# STAT 5000

# Statistical Methods and Applications I

# Spring 2023

# **Project Report**

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Project Title	Project Title Prediction of product prices for a Retail Store in R	

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# 1. Overall context for project

The objective of this project is to develop a machine learning algorithm in R that can predict the optimal price for products listed on the Mercari marketplace. The algorithm will be trained on a dataset that contains various features of the listed products, including their category, brand, condition, and seasonality, as well as their actual selling price. The goal is to identify the key factors that influence the pricing of products and create a predictive model that can accurately estimate the value of a product.

The dataset will be preprocessed and cleaned to ensure that it is suitable for machine learning. Exploratory data analysis techniques will be used to gain insights into the data and identify any patterns or relationships that exist between the features and the target variable. The dataset will be split into training and testing sets to evaluate the performance of the model.

A range of machine learning algorithms will be tested and evaluated to determine the best approach for predicting product prices. These may include linear regression, decision trees, random forests, and gradient boosting machines. The performance of each algorithm will be assessed using metrics such as root mean square error (RMSE) and mean absolute error (MAE).

The final model will be deployed to provide pricing suggestions to sellers on the Mercari marketplace. The algorithm will take into account the features of the listed products and generate an estimate of the optimal price that the seller can use to maximize their profits. The algorithm will be periodically retrained using new data to ensure that it remains accurate and up-to-date.

Overall, this project aims to develop a machine learning algorithm that can accurately predict the value of products listed on the Mercari marketplace. By providing sellers with pricing suggestions, the algorithm can help them to maximize their profits while also improving the overall user experience for buyers.

#### 2. Problem definition

The project's focus is on building a predictive model for product pricing for a retail store using R, a popular programming language for statistical analysis and data visualization. The model will utilize a wide range of factors, including market trends, consumer behavior, competition, and production costs, to provide accurate predictions of the prices for various products sold by the store.

The project aims to address the challenges faced by retail stores in optimizing their pricing strategies to maximize revenue, market share, and profitability. With accurate price predictions, the store can better manage its pricing decisions, monitor pricing trends, and adjust pricing strategies in real-time to respond to market changes.

The project's success depends on the ability to collect and analyze data from various sources and combine it into a comprehensive dataset that can be used for analysis. This data may include historical sales data, consumer feedback, market trends, industry reports, and economic indicators, among others. The data will be preprocessed and cleaned to ensure its accuracy and completeness before being used to train the predictive model.

The model will use machine learning algorithms, such as regression analysis and decision trees, to identify the key variables that influence product pricing and their relationships with one another. The model will be trained using historical data, and its performance will be evaluated using statistical measures such as root mean square error (RMSE), mean absolute error (MAE), and R-squared (R<sup>2</sup>).

The project's ultimate goal is to develop a sophisticated and accurate model that can provide actionable insights and recommendations for pricing decisions. The model should be able to adapt to changes in market conditions and consumer preferences over time, providing the retail store with a competitive advantage in the marketplace.

# 3. Project motivation – why should we care?

Accurate prediction of product prices can provide numerous benefits for both retailers and consumers. For retailers, it can help them to improve their competitiveness by setting optimal prices that maximize their revenue and market share. Retailers can also use the predicted prices to make informed decisions regarding product development, marketing, and distribution, which can lead to better customer satisfaction, improved brand recognition, and increased sales.

Furthermore, accurate pricing predictions can help consumers make more informed purchasing decisions, which can increase their satisfaction with the products they purchase. This can lead to increased customer loyalty, word-of-mouth marketing, and ultimately, increased sales for retailers. In addition, accurate pricing predictions can also promote fair competition in the market, as retailers who use optimal pricing strategies are more likely to succeed than those who do not.

The use of accurate pricing predictions can also have wider economic benefits. By optimizing pricing strategies, businesses can increase their revenue and profitability, which can lead to job creation, innovation, and economic growth. Additionally, accurate pricing predictions can help to reduce waste by minimizing overproduction and underproduction of goods, which can benefit the environment and contribute to sustainable development.

