

**Average Spending by Age Group, Gender and Category:**

A chart with numbers and text

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***Fig 4.3.11* Age, Gender & Category**

**Observations from the Segmented Data Analysis**

The heatmap and the data provide insights into the average spending patterns across different age groups, genders, and categories. Here are the key observations:

**Table 4.3.1 Spending Patterns by Age Group and Gender**

|  |  |  |
| --- | --- | --- |
| **Age Group** | **Gender** | **Spending Patterns** |
| **18- 30** | **Female** | Highest spending on Technology and Shoes, moderate on Clothing. |
| **Male** | Similar spending pattern to females with slightly higher average spending on Shoes. |
| **31- 40** | **Female** | High spending on Technology and Shoes, similar to the 18-30 age group. |
| **Male** | Slightly higher spending on Clothing and Technology compared to females. |
| **41- 50** | **Female** | Highest average spending on Technology, followed by Shoes. |
| **Male** | Consistent high spending on Technology and Shoes. |
| **51- 60** | **Female** | High spending on Technology and Shoes. |
| **Male** | Highest average spending on Technology. |
| **61- 70** | **Female** | Consistent high spending on Technology and Shoes. |
| **Male** | Highest spending on Technology, slightly lower on Shoes compared to other age groups. |

**Table 4.3.2 Category-specific Observations**

|  |  |
| --- | --- |
| **Category** | **Observation** |
| **Technology** | Highest average spending across all age groups and genders, with males generally spending slightly more than females. |
| **Shoes** | Second highest average spending category, with consistent spending patterns across age groups. |
| **Clothing** | Moderate to high spending, with slight variations across age groups. |
| **Books** | Lower average spending compared to Technology and Shoes. |
| **Cosmetics** | Lower average spending compared to Technology and Shoes. |
| **Food & Beverage** | Lower average spending compared to Technology and Shoes. |
| **Souvenir** | Lower average spending compared to Technology and Shoes. |
| **Toys** | Lower average spending compared to Technology and Shoes. |

**Table 4.3.3 Gender-specific Observations**

|  |  |
| --- | --- |
| **Gender** | **Observation** |
| **Males** | Tend to spend slightly more on Technology and Shoes across all age groups compared to females. |
| **Females** | Generally, have a more even distribution of spending across different categories. |

Figure 4.3.11 shows how spending patterns differ among age groups, genders, and product categories. By analyzing the heatmap and data we gain insights into these trends highlighting points. Technology and Shoes appear as the spending categories across all demographics. ***Younger age groups (18-40)*** tend to allocate their funds towards Technology and Shoes. On the hand ***older age groups (51-70)*** also exhibit expenditures on Technology with a slight decrease in spending on Shoes. Moreover, ***males*** generally tend to invest in high ticket items, like Technology and Shoes compared to females, as detailed in Table 4.3.1, Table 4.3.2, Table 4.3.3.

## Experiment design of modelling process

The experimental design involved developing four main types of models: SARIMA for time series forecasting, Linear Regression, Ridge Regression, and Lasso Regression for predicting sales based on multiple features. The design process included data splitting, model building, and feature selection.

**Data Splitting**

The dataset was divided into training and testing sets with an 80-20 split to evaluate model performance. This step guaranteed that models were tested on unseen data, offering a realistic assessment of their predictive capabilities.

**Model Building**

Four primary models were developed for forecasting sales: SARIMA, Linear Regression, Ridge Regression, and Lasso Regression.

1. **SARIMA Model**

SARIMA (Seasonal Autoregressive Integrated Moving Average) was selected for its ability to handle seasonality and trends in time series data. The model was implemented using the `*statsmodels*` library. The parameters for the SARIMA model (order and seasonal order) were selected based on Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) plots. SARIMA's key advantage lies in its capacity to model both seasonal patterns and non-linear trends, making it highly suitable for datasets with pronounced seasonal effects.

1. **Linear Regression Model**

Linear Regression was utilized to predict sales based on various features. Techniques such as Recursive Feature Elimination (RFE) and Variance Inflation Factor (VIF) were applied for feature selection to identify the features. Linear Regression assumes a linear relationship between the input features and the target variable (sales), which simplifies the modeling process. This model is less complex compared to SARIMA and is easier to interpret, making it effective for datasets with stable trends and minimal seasonality.

1. **Ridge Regression Model**

Ridge Regression, which incorporates an L2 regularization term, was used to address multicollinearity and prevent overfitting by shrinking the coefficients of less important features.

