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| RESEARCH ARTICLE

Ethical Considerations in AI-driven Dynamic Pricing in the USA: Balancing Profit Maximization with Consumer Fairness and Transparency

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| ABSTRACT
Organizations in the USA are progressively employing AI-driven dynamic pricing as a strategic intervention to flexibly modify their prices based on competition, market demand, and various other factors. This research paper focused on the ethical dimensions of AI-driven dynamic pricing and the crucial interplay between profitability and the establishment of unwavering consumer transparency and fairness. The recommended models for dynamic pricing solutions entailed ensemble learning methods, notably, XG-Boost, Light-GBM, Cat-Boost, and X-NGBoost models. Particularly, the proposed model consolidated the XG-Boost algorithm and the NG-Boost model, resulting in a novel methodology termed the X-NGBoost. To compare and contrast the performance of the proposed models, these algorithms were trained and subjected to the same dataset. The comparison between the models was mainly grounded on the root-mean-square error (RMSE) metric, which was quantified in meters. The results indicated that X-NGBoost had the lowest RMSE on both the testing and training sets, at 4.23 and 5.34 respectively. This indicated that X-NGBoost performed very well on both seen and unseen data. Therefore, from the outcomes it was deduced that, for the provided data set, the X-NGBoost model provided the accurate pricing solution.

| KEYWORDS
AI; Dynamic Pricing; XG-Boost; Light-GBM; Cat-Boost; XNG-Boost; Transparency; Fairness

| ARTICLE INFORMATION
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1. Introduction
Chauhan (2023) contended that in the ever-changing domain of marketing, artificial intelligence (AI) has arisen as a revolutionary force, assisting organizations in the USA to navigate the digital landscape with remarkable accuracy and precision. AI-based marketing techniques, comprising predictive analytics and recommendation engines, have transformed how organizations interact with their target audiences. These inventions hold huge capabilities for streamlining operations, boosting profitability, and reinforcing consumer relationships. Nevertheless, under the surface of these technological inventions, a sophisticated network of ethical considerations emerges, demanding a delicate balance between profit-oriented goals and the preservation of consumer trust and fairness. Faster-Capital (2024), asserts that as companies eagerly embrace AI to attain a competitive edge and elevate their respective revenue streams, they should concurrently maneuver a challenging ethical landscape. AI-powered marketing strategies hold the capacity to unravel an unparalleled level of personalization and relevance in consumer interactions. This research paper focuses on the ethical dimensions of AI-driven dynamic pricing and the crucial interplay between profitability and the establishment of unwavering consumer transparency and fairness.

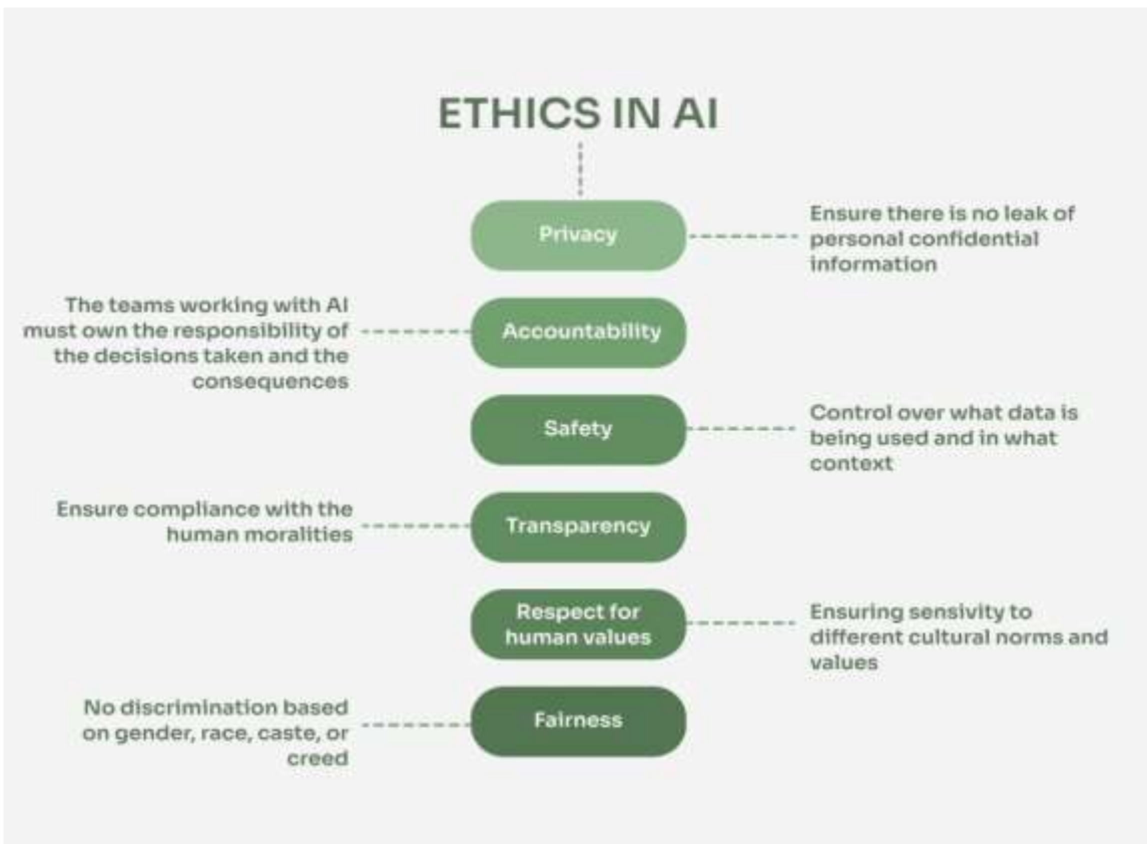
Gerlick and Liozu (2020), indicates that organizations in the USA and worldwide are progressively employing AI-driven dynamic pricing as a strategic intervention to flexibly modify their prices based on the competition, market demand, and various other factors. This intervention has gained massive popularity because of its capacity to produce higher revenue and improve customer engagement. Nonetheless, it is pivotal for companies to resolve the ethical implications related to dynamic pricing. This pricing strategy can be perceived as discriminatory, unfair, and possibly detrimental to specific customer segments. Therefore, it is instrumental for organizations to exercise restraint and uphold ethical principles by affirming transparency in their dynamic pricing strategies.