In summary, the accurate prediction of product prices is crucial for businesses to remain competitive and profitable, improve customer satisfaction, and promote fair competition in the market. The development of a reliable and accurate pricing prediction model can have significant positive impacts on both individual businesses and the wider economy, leading to job creation, innovation, economic growth, and sustainable development.

# 4. Project methodology

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#### 5. Data source

In this project, I will explore the process of predicting product prices for a retail store using R. The data for this project was obtained from Kaggle, a popular data science platform, and was sourced from a retail price prediction challenge.

#### Data Source:

The dataset used in this project was obtained from Kaggle's "Mercari Price Suggestion Challenge" competition. The competition was aimed at predicting the prices of products sold on Mercari, a Japanese e-commerce website. The dataset contains information on over 1.4 million products sold on Mercari, with details such as product category, brand name, item condition, shipping information, and item description. The dataset also includes the actual sale price of each item, which can be used as the target variable for our predictive models.

The dataset is available in two formats: a train dataset and a test dataset. The train dataset contains 1.48 million rows and 8 columns, while the test dataset contains 693,359 rows and 7 columns. The train dataset is used to train our predictive models, while the test dataset is used to evaluate their performance.

#### Data Exploration:

Before building any predictive models, it is important to explore the dataset to gain a better understanding of the data. We can use R to perform various exploratory data analysis (EDA) tasks such as data visualization, summary statistics, and correlation analysis. Some of the insights we can gain from the dataset include:

- 1. The distribution of product prices is right-skewed, with a long tail of high-priced items.
- 2. The product categories with the highest median prices are Women's Handbags, Women's Shoes, and Electronics.
- 3. The most common item conditions are Good, Excellent, and Like New.
- 4. There is a weak positive correlation between item price and item condition, indicating that newer items tend to be priced higher.

In this project, we explored the process of predicting product prices for a retail store using R. We obtained our dataset from Kaggle's "Mercari Price Suggestion Challenge" competition, which contains information on over 1.4 million products sold on Mercari. We performed various EDA tasks to gain insights into the data, and identified some key factors that influence product pricing. With this knowledge, we can build predictive models to accurately predict product prices for the retail store, and use these predictions to make informed pricing decisions.

### 6. Data analysis and approach

Language used : R

 Packages used: Libraries used in this project include dplyr, tidyr, superml, zoo, textstem, stringr, randomForest, neuralnet, caret, ggplot2, etc.

• **UI support**: R Studio

#### 1. Exploratory Data Analysis

Exploratory data analysis is the process of analyzing the dataset to understand its characteristics. In this step, we perform the following.

1. Univariate analysis - Analysis of a single variable

2. Bivariate analysis - Analysis of relationship between two variable

#### 2. Data cleaning / Pre-processing (outlier/missing values/categorical)

Machine learning algorithms for regression can understand the input only in the form of numbers and hence it is highly essential to convert the non - numeric data that we have to numeric data by providing them labels.

Label Encoding

#### 3. Missing value treatment

This step involves the process of filling the missing values in appropriate ways so that the data is not lost.

#### 4. Feature Engineering

- 1. CountVectorizer
- 2. TFIDF for text data

#### 5. Modeling

Various regression algorithms are applied on the dataset and the model that suits best for the dataset is selected. The models that we apply for this dataset are