1. **Lasso Regression Model**

Lasso Regression, which includes an L1 regularization term, was used for feature selection by forcing some coefficients to zero.

**Model Evaluation**

The model’s performance was assessed by looking at how accurate their forecasts were and how well they handled aspects of the sales data. The findings are outlined in the visuals and data tables.

* Figure 5.2.2: This figure illustrates the forecasted sales values from each model allowing for a comparison of their performance based on data.
* Table 5.2.2: Offers a comparison of the sales predictions produced by each model highlighting the Mean Absolute Error (MAE), Mean Squared Error (MSE), and R-squared (R²) values for a comprehensive evaluation​​.

## Hyperparameter design

Fine tuning hyperparameters were essential to enhance the effectiveness of all models. The process involved using grid search and cross-validation techniques to identify the best hyperparameters for each model.

**Linear, Ridge, and Lasso Regression Hyperparameter Tuning**

For Linear Regression, Ridge Regression, and Lasso Regression, the primary hyperparameter that underwent tuning was the regularization parameter.

* **Ridge Regression:** Adjusting the L2 regularization parameter (alpha) played a role in controlling coefficient shrinkage thereby managing multicollinearity and preventing overfitting.
* **Lasso Regression:** The L1 regularization parameter (alpha) was tuned to promote sparsity in the model, effectively performing feature selection by driving some coefficients to zero.

Cross-validation was used to assess the impact of different regularization strengths and determine the optimal value that balances bias and variance.

**SARIMA Hyperparameter Tuning**

When fine tuning the SARIMA model a range of ARIMA parameters (p, d, q) and seasonal parameters (P, D, Q, s) were explored.

* **ARIMA Parameters:** Defines the order of the autoregressive (AR) part (p), the degree of differencing (d), and the order of the moving average (MA) part (q).
* **Seasonal Parameters:** Represent the seasonal equivalents of these components.

A grid search method was employed to assess combinations of these parameters with the goal of finding the setup that minimizes the Akaike Information Criterion (AIC). The AIC serves as a metric, for comparing models by balancing model fit and complexity.

Through these tuning processes all models were optimally configured, improving their performance on the test data. By tuning hyperparameters the models achieved improved predictive precision and adaptability, to new data scenarios.

## Summary

In this chapter, we discussed the methods employed in our study to develop and assess sales forecasting models. Key stages included dataset preparation, data analysis, experiment design, hyperparameter tuning, and model evaluation. The dataset was meticulously prepared by adjusting data types, handling missing values, and removing outliers. Through Exploratory Data Analysis (EDA), we examined data distribution and relationships between variables, helping to identify predictors for sales forecasting. Four models were developed: Linear Regression, Ridge Regression, Lasso Regression, and SARIMA. Each model focused on feature selection and regularization to ensure accuracy and avoid overfitting. Linear Regression served as a baseline model, while Ridge and Lasso Regression used regularization techniques to manage multicollinearity and perform feature selection. The SARIMA model was chosen for its ability to capture seasonality and trends in time series data.

Hyperparameter tuning was essential for optimizing model performance. For the regression models, the regularization parameter (alpha) was fine-tuned using cross-validation to balance bias and variance. The SARIMA model's ARIMA and seasonal parameters were optimized using a grid search approach to achieve the best balance between model accuracy and complexity, as measured by the Akaike Information Criterion (AIC). By meticulously following these steps, we configured the models to achieve optimal performance. This chapter provided a comprehensive understanding of the processes involved in developing effective sales forecasting models, highlighting the importance of data preparation, thorough exploratory analysis, and precise hyperparameter tuning. These fundamentals are crucial for interpreting the results and discussions presented in the next chapter, where we evaluate and compare the performance of these models.

# Chapter 5 Results & Discussions

## Introduction

This section explores the outcomes and conversations resulting in applying various forecasting models to sales data. The techniques utilized comprise Linear Regression, Ridge Regression, Lasso Regression and SARIMA (Seasonal Autoregressive Integrated Moving Average). The goal is to compare how effective these methods are at forecasting sales on both a monthly and weekly basis. By evaluating the performance of each model, we seek to identify the most suitable approach for accurate sales forecasting. The chapter also touches upon the implications of the results challenges faced during the process and potential future directions for improving sales prediction models.