2. Literature Review

2.1 AI-Driven Dynamic Pricing

Kinoti (2023) argues that dynamic pricing revolves around a flexible pricing strategy that considers various components to determine the price of a service or product. Contrary to static pricing, where a fixed price is stipulated for a longer duration, AI-driven dynamic pricing enables companies to modify their prices in real time based on several dynamic variables. These variables include components such as time, demand, customer behavior, availability, and market conditions. By employing complex algorithms and performing data analysis, dynamic pricing facilitates organizations to enhance their pricing strategies for maximum competitiveness and revenue. This method enables businesses to react swiftly to changes in the market and adjust their prices respectively. For instance, during seasons of high demand, dynamic pricing may culminate in higher prices to leverage the increased willingness of consumers to pay more. By contrast, during seasons of low demand, prices may be reduced to stimulate sales and maintain market share.

2.2 Ethical Considerations in Dynamic Pricing



Data privacy and informed consent is a significant pillars in the domain of AI-driven pricing dynamics. It is paramount to resolve these concerns since gathering and processing personal data without informed consent can breach consumers' privacy rights and result in regulatory repercussions (Namburu et al, 2022). To combat these risks, companies should prioritize getting informed and direct consent from customers concerning the usage of their data. This includes presenting transparent and clear information regarding how the data will be shared and utilized. Besides, companies should deploy comprehensive data safeguards procedures to affirm the security integrity of personal information (Namburu et al, 2022). This comprises applying encryption methods, access control procedures, and progressive security audits.

As per Gerlick and Liozu (2020), accountability and transparency are equally considered a central tenet of ethical AI-powered dynamic pricing. Consumers should be informed how prices are set, and why certain clients are being charged different prices. This implies that companies should be open about their pricing strategies, and should submit clear information regarding how prices are set. With clients becoming more acquainted with the data-centric nature of modern marketing, there is an escalating demand for solid transparency regarding data gathering, usage, and the decision-making systems underlying dynamic pricing. When AI-based pricing lacks transparency, it can lead to a loss of trust, therefore causing reputational harm and diminished customer loyalty.

Moreover, the issue of fairness in AI dynamic pricing is of utmost significance and demands significant attention. Biased AI dynamic pricing can cause discrimination by unmistakably overpricing, underpricing, excluding or favoring specific demographic categories based on components such as gender, race, or age (Namburu et al., 2022). It is imperative to resolve bias not only from an ethical point of view but also because of legal consequences, such as discriminatory practices can cause severe legal consequences and harm a brand's reputation. Therefore, it is paramount to progressively monitor and perform rigorous fairness assessments to affirm that AI algorithms are devoid of discrimination and bias. This comprises continuously assessing the outputs of AI systems and scrutinizing them for any unfairness or unintended biases.

2.3 Machine Learning in Dynamic Pricing

Toolify.ai. (2024) articulates that machine learning is a branch of artificial intelligence that equips computers to learn from data and optimize their performance without explicit supervision. By utilizing machine learning algorithms, companies can efficiently analyze large volumes of data relevant to market trends, consumer behavior, and other pertinent factors. This assessment facilitates the detection of trends and the forecasting of future demand—an invaluable capacity for deploying dynamic pricing strategies that optimize profitability.

Machine learning has massive applications in dynamic pricing. Firstly, machine learning technologies can process real-time data including competitor pricing, market demand, and other relevant factors, facilitating organizations to make rapid price adjustments. For example, an e-commerce organization could use machine learning to dynamically adjust product prices based on variables such as consumer demand, product availability, and competitor pricing (Toolify.ai., 2024). This technique enables revenue maximization and the continuation of competitiveness by facilitating rapid responses to market fluctuations.

Secondly, AI algorithms reinforce companies to tailor personalized pricing strategies based on customer insights. Through assessing consumer data involving demographics, purchase history, and online interactions, companies can tailor precise promotions and discounts targeting specific consumer segments. This individualized approach promotes enhanced consumer loyalty and reinforces sales by matching pricing with individual customer preferences.