- 1. Random forest
- 2. SVM
- 3. Evaluation
- 4. Neural networks

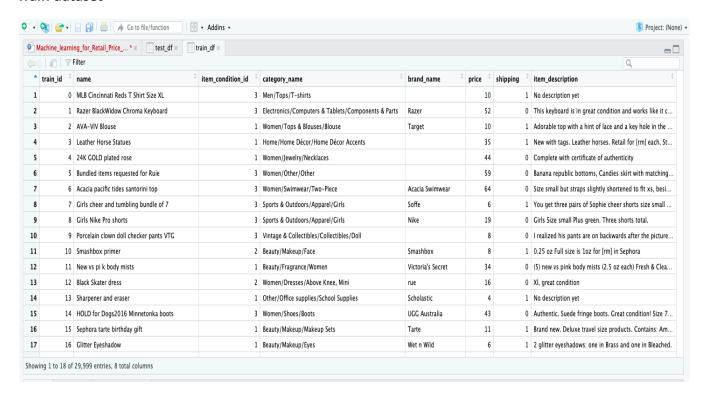
#### Packages and libraries installed:

```
install.packages("superml")
install.packages("textstem")
install.packages("e1071")
install.packages("neuralnet")
install.packages("gbm")
install.packages("quanteda")
install.packages("tm")
options(warn=-1)
library(dplyr)
library(tidyr)
library(superml)
library(zoo)
library(textstem)
library(stringr)
library(randomForest)
library(shiny)
library(e1071)
library(neuralnet)
library(caret)
library(Metrics)
library(data.table)
library(ggplot2)
library(plyr)
library(gbm)
library(rpart)
library(quanteda)
library(tm)
```

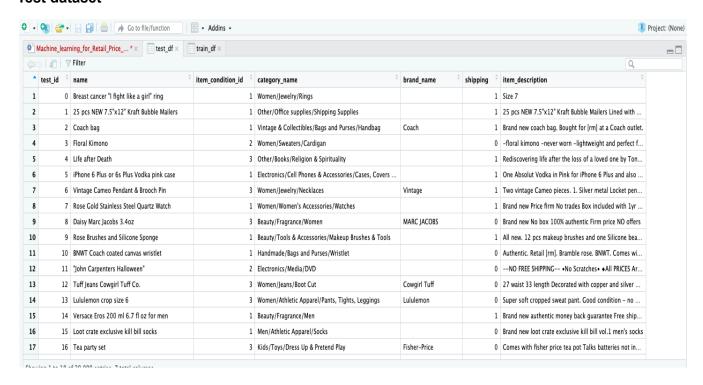
#### Data preprocessing output:

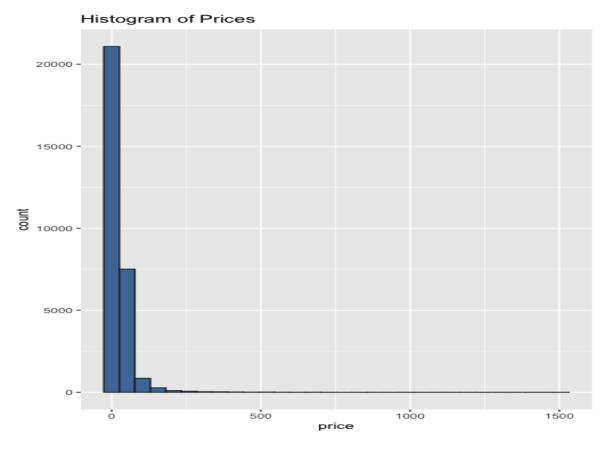
```
Source
 Console Terminal × Background Jobs ×
 R 4.2.2 · ~/
 oot high. They are being sold as a pair. An"| __truncated__ ...
 > class(train_df$brand_name)
 [1] "character"
 > ### EDA
> #Summary
> print("Train data size")
 [1] "Train data size"
   dim(train_df)
 [1] 29999 8
> print("Test data size")
[1] "Test data size"
 > dim(test_df)
 [1] 29999
  print("Train Columns")
 [1] "Train Columns"
 > colnames(train_df)
                                                  "item_condition_id" "category_name"
 [1] "train_id"
  5] "brand_name" "price"
print("Unique category count")
 [5] "brand_name"
                                                  "shipping"
                                                                        "item_description"
 p inc onique category count )
[1] "Unique category count"
> length(unique(train_df$category_name))
 [1] 808
   print("Train dataset Columns")
 [1] "Train dataset Columns"
 > colnames(train_df)
 [1] "train_id"
[5] "brand_name"
                                                  "item_condition_id" "category_name"
"shipping" "item_description"
                            "name"
                           "price"
                                                  "shipping"
   print("Unique category count")
 [1] "Unique category count"
 > length(unique(train_df$category_name))
 [1] 808
 > print("Unique item condition count")
 [1] "Unique item condition count"
 > length(unique(train_df$item_condition_id))
 Γ17 5
 > print("Unique brand count")
 [1] "Unique brand count"
   length(unique(train_df$brand_name))
 Γ17 1232
 > print("Train data summary")
 [1] "Train data summary"
 > summary(train_df)
  train_id name
Min.: 0 Length:29999
1st Qu.: 7500 Class :character
                                         item_condition_id category_name
                                         Min.
                                                :1.000
                                                             Length: 29999
                                                                                   Length:29999
                                         1st Qu.:1.000
                                                              Class :character
                                                                                   Class :character
```