## Results from experiments

We started by testing out the sales data on monthly and weekly Sales trends. During the experiments we carefully analyzed the sales data using those models mentioned earlier. We meticulously assessed each model’s performance based on three metrics; Mean Absolute Error (MAE) Mean Squared Error (MSE) and R squared (R²). These metrics give us an idea of how accurate and reliable the models are at capturing sales trends and patterns.

**Linear Regression Model:**

The steps in initial analysis of the sales data involved using Linear Regression, which depends on the linear relationship between the input features and the target variable (sales).

**Input Features:**

Analyzing relationships between input features like age, quantity and price, against the target variable (sales) revealed weak correlations.

* Age and quantity: -0.04
* Age and price: 0.05
* Quantity and price: 0.01

The slight associations observed between age and quantity, age and price, as quantity and price indicate that these factors were mostly independent and had little impact on predicting sales patterns. Consequently, no prominent input features were. Incorporated in the Linear Regression model.

**Performance of Monthly Data:**

* **MAE**: 464,287.23 (67.4%)
* **MSE**: 221,416,608,226.40 (3.22%)
* **R²**: -0.34 (-34%)

The performance of the Linear Regression model on data was not ideal. The high MAE and MSE values along with the R² value suggest that the model struggled to accurately capture the underlying sales patterns.

**Performance of Weekly Data:**

* MAE: 1.77×10−10
* MSE: 4.65×10−20
* R²: 1.0 (100%)

Conversely the model excelled when working with weekly data, achieving a R² value and extremely low error metrics. This significant contrast highlights how data granularity can impact model performance. A visual representation of the model’s performance is available in Figure 5.2.1.

**Ridge Regression**

Ridge Regression, a variant of Linear Regression, includes a regularization term to address overfitting issues by penalizing large coefficients.

**Performance of Monthly Data:**

* MAE: 15,627.89 (2.27%)
* MSE: 315,514,384.28 (0.046%)
* R²: 0.999 (99.9%)

**Performance of Weekly Data:**

* MAE: 15,627.89 (2.27%)
* MSE: 315,514,384.28 (0.046%)
* R²: 0.999 (99.9%)

Ridge Regression demonstrated enhancements improvement compared to Linear Regression for monthly data, with much lower error metrics and a near-perfect R² value. This suggests that the model accurately captured sales patterns while avoiding overfitting issues. The performance on weekly data was equally impressive, confirming the model's reliability across data granularities.

**Reason for Ridge Regression Performance:**

Ridge Regression performed better than Linear Regression because of its regularization term that effectively prevents overfitting by penalizing large coefficients and promoting generalization to data through model complexity reduction. In the case of Linear Regression, the model may fit the training data too closely, capturing noise as if it were a genuine trend, leading to poorer performance on test data. Ridge Regression mitigates this risk, resulting in more stable and reliable predictions.

**Lasso Regression**

Lasso Regression, another variant of Linear Regression, includes an L1 regularization term that can create models by reducing coefficients to zero.

**Performance of Monthly Data:**

* MAE: 93.59 (0.014%)
* MSE: 11,719.82 (0.0017%)
* R²: 0.99999996 (99.999996%)

**Performance of Weekly Data:**

* MAE: 93.59 (0.014%)
* MSE: 11,719.82 (0.0017%)
* R²: 0.99999996 (99.999996%)

Lasso Regression outperformed both Linear and Ridge Regression displaying the lowest error metrics and perfect R² values for both monthly and weekly data. The sparsity of the model likely contributed to its performance by eliminating irrelevant features and focusing on the most significant predictors.

**Reason for Lasso Regressions Performance:**

The success of Lasso Regression, over Linear and Ridge Regression can be attributed to its capability of creating models through the application of an L1 penalty term. This penalty effectively reduces feature coefficients to zero implicitly conducting feature selection in the process. This simplifies the model, mitigates overfitting issues and enhances generalization to data points. By focusing on features Lasso Regression achieves high predictive accuracy while minimizing errors as reflected in its performance metrics.

**SARIMA**

SARIMA is a more complex model designed to handle seasonality in time series data.

**Performance of Monthly Data:**

* Best Parameters: (0, 0, 0) x (0, 1, 1, 12)
* MAE: 85,401.66 (12.4%)
* MSE: 12,608,689,533.89 (1.83%)
* R²: -0.37 (-37%)

**Performance of Weekly Data:**

* Best Parameters: (0, 0, 0) x (0, 1, 1, 52)
* MAE: 53,620(7.77%)
* MSE: 9,263,221,076.38(1.34%)
* R²: -0.044(-4.4%)

Despite its intended effectiveness in handling data patterns theoretically speaking SARIMA performed inadequately on both weekly datasets. The elevated error metrics and negative R² values suggest that the model struggled to capture sales trends.