3. Methodology

3.1 Dataset

The dataset utilized in this research was obtained from Kaggle, a renowned forum for machine learning and data science resources. Particularly, the dataset was referred to as *E-Commerce Participants Data* It included approximately 2,453 records in the training dataset, which were utilized to train the model, and 1,052 records in the testing dataset, which were used for model testing and evaluation purposes. The dataset included 12 columns, particularly, featuring characteristics such as laptop specifications, entailing screen size, RAM, CPU, GPU, and operating system (proAIrokibul, 2024). Besides, the dataset also entailed the weight of the laptops and their subsequent prices. The dataset was subdivided into two different parts to moderate model testing and evaluation. The first section was the training dataset sample, which is portrayed in Table 1. This subset of data was adopted to train the model and facilitate it to learn relationships, trends, and patterns within the dataset. This dataset acted as an independent evaluation set to evaluate the model's generalization and performance capabilities. It facilitates the examination of how well the trained model can forecast results or make accurate approximations when exposed to unseen or new data.

Name	Description
Product_ Brand	The brand to which the item belongs.
Product	Name of the item.
Item_ Category	The wider group of products the item belongs to
Subcategory_ 1	The sub-group the item belongs to is one degree deep
Subcategory_ 2	In specific groups, the product belongs to degrees deep
Date	Specific timeline in which the item was sold at a specific price
Item_ Rating	The reviewed rating scored by clients of the item
Selling_ Price	Price of the item sold in a specific timeframe.

Table 1: Displays characteristics of the dataset

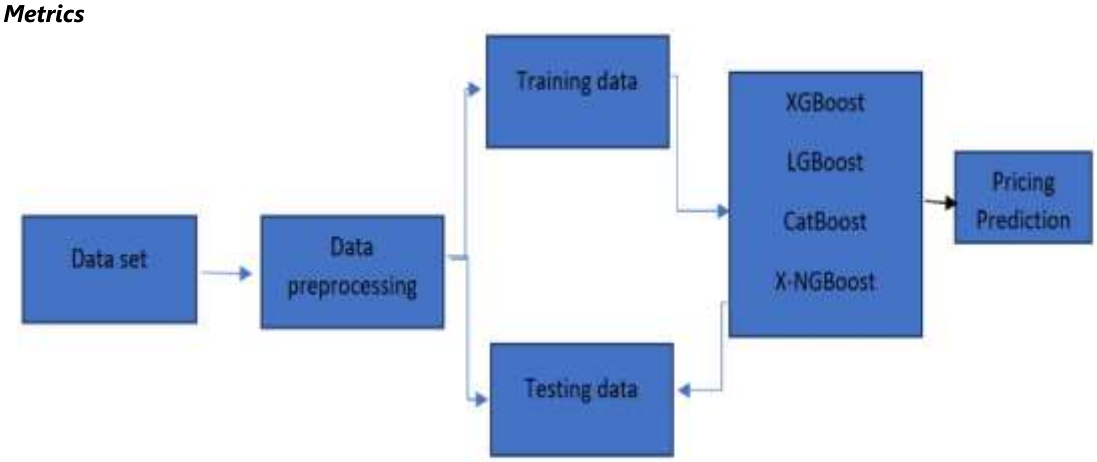
3.2 Preprocessing

After plotting the features, it was observed that the target variable, 'Selling Price,' portrayed a highly left-skewed distribution. Subsequently, the output produced by the models also exhibited a left-skewed trend. To resolve the non-normal distribution of the data, a logarithmic transformation was deployed to estimate a relatively normal distribution. This transformation was performed to improve the efficiency of statistical analysis of the data. By employing the logarithmic conversion, the skewness of the initial data was substantially diminished or eliminated, culminating in a more symmetric distribution (proAIrokibul, 2024). The entire dataset went through normalization via the logarithmic conversion. The result of this normalization protocol is portrayed by the normalized variable.

3.3 Feature Engineering and Selection

Considering the different factors impacting pricing, the researcher included date timeline features and statistical features retrieved from categorical variables to enhance predictive accuracy. Subsequently, categorical variables were encoded utilizing the label encoding method to facilitate their efficient utilization in the models. After the preprocessing stages, several models were developed, notably, LGBM, XG-Boost, Cat-Boost, and X-NGBoost. To enhance the performance of these models, parameter modification was performed, comprising the use of early stopping methods to accomplish a favorable cross-validation score.

3.4 Models and Metrics



The proposed models for dynamic pricing solutions entail ensemble learning methods, particularly, XGBoost, LightGBM, CatBoost, and X-NGBoost models. Ensemble learning provides a systematic method to consolidate the predictive capacities of multiple learners. These models are adopted because depending solely on the outcomes of a single machine learning model may not be enough to accomplish optimal results. By employing ensemble learning methods, the pricing resolutions aim to improve the overall predictive performance and produce more reliable and accurate pricing predictions.