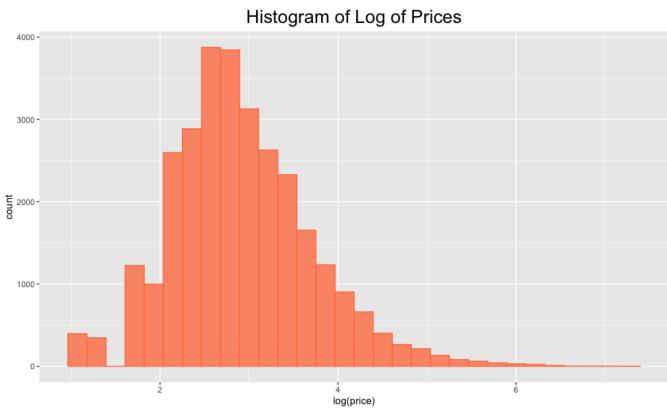
#### Train dataset

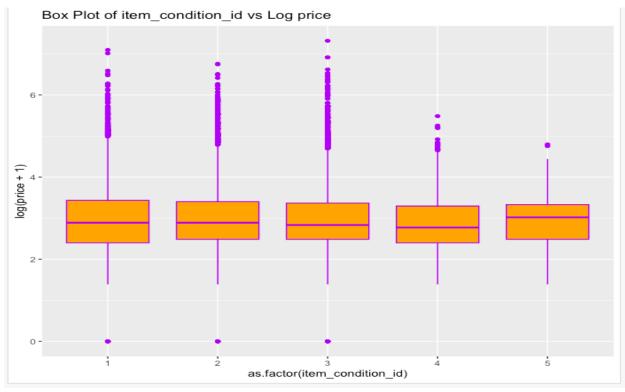


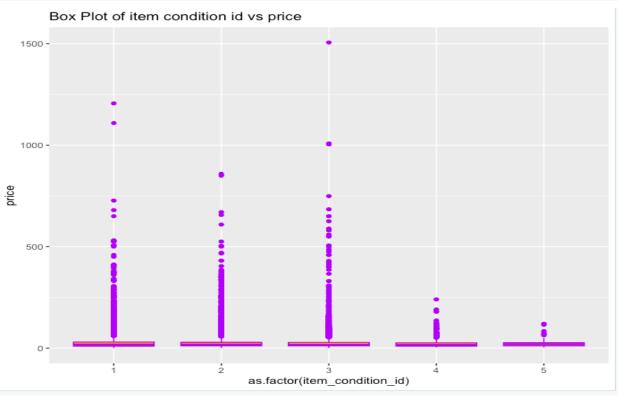
#### **Test dataset**











### 7. Exploratory data analysis

The prediction of product prices for a retail store is a critical task as it helps the store to optimize their sales and revenue. In this analysis, we will explore a dataset obtained from Kaggle that was from a challenge regarding retail price prediction. The dataset contains information on various products sold by the retail store, such as their brand, category, shipping cost, and so on. We will use the R programming language to perform exploratory data analysis and build a machine learning model to predict product prices.