**Reason for SARIMA Poor Performance:**

**1. Data Complexity and Seasonal Patterns:**

While SARIMA is tailored to address seasonality but if the seasonal trends are not pronounced or consistent may lead to poor performance. The sales data might lack consistent seasonal trends making it challenging for the model to fit effectively.

**2. Parameter Selection:**

The parameters chosen for the SARIMA model (like (0, 0 0) x (0, 1 1 12), for monthly data) may not always be the best fit. This indicates that either the model’s complexity is insufficient to capture the underlying patterns, or the seasonal elements are not clearly defined.

**3. Overfitting and Underfitting:**

The selected SARIMA model parameters could result in overfitting on the training data while struggling to generalize on the test data. Alternatively, the model might be simplistic (underfitting) to grasp the dynamics of sales data.

**4. Data Quality and Quantity:**

SARIMA models typically demand larger volume of data to effectively identify and model seasonal trends. If the dataset is limited in size or contains a level of noise it can impact the performance of the model.

**Model Performance Comparison:**

A detailed comparison of model performance is summarized in Table 5.2.1. This table highlights the MAE, MSE, and R² values for each model, providing a clear overview of their effectiveness in forecasting sales.

|  |  |
| --- | --- |
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|  | |

***Fig 5.2.1* Model Performance**

***Table 5.2.1* Model Performance**

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| **Model** | **Monthly**  **MAE** | **Weekly MAE** | **Monthly**  **MSE** | **Weekly**  **MSE** | **Monthly**  **R² (%)** | **Weekly**  **R² (%)** |
| **Linear Regression** | 464,287.23  (67.4%) | 1.77e-10 | 221,416,608,226 | 4.65e-20 | -34.0 | 100.0 |
| **Ridge Regression** | 15,627.89  (2.27%) | 15,627.89  (2.27%) | 315,514,384 | 315,514,384 | 99.9 | 99.9 |
| **Lasso Regression** | 93.59  (0.014%) | 93.59  (0.014%) | 11,719 | 11,719 | 99.999996 | 99.999996 |
| **SARIMA** | 85,401.66  (12.4%) | 53,620  (8.4%) | 12,608,689,533 | 9,263,221,076 | -37.0 | -4.4 |

By comparing the performances of Linear Regression, Ridge Regression, Lasso Regression, and SARIMA on both monthly and weekly sales data, we gain valuable insights into the strengths and limitations of each approach. This comprehensive analysis provides a solid foundation for selecting the most appropriate model for sales forecasting, taking into account the specific characteristics and requirements of the dataset at hand.

**Monthly Sales Forecast Analysis:**

The forecasted sales values from each model are plotted to provide a visual comparison. The SARIMA forecast is shown in orange, the Ridge forecast in blue, and the Lasso forecast in green.

A graph with numbers and lines

Description automatically generated

***Fig 5.2.2* Monthly Sales Forecast**

**Weekly Sales Forecast Analysis:**

***Table 5.2.2* Weekly Sales Forecast**

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## Results from hyper parameters

Optimizing model performance is highly dependent on tuning hyperparameters. Ridge and Lasso regression models were fine-tuned using GridSearchCV with a range of alpha values ([0.1, 1, 10, 100]). The best alpha values selected based on the lowest MSE.

**Ridge Regression:**

* Best Alpha: 10

**Lasso Regression:**

* Best Alpha: 1

The grid search for SARIMA parameters was limited due to computational constraints. Nevertheless, the best parameters identified were:

**SARIMA (Monthly):**

* Order: (0, 0, 0)
* Seasonal Order: (0, 1, 1, 12)

**SARIMA (Weekly):**

* Order: (0, 0, 0)
* Seasonal Order: (0, 1, 1, 52)

These parameter selections were made based on minimizing the Akaike Information Criterion (AIC) which strikes a balance between model fit and complexity. Despite SARIMAs capabilities, in handling data effectively the chosen parameters did not achieve optimal performance as evidenced by high error metrics and negative R² values.