1. XG-Boost

XG-Boost is a consolidation algorithm that integrates decision trees with the gradient boosting algorithm. Contrary to conventional search-based techniques, XG-Boost utilizes the first and second derivatives of the loss function to boost performance. It integrates methods such as pre-ordering and node number of bits to further reinforce algorithm effectiveness. Through the integration of a regularization term, XG-Boost efficiently confines the contribution of weak learners (decision trees) in every iteration, affirming that they do not overshadow the final model. This regularization d helps prevent overfitting and improves the model's generalization capabilities.

$$O^{(t)} = \sum_{i=1}^{n} [l(y_i, \hat{y}_i^{(t-1)}) + p_i f_t(x_i) + \frac{1}{2} q_i f_t^2(x_i)] + \Omega((f_t)$$

Here, "i" denotes the index of the ith sample, while "t" represents the iteration number. The expression "yi" stands for the actual value of the ith sample, and (ft-1)i corresponds to the predicted outcome of the (t - 1)th iteration. The expression "pi" and "qi" denotes the first and second derivatives, accordingly.

2. Light-Boost

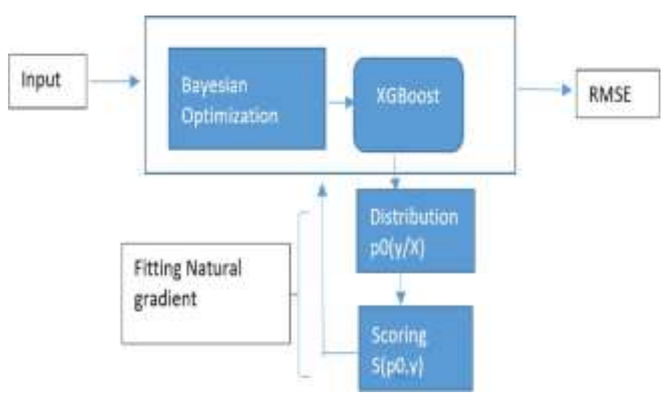
Light-Boost is equally another boosting algorithm that is premised on decision trees and follows the gradient boosting model. One of the key differences between Light-Boost and XG-Boost is that Light-Boost adopts a histogram-based algorithm. This technique involves transforming floating-point values into k bins of discrete values to design a histogram. Light-Boost illustrates solid performance when dealing with categorical attributes that have been integer-encoded. Therefore, it is preferable to adopt label encoding instead of one-hot encoding when utilizing Light-Boost models, as label encoding often yields better results.

3. Category Boosting (CAT-Boosting)

The Category Boosting technique mainly underscores permutation and target-oriented statistics. It showcases solid performance when handling data that comprises multiple sub-categories and finds substantial application across various organizational challenges. Contrary to other techniques, it does not require direct data preprocessing to transform categorical variables into numerical values. Rather, it employs a consolidation of internal classification features and statistical information to convert classification values into numerical representations. This technique facilitates efficient management of large datasets while utilizing relatively lesser memory resources. Moreover, it minimizes the probability of overfitting, leading to more generalized models. Regarding categorical encoding, the Category Boosting method adopts a sorting principle entitled Target Based with Previous (TBS). This approach draws motivation from online learning, where training incidents are sequentially obtained over time.

3.4 Proposed Model

The prime focus of this study was to develop an innovative AI-based method for predicting product prices. The proposed model consolidates the XGBoost algorithm and the NG-Boost model, resulting in a novel methodology termed the X-NGBoost. The flow chart highlighting the model's process is portrayed in Figure 3. In the proposed framework, the preprocessed dataset goes through processing using XG-Boost, which is modified with a natural probability prediction algorithm as the fundamental learning model. The preliminary training data is used to start the model training procedure with XG-Boost. Hyperparameters of XG-Boost are then chosen via trial and error, followed by optimization utilizing Bayesian optimization methods. Based on the approximated scores, the optimized parameters are attained via Bayesian optimization. The suggested optimized predictive models significantly elevate accuracy, thereby enhancing the overall performance of the price prediction system.



4. Experimental Results

Python was selected as the principal tool for both preprocessing and modeling in this experiment. Its versatility and popularity in the domain of data science, specifically in web development, are widely utilized. Python's comprehensive usage in data science is unquestionable, owing to its wide ecosystem of specialized libraries tailored for data processing and modeling. In this research, various prominent data science libraries were used to execute essential tasks. In particular, the panda's library was adopted for effective data analysis and manipulation. Furthermore, matplotlib was adopted to produce a wide spectrum of data visualizations, including graphs and charts. NumPy played a pivotal role in performing scientific calculations. Furthermore, the sci-kit-learn library played a paramount role in the designing of computational models for this research.

4.1 Importing Libraries

The analyst began the project by importing necessary Python libraries necessary for the task at hand. These libraries provide specific tools and functionalities that assist in modeling and data analysis. By importing the dataset, the investigator attained access to the data and its related features. This dataset consisted of multiple columns and variables, each representing a distinct aspect of the data.