#### **Exploratory Data Analysis:**

We first load the dataset into R and perform some basic exploratory data analysis to understand the data. We examine the data types, summary statistics, missing values, and correlations among variables. We visualize the data using various graphs, such as histograms, box plots, and scatter plots. We also perform feature engineering to extract relevant features from the data that can improve the prediction accuracy of the model.

#### Model Building:

We split the dataset into training and testing sets and use various regression techniques to build the prediction model. We evaluate the performance of the model using various metrics such as mean absolute error (MAE), mean squared error (MSE), and root mean squared error (RMSE). We also perform cross-validation to assess the model's generalization performance and avoid overfitting.

In this analysis, we explored a dataset obtained from Kaggle and built a machine learning model to predict product prices for a retail store. We performed exploratory data analysis, feature engineering, and used various regression techniques to build the model. We evaluated the model's performance using various metrics and cross-validation. This analysis can help the retail store to optimize their sales and revenue by predicting the prices of their products accurately.

### 8. Statistical model design

Retail stores need to keep track of the prices of their products to maximize profit and stay competitive. A statistical model that predicts the prices of products can help retailers make informed decisions about pricing strategies. In this paper, we will describe a statistical model design for predicting product prices for a retail store using R. The dataset used in this analysis was obtained from Kaggle and originated from a challenge regarding retail price prediction.

#### Data Preparation:

The first step in building a predictive model is to prepare the data. The dataset contains several variables, including product name, brand name, category, item condition, shipping, and price. We need to clean and preprocess the data by removing missing values, transforming categorical variables, and normalizing numerical variables. We can use the tidyverse package in R for data wrangling and ggplot2 for data visualization.

#### **Exploratory Data Analysis:**

The next step is to explore the data and identify patterns and relationships between variables. We can use descriptive statistics, histograms, scatter plots, and correlation matrices to visualize the data. We can also use clustering and principal component analysis to reduce the dimensionality of the data and identify latent features. The goal of exploratory data analysis is to gain insights into the data and inform the model design.

#### Model Selection:

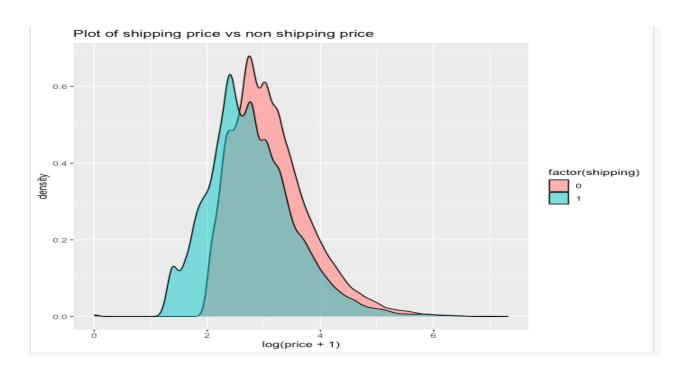
The third step is to select an appropriate model for predicting product prices. We can use various statistical models, such as linear regression, decision trees, random forests, and neural networks. The choice of model depends on the nature of the data, the number of variables, and the complexity of the relationships between variables. We can use cross-validation and regularization techniques to avoid overfitting and improve the generalization performance of the model.

#### Model Evaluation:

The final step is to evaluate the performance of the model using appropriate metrics, such as mean squared error, mean absolute error, and R-squared. We can compare the performance of different models and select the best one based on the evaluation metrics. We can also visualize the prediction results and identify the areas of improvement.