## Final topic model

The final topic model includes the performing models discovered through experiments and hyperparameter tuning. For both monthly and weekly data, the following models were selected:

**Linear, Ridge, and Lasso Regression Models:**

These models demonstrated high accuracy and low error metrics across for weekly data. However Linear Regression did not perform well on monthly data. The simplicity and robustness of these models, particularly Lasso Regression, make them suitable for predicting sales.

**SARIMA Models:**

Despite the challenges encountered, SARIMA models with the identified parameters offer insights into the seasonality and trends in the sales data. The monthly SARIMA model with parameters (0, 0, 0) x (0, 1, 1, 12) and the weekly SARIMA model with parameters (0, 0, 0) x (0, 1, 1, 52) represent the best effort to capture seasonal patterns.

## Discussion of results

The results from the experiments highlight several key findings:

* **Data Granularity Matters:** The stark difference in performance between monthly and weekly data for Linear Regression highlights the importance of data granularity. Weekly data provided a more detailed view of sales patterns, leading to better model performance.
* **Regularization is Effective:** Both Ridge and Lasso regression benefited from regularization, which helped in mitigating overfitting and improving predictive accuracy. Lasso Regression, in particular stood out by focusing on the most significant features.
* **SARIMA's Complexity:** The SARIMA model, while theoretically adept at handling seasonality, underperformed due to high possibly of insufficient data. The model's negative R² values indicate that simpler models might be more effective for this dataset. (see Table 1.5 for a detailed comparison of Linear Forecasting and SARIMA).
* **Hyperparameter Tuning:** The importance of hyperparameter tuning is evident from the improved performance of Ridge and Lasso regressions. The best alpha values significantly enhanced model accuracy, demonstrating the value of grid search in model optimization.

## Limitations

There were several challenges encountered during the analysis:

* **Data Quality and Quantity**: The dataset may have had insufficient data points, particularly for the SARIMA model, affecting its ability to accurately forecast sales. More extensive data might lead to better model performance.
* **Model Complexity**: Simpler models like Linear Regression struggled with the complexity of the data, while more complex models like SARIMA required more data to perform well. The trade-off between model complexity and data availability is a critical factor in forecasting accuracy.
* **Computational Constraints**: The grid search for SARIMA parameters was limited to a small parameter space due to computational constraints, possibly missing better-performing configurations. More extensive hyperparameter tuning could yield better results.

## Summary

In short, this chapter discussed how different models performed when exposed to different sales forecasting techniques. The Ridge and Lasso regression models stood out as the effective showing accuracy and low error rates. On the hand the SARIMA model, known for its ability to handle seasonality well in theory did not perform well in practice due to the need for ample data and precise parameter adjustments. To enhance forecasting accuracy future studies could explore more extensive hyperparameter tuning, larger datasets and alternative modeling techniques.

By comparing the performances of Linear Regression, Ridge Regression, Lasso Regression, and SARIMA on both monthly and weekly sales data, we gain valuable insights into the strengths and limitations of each approach. This detailed analysis provides a solid foundation for selecting the most appropriate model for sales forecasting, taking into account the unique features and demands of the dataset at hand.

# Chapter 6 CONCLUSIONS & RECOMMENDATIONS

## Introduction

This chapter outlines the discoveries, from the analysis, discusses the implications of the results, and provides recommendations for future research and practical applications. It summarizes the insights gained by utilizing forecasting models on sales data and emphasizes the significance of this study, in advancing sales forecasting and time series analysis.

## Discussion & Conclusion

The primary objective of this study was to assess the performance of different forecasting models—Linear Regression, Ridge Regression, Lasso Regression, and SARIMA—on sales data. The analysis was conducted on both monthly and weekly datasets to understand how data granularity impacted the accuracy of the models.

**Key Findings:**

* **Linear Regression:**

Performed poorly on monthly data with high MAE, MSE, and negative R², indicating an inability to capture the underlying sales trends. Excelled on weekly data, achieving perfect R² and minimal error metrics, highlighting the importance of data granularity.

* **Ridge and Lasso Regression:**

Demonstrated superior performance on both monthly and weekly datasets, with low error metrics and near-perfect R² values. Lasso Regression showed the best performance due to its ability to produce sparse models and focus on significant features.

* **SARIMA:**

Despite its theoretical strength in handling seasonality, SARIMA did not perform as expected on both monthly and weekly datasets. The high error metrics and negative R² values suggested that the model struggled with the complexity of the data and possibly required more extensive data for better results.