Output:

Out[65]:

	Unnamed: 0	Company	TypeName	Inches	ScreenResolution	Cpu	Ram	Memory	Gpu	OpSys	Weight	Pric
0	0	Apple	Ultrabook	13.3	IPS Panel Retina Display 2560x1600	Intel Core i5 2.3GHz	8GB	128GB SSD	Intel Iris Plus Graphics 640	macOS	1.37kg	71378.683
1	1	Apple	Ultrabook	13.3	1440x900	Intel Core i5 1.8GHz	8GB	128GB Flash Storage	Intel HD Graphics 6000	macOS	1.34kg	47895.523
2	2	HP	Notebook	15.6	Full HD 1920x1080	Intel Core i5 7200U 2.5GHz	8GB	256GB SSD	Intel HD Graphics 620	No OS	1.86kg	30636.000
3	3	Apple	Ultrabook	15.4	IPS Panel Retina Display 2880x1800	Intel Core i7 2.7GHz	16GB	512GB SSD	AMD Radeon Pro 455	macOS	1.83kg	135195.336
4	4	Apple	Ultrabook	13.3	IPS Panel Retina Display 2560x1600	Intel Core i5 3.1GHz	8GB	256GB SSD	Intel Iris Plus Graphics 650	macOS	1.37kg	96095.808
...	...	...	...	...	...	...	...	...	...	...	...	.
1298	1298	Lenovo	2 in 1 Convertible	14.0	IPS Panel Full HD / Touchscreen 1920x1080	Intel Core i7 6500U 2.5GHz	4GB	128GB SSD	Intel HD Graphics 520	Windows 10	1.8kg	33992.640
1299	1299	Lenovo	2 in 1 Convertible	13.3	IPS Panel Quad HD+ / Touchscreen 3200x1800	Intel Core i7 6500U 2.5GHz	16GB	512GB SSD	Intel HD Graphics 520	Windows 10	1.3kg	79866.720
1300	1300	Lenovo	Notebook	14.0	1366x768	Intel Celeron Dual Core N3050 1.6GHz	2GB	64GB Flash Storage	Intel HD Graphics	Windows 10	1.5kg	12201.120
1301	1301	HP	Notebook	15.6	1366x768	Intel Core i7 6500U 2.5GHz	6GB	1TB HDD	AMD Radeon R5 M330	Windows 10	2.19kg	40705.920
1302	1302	Asus	Notebook	15.6	1366x768	Intel Celeron Dual Core N3050 1.6GHz	4GB	500GB HDD	Intel HD Graphics	Windows 10	2.2kg	19660.320

1303 rows × 12 columns

Subsequently, the analyst then performed exploratory data analysis and evaluation to have a relatively better look at the descriptive statistics of the data.

```
In [66]: df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1303 entries, 0 to 1302
Data columns (total 12 columns):
 #   Column            Non-Null Count  Dtype
---  ------            --------------  -----
 0   Unnamed: 0        1303 non-null   int64
 1   Company           1303 non-null   object
 2   TypeName          1303 non-null   object
 3   Inches            1303 non-null   float64
 4   ScreenResolution  1303 non-null   object
 5   Cpu               1303 non-null   object
 6   Ram               1303 non-null   object
 7   Memory            1303 non-null   object
 8   Gpu               1303 non-null   object
 9   OpSys             1303 non-null   object
 10  Weight            1303 non-null   object
 11  Price             1303 non-null   float64
dtypes: float64(2), int64(1), object(9)
memory usage: 122.3+ KB
```

```
In [67]: df.describe()
```

Output:

Out[67]:

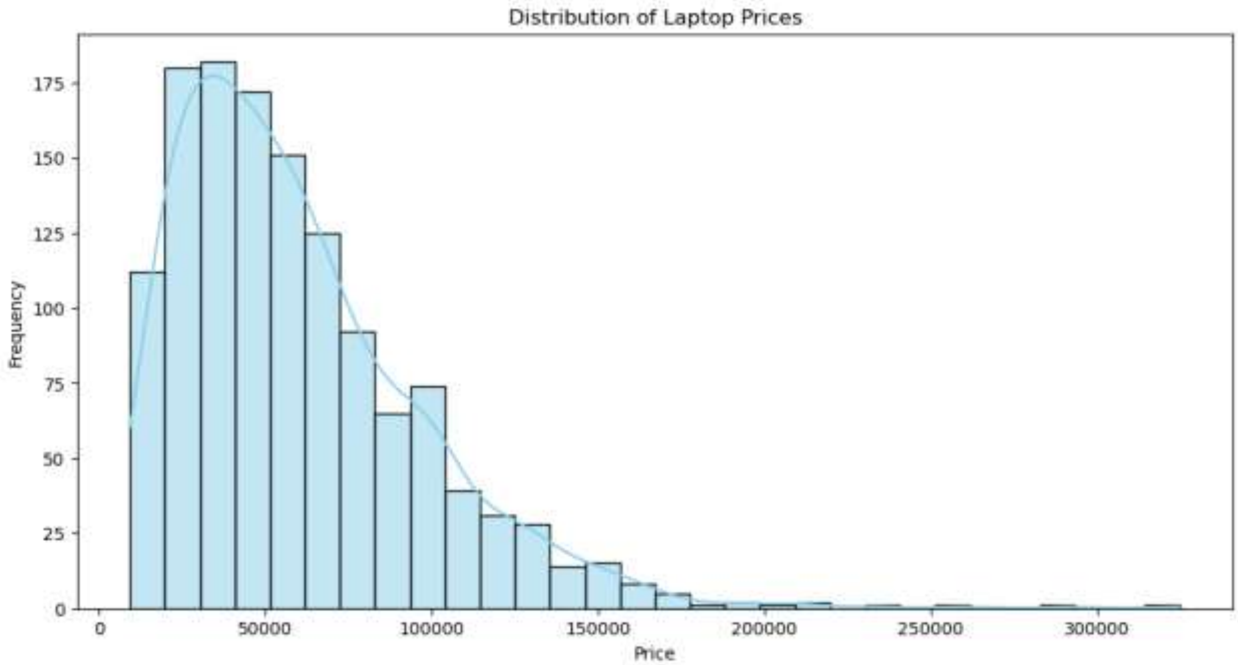
	Unnamed: 0	Inches	Price
count	1303.00000	1303.000000	1303.000000
mean	651.00000	15.017191	59870.042910
std	376.28801	1.426304	37243.201786
min	0.00000	10.100000	9270.720000
25%	325.50000	14.000000	31914.720000
50%	651.00000	15.600000	52054.560000
75%	976.50000	15.600000	79274.246400
max	1302.00000	18.400000	324954.720000