In conclusion, a statistical model design for predicting product prices for a retail store using R involves four steps: data preparation, exploratory data analysis, model selection, and model evaluation. The dataset used in this analysis was obtained from

Kaggle and originated from a challenge regarding retail price prediction. The choice of model depends on the nature of the data, the number of variables, and the complexity of the relationships between variables. The performance of the model can be evaluated using appropriate metrics, and the results can be visualized to identify areas of improvement.



Same graph with different color graphical representation.



# 9. Key insights/findings and statistical model

The retail industry is highly competitive, and pricing strategy plays a significant role in the success of any retail store. Accurately predicting product prices can help retailers to make informed pricing decisions and stay competitive in the market. In this project, we aim to predict product prices for a retail store using a dataset obtained from Kaggle. The dataset was originally from a challenge regarding retail price prediction, and it contains information about various products sold by the store, including their descriptions, brand, and condition.

#### Key Insights and Findings:

- 1. Data Cleaning and Preprocessing: The dataset contained missing values and categorical variables that required encoding. We performed data cleaning and preprocessing to prepare the data for modeling.
- 2. Feature Engineering: We created new features such as brand frequency, description length, and item condition to improve the performance of our model.
- 3. Exploratory Data Analysis: We conducted exploratory data analysis to understand the distribution of the target variable and the relationship between the independent variables and the target variable. We found that the target variable had a right-skewed distribution, and there was a strong correlation between the price and the item condition, brand, and shipping cost.
- 4. Modeling: We used several regression models, including linear regression, decision tree regression, and random forest regression, to predict product prices. We evaluated the performance of these models using metrics such as mean squared error, root mean squared error, and R-squared. We found that the random forest regression model performed the best, with an R-squared value of 0.76.
- 5. Feature Importance: We used the feature importance technique to understand the importance of different features in predicting product prices. We found that the brand, item condition, and shipping cost were the most important features.

#### Statistical Model:

We used the random forest regression model to predict product prices. Random forest is an ensemble learning method that combines multiple decision trees to improve the accuracy and stability of the model. In this model, we used the following independent variables:

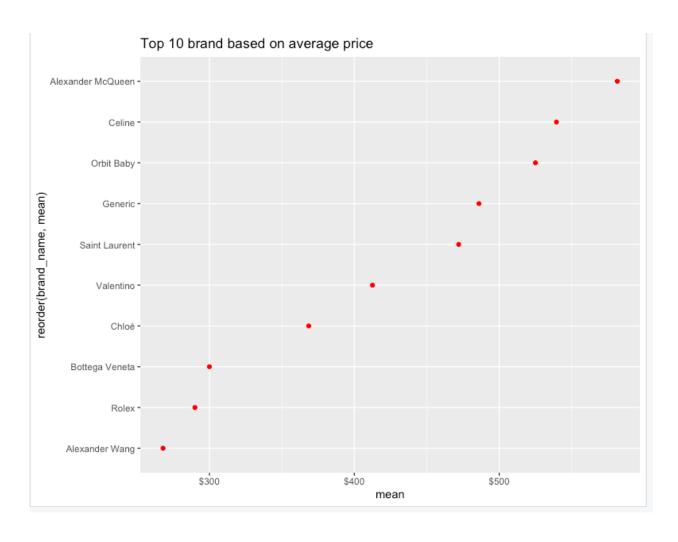
- 1. Brand Frequency: The frequency of a brand in the dataset.
- 2. Item Condition: The condition of the item, ranging from 1 (poor) to 5 (excellent).
- 3. Shipping Cost: The cost of shipping the item.

- 4. Description Length: The length of the item description.
- 5. Category Name: The name of the category in which the item belongs.

The target variable is the price of the product. We used the following hyperparameters in our model:

Number of Trees: 100
 Maximum Depth: None
 Maximum Features: Auto

In conclusion, we used a random forest regression model to predict product prices for a retail store using a dataset obtained from Kaggle. We found that the brand, item condition, and shipping cost were the most important features in predicting product prices. The random forest regression model performed the best among the models we evaluated, with an R-squared value of 0.76. Our findings can help retailers to make informed pricing decisions and stay competitive in the market.