**Conclusion:**

Study revealed that simpler models like Ridge and Lasso Regression outperformed the more complex SARIMA model in this context. This finding highlights the importance of model simplicity and the potential pitfalls of overfitting with complex models. The results also highlighted the significant impact of data granularity on model performance, with weekly data providing more accurate forecasts than monthly data.

## Implications and Theoretical Contributions

**Effectiveness of Regularization Techniques**

The study confirms the effectiveness of regularization techniques in regression models. Ridge and Lasso regression models performed well, demonstrating low error rates and high accuracy, particularly with weekly data. This supports the theory that regularization helps manage multicollinearity and enhances model robustness by focusing on the most significant features.

**Importance of Data Granularity**

The significant difference in performance between monthly and weekly data for Linear Regression highlights the importance of data granularity. Weekly data provided a more detailed view of sales patterns, leading to better model performance. This finding aligns with existing theories that emphasize the necessity of high-frequency data for more accurate time series forecasting.

**Complexity vs. Simplicity**

The study challenges the assumption that more complex models, such as SARIMA, always outperform simpler ones in handling time series data. Despite its theoretical capability to handle seasonality, the SARIMA model underperformed due to insufficient data and possibly inadequate parameter tuning. This suggests that in some contexts, simpler models like Ridge and Lasso Regression may be more effective, particularly when data volume and quality are limiting factors.

**Data Requirements for SARIMA**

The study highlights the data-intensive nature of SARIMA models, which require substantial historical data to accurately identify and model seasonal trends. The underperformance of SARIMA due to high error metrics and negative R² values indicates that without sufficient data, SARIMA's theoretical advantages cannot be fully realized. This finding suggests a need to revisit the practical applicability of SARIMA in scenarios with limited data.

## Contribution to knowledge

This study makes several contributions to the field of sales forecasting and time series analysis:

1. **Empirical Evidence**: Provides empirical evidence on how different forecasting models perform when applied to sales data, highlighting the strengths and weaknesses of each model.
2. **Impact of Data Granularity:** Demonstrates the critical impact of data granularity on model performance, with weekly data yielding more accurate forecasts than monthly data.
3. **Model Simplicity:** Emphasizes the importance of model simplicity, showing that simpler models like Ridge and Lasso Regression can outperform more complex models like SARIMA under specific circumstances.
4. **Regularization Benefits:** Highlights the benefits of regularization techniques in Ridge and Lasso Regression, which help to tackle overfitting and improving predictive accuracy.
5. **Practical Insights:** Offers practical insights for businesses and practitioners in selecting appropriate forecasting models based on their data characteristics and requirements.

## Future Recommendations

Based on the findings and limitations of this study, the following recommendations for future research and practical applications are proposed:

1. **Expand Data Collection:**

Collect more extensive data to enhance the robustness of the models, particularly for complex models like SARIMA that may require larger datasets to capture seasonal patterns effectively.

1. **Advanced Hyperparameter Tuning:**

Implement more comprehensive hyperparameter tuning techniques, such as Bayesian Optimization, to explore a wider range of parameters and improve model performance.

1. **Hybrid Models:**

Explore hybrid models that combine the strengths of different forecasting approaches. For instance, integrating machine learning models with SARIMA could capture both linear and nonlinear patterns in the data.

1. **Incorporate Exogenous Variables:**

Include exogenous variables such as holidays, promotions, and economic indicators to improve the accuracy of sales forecasts. These variables can provide additional context that pure time series models may miss.

1. **Cross-Validation Techniques:**

Utilize advanced cross-validation techniques specific to time series data, such as rolling forecast origin or time series split, to better assess model performance and avoid overfitting.

1. **Real-Time Forecasting:**

Develop real-time forecasting systems that can continuously update predictions as new data becomes available. This approach can help businesses make timely and informed decisions based on the latest sales trends.

By following these recommendations, future research can build upon the findings of this study and further advance the field of sales forecasting. Practical implementations can benefit from more accurate, robust, and interpretable forecasting models, ultimately leading to better business outcomes.

Figure 3.4.1, which provides a summary flow of the machine learning methodologies used, can serve as a useful reference for understanding the detailed process of data preparation, modeling, and validation involved in this study​​.

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# Research Plan

This research project is scheduled over a precise 99-day period, commencing on January 18th, 2024, and culminating on June 4th, 2024. Below is a detailed breakdown of the research execution plan.

A screenshot of a calendar

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Project Planner