Afterward, the analyst aimed to create histograms to be able to visualize the distribution of laptop prices:

```
In [72]: import matplotlib.pyplot as plt
         import seaborn as sns

         # Visualize the distribution of prices
         plt.figure(figsize=(12, 6))
         sns.histplot(df['Price'], bins=30, kde=True, color='skyblue')
         plt.title('Distribution of Laptop Prices')
         plt.xlabel('Price')
         plt.ylabel('Frequency')
         plt.show()
```

Output:

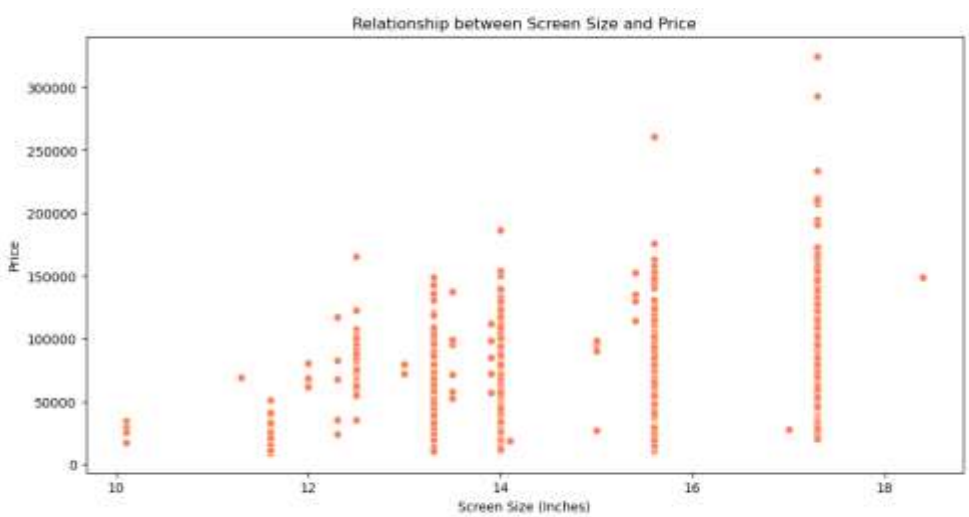


The researcher also intended to plot a scatter plot graph displaying the relationship between the screen size and price:

In [73]:

```
# Visualize the relationship between screen size and price
plt.figure(figsize=(12, 6))
sns.scatterplot(x='Inches', y='Price', data=df, color='coral')
plt.title('Relationship between Screen Size and Price')
plt.xlabel('Screen Size (Inches)')
plt.ylabel('Price')
plt.show()
```

Output:



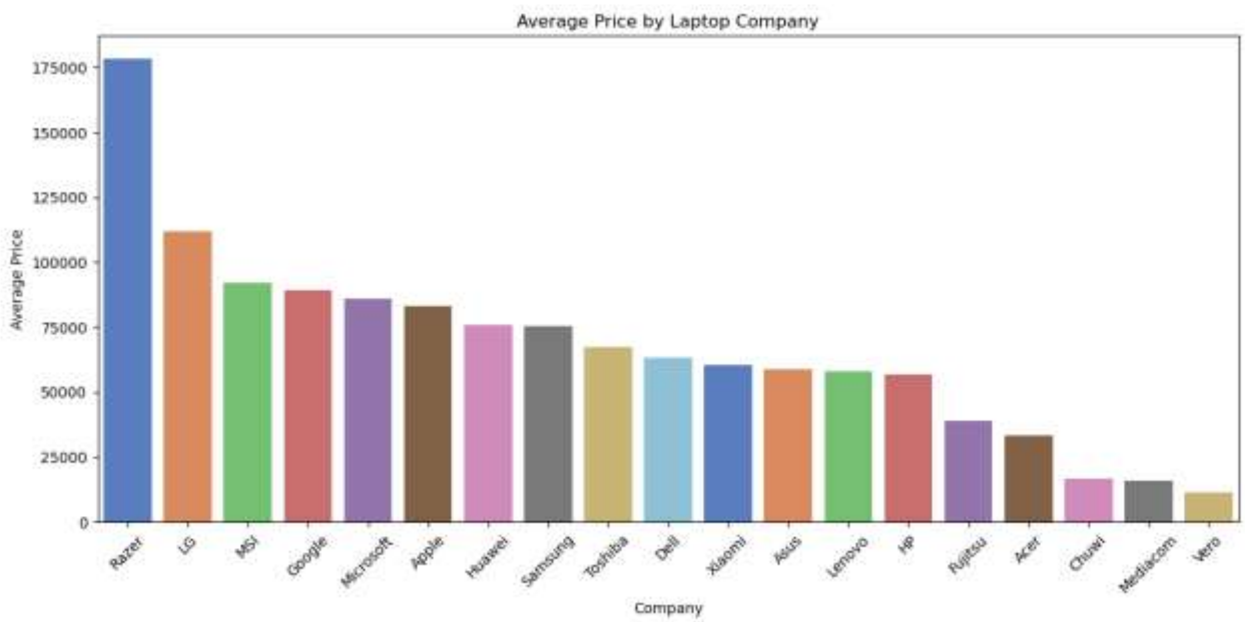
From the scatter plot graph above, it was evident that there was a linear distribution that demonstrated one variable was directly proportional to the other i.e. (an increase in screen size subsequently led to a corresponding increase in the price of the laptop) which made sense because it was expected the bigger the screen size the higher the price of the laptop.