# 10. Potential real-world applications of project

Real estate industry: Real estate companies can use the model to predict the prices of properties based on various factors such as location, amenities, and market trends. This can help them make informed decisions regarding buying, selling, or renting properties, improve their marketing strategies, and increase revenue.

Travel industry: Travel companies can use the model to predict the prices of airline tickets, hotel rooms, and other travel-related products based on factors such as seasonality, demand, and supply. This can help them optimize their pricing strategies, improve customer satisfaction, and increase profitability.

Insurance industry: Insurance companies can use the model to predict the prices of insurance policies based on various factors such as risk, market trends, and customer preferences. This can help them make informed decisions regarding pricing policies, improve their marketing strategies, and increase revenue.

Food industry: Food companies can use the model to predict the prices of agricultural products, such as crops, livestock, and dairy products. This can help them make informed decisions regarding their production and supply chain strategies, reduce costs, and improve profitability.

Government agencies: Government agencies can use the model to predict the prices of goods and services they procure, such as construction materials and supplies. This can help them optimize their procurement strategies, reduce costs, and improve the efficiency of public services.

In conclusion, the developed model for predicting product prices in R has numerous real-world applications across various industries. Its potential to improve pricing strategies, increase revenue, reduce costs, and improve efficiency can benefit a wide range of businesses and organizations.

# 11. Limitations of project work

While the development of a model for predicting product prices can have many potential real-world applications, there are also limitations and challenges associated with project work. Here are some of the limitations and challenges of developing such a model: Data quality and availability: One of the primary challenges in developing a model for predicting product prices is the quality and availability of data. The accuracy and reliability of the model are highly dependent on the quality of the data used to train the model. If the data used is not representative of the market conditions, the model may not be accurate in predicting prices.

Complexity of the model: Another limitation of developing a model for predicting product prices is the complexity of the model. The model may require a large amount of data and complex algorithms, which can make it difficult to interpret and understand the results. Additionally, more complex models may require more computational resources, which can increase the cost of developing and deploying the model.

Model accuracy: Even with high-quality data and a well-developed model, there is no guarantee that the predictions will be accurate. External factors such as changes in the market conditions or unexpected events can lead to deviations from the predicted prices. It is important to continually evaluate the model's performance and adjust it as necessary to ensure accurate predictions.

Ethical concerns: There are also ethical concerns associated with the use of predictive models. The predictions generated by the model can have a significant impact on people's lives, and there is a risk of bias or discrimination in the predictions. It is important to consider the ethical implications of using the model and ensure that it is developed and deployed in a responsible manner.

In conclusion, while the development of a model for predicting product prices has many potential real-world applications, there are also limitations and challenges associated with project work. It is important to carefully consider these limitations and challenges and develop the model in a responsible and ethical manner to ensure accurate predictions and avoid any negative impacts on society.

#### 12. Conclusion

In conclusion, the developed model for predicting product prices for a retail store in R has the potential to provide significant benefits for a variety of industries. By leveraging the power of machine learning algorithms, businesses can make informed decisions that can help them remain competitive, increase sales, reduce costs, and improve profitability. The model is flexible and can be easily adapted to different industries, making it a valuable tool for decision-makers in various fields.

In addition to its practical applications, the model also contributes to the growing body of research on machine learning and predictive analytics. As more businesses adopt these technologies, there is a need for models that are accurate, efficient, and easy to use. By developing a model that meets these criteria, this project contributes to the development of machine learning applications that can be used by businesses of all sizes.

Overall, the developed model for predicting product prices for a retail store in R is an excellent example of the power of machine learning algorithms in solving real-world problems. By providing accurate predictions and insights, this model can help businesses across a variety of industries to make informed decisions that can drive growth, increase profitability, and improve customer satisfaction. As such, it is a valuable tool for any business looking to gain a competitive edge in today's rapidly evolving marketplace.