Furthermore, the analyst equally went ahead to visualize the relationship between the average price and the respective companies which can be displayed as follows:

Laptop Type

In [76]:
```
# Visualize the average price per company
plt.figure(figsize=(14, 6))
avg_price_by_company = df.groupby('Company')['Price'].mean().sort_values(ascending=False)
sns.barplot(x=avg_price_by_company.index, y=avg_price_by_company.values, palette='muted')
plt.title('Average Price by Laptop Company')
plt.xlabel('Company')
plt.ylabel('Average Price')
plt.xticks(rotation=45)
plt.show()
```

Output:

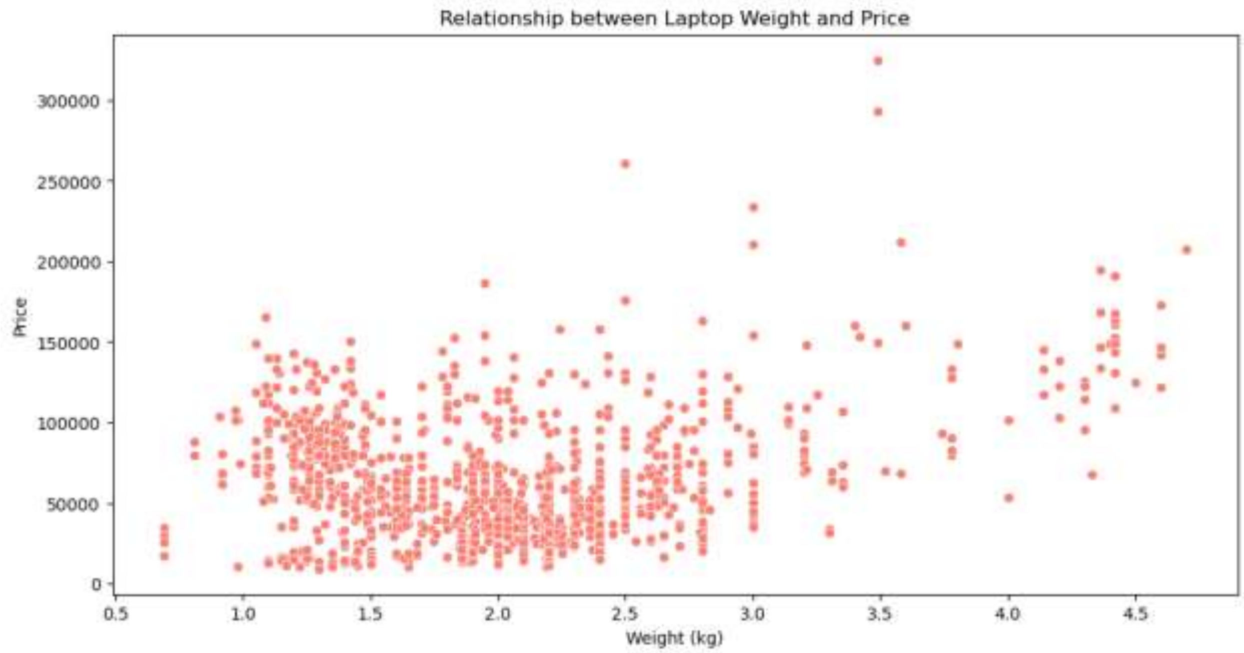


By referring to the above chart it was evident that the top 3 companies with the highest price was Razer which had the highest average price, followed by LG. Conversely, the top 3 companies with the lowest average price were Vero, Mediacom, and Chuwi.

Aside from that, the analyst also visualized the relationship between the weight of the laptop and their corresponding prices:

In [77]:
```
# Visualize the relationship between weight and price
plt.figure(figsize=(12, 6))
sns.scatterplot(x='Weight', y='Price', data=df, color='salmon')
plt.title('Relationship between Laptop Weight and Price')
plt.xlabel('Weight (kg)')
plt.ylabel('Price')
plt.show()
```

Output:



From the scatter plot graph above it was apparent that the distribution was non-linear from one variable to the other, therefore the analyst inferred that there is no explicit relationship between the weight of the laptop and their corresponding prices.

4.2 Models Performance Evaluation

To compare and contrast the performance of the proposed models, notably, XGBoost, LightBoost, and CatBoost, these models were trained and subjected to the same dataset. The comparison between the models was mainly grounded on the root-mean-square error (RMSE) metric, which was quantified in meters. RMSE is a globally employed measurement when it comes to evaluating the accuracy of predictions and computing the magnitude of errors. By using RMSE, which is specifically sensitive to errors, the comparison facilitates a comprehensive evaluation of the model's performance on the dataset.

Models	RMSE Testing	RMSE Training
Light-GBM	6.62	7.44
XG-Boost	7.48	6.62
Cat-Boost	6.96	5.91
XNG-Boost	5.34	4.23

Table 2: Displays the Root_ Mean_ Square_ Error of the Models

By referring to the above table, it was evident that X-NGBoost had the lowest RMSE on both the testing and training sets, at 4.23 and 5.34 respectively. This indicated that X-NGBoost performed very well on both seen and unseen data. Therefore, from the outcomes it can be deduced that, for the provided data set, the X-NGBoost model provided the accurate pricing solution. hence, it would be the suitable model among the boosting ensemble algorithms for offering pricing solutions for the considered dataset. Cat-Boost came in second with a testing RMSE of 6.96 and a training RMSE of 5.91. Conversely, Light GBM and XG-Boost had the greatest RMSE among the four models. Particularly, their training RMSE was 6.62 and their testing RMSE was 7.44 and 7.48 respectively.

4.3 Business Impact

Traditionally, the majority of businesses in the USA have been using algorithms such as the Time series models, comprising Seasonal Decomposition of Time Series (STL) and autoregressive Integrated Moving Average (ARIMA) which were frequently adopted to capture the temporal patterns and trends in pricing data. While time series algorithms can capture seasonal trends to some degree, they may struggle with irregular or complex seasonality. Therefore, the proposed XNG-Boost is suitable to assist businesses in combating and mitigating the weaknesses of the traditional methods.

4.4 How to Use the Proposed Model

1. **Data gathering and Preprocessing**: Collect historical data on product sales, entailing quantity sold, price, competitor pricing (where applicable), promotional periods, and consumer demographics (if anonymized). Subsequently, clean the data by eliminating outliers, missing values, and inconsistencies.
2. **Feature Engineering Selection**: Formulate new features that may impact price, such as time-oriented features (season, day of the week), product attributes (size, weight, color), and consumer segmentation data.
3. **Model Training and Selection**: Split the data into training and testing sets. The training set will be utilized to develop the model, and the testing set will be adopted for the final assessment of the model's performance. Subsequently, implement the XNGboost algorithm in the chosen programming language (Python with libraries like sci-kit-learn and XGBoost is a popular choice). Afterward, compare and contrast, XNGboost with other algorithms such as LightGBM or CatBoost on the validation set employing metrics such as RMSE and Mean Absolute Error (MAE) to select the best performer.
4. **Model Deployment and Monitoring:** After you have selected the best model, train it again using the entire training data. Subsequently, execute the model in an organizational setting where it can obtain real-time data on product variation, competitor pricing, and other pertinent factors. The algorithm will predict the optimal best price for each item based on these real-time inputs. Progressively monitor the algorithm's performance on the testing set and real-world data. Track metrics such as RMSE and actual revenue generated to affirm that the framework is still effective.

4.5 Benefits to the American Businesses

1. **Enhanced Pricing Accuracy:** XNGboost can assist companies in the USA set optimal prices based on real-time market data. This minimizes the risk of underpricing and overpricing.
2. **Resource Optimization:** By optimizing prices, organizations in the USA can maximize profits and possibly reinvest in aspects such as marketing product development, or staff training. Consequently, this promotes a more competitive landscape.
3. **Fairer Pricing**: XNGboost takes into consideration a myriad of factors, possibly leading to more fair and dynamic pricing for customers. Consequently, this can lead to increased consumer satisfaction and loyalty.

4.6 Benefits to the USA Economy

1. **Economic Growth**: The XNG Boost Model will most probably improve efficiency and consumer satisfaction which in turn will lead to increased economic activity, possibly contributing to GDP growth.
2. **Innovation:** The accuracy of the XNG boost in dynamic pricing will undoubtedly encourage further investment in data analytics and AI, therefore, promoting innovation in the technology sector.

5. Conclusion

The prime focus of this study was to develop an innovative AI-based method for predicting product prices. The recommended models for dynamic pricing solutions entailed ensemble learning methods, notably, XG-Boost, Light-GBM, Cat-Boost, and X-NGBoost models. Particularly, the proposed model consolidated the XG-Boost algorithm and the NG-Boost model, resulting in a novel methodology termed the X-NGBoost. To compare and contrast the performance of the proposed models, these algorithms were trained and subjected to the same dataset. The comparison between the models was mainly grounded on the root-mean-square error (RMSE) metric, which was quantified in meters. The results indicated that X-NGBoost had the lowest RMSE on both the testing and training sets, at 4.23 and 5.34 respectively. This indicated that X-NGBoost performed very well on both seen and unseen data. Therefore, from the outcomes it was deduced that, for the provided data set, the X-NGBoost model provided the accurate pricing solution. Therefore, by adopting XNGboost model, private and government companies in the USA can set optimal prices based on real-time market data, therefore leading to stable and uniform economic growth.

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