DATA ANALYSIS USING PYTHON



A capstone project

Bachelor of Technology

in

Computer Science & Artificial Intelligence

By

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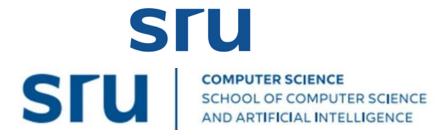
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Submitted to



SCHOOL OF COMPUTER SCIENCE & ARTIFICIAL INTELLIGENCE SR UNIVERSITY, ANANTHASAGAR, WARANGAL March, 2025.

1. Numerical Dataset-1:

1.Abstract:

This research explores the effect of interventions on customer satisfaction and sales through various segments of customers. Employing a 10,000-entry dataset, identification of key performance indicators like Sales Before, Sales After, Customer Satisfaction Before, and Customer Satisfaction After was conducted. Machine learning models like Linear Regression, Support Vector Machines (SVM), and Random Forests (RF) were used to forecast and measure improvements in performance. Exploratory data analysis using scatter plots, histograms, box plots, and heatmaps were used to uncover patterns, outliers, and relationships.

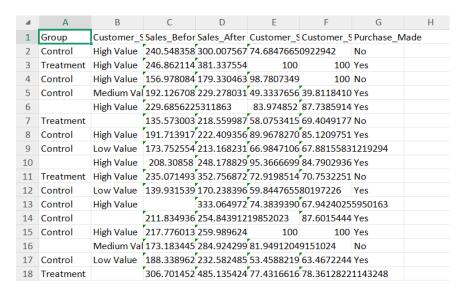
2. Introduction:

Organizations are constantly looking for ways to improve customer satisfaction and generate sales. Monitoring the effect of marketing or operating interventions is vital. This research aims to examine the effectiveness of such interventions through the analysis of changes in levels of sales and satisfaction before and after the intervention. The dataset includes sales and customer satisfaction measurements, categorized by group and type of customer, and thus lends itself well to performance modeling and predictive analysis.

3.Dataset Description:

The data set has 10,000 records of customer behavior prior to and subsequent to an intervention. It has both numerical and categorical features appropriate for supervised learning.

- Group: Control or Treatment group
- Customer_Segment: Customer segments (e.g., High Value, Medium Value).
- Sales_Before / Sales_After: Sales values pre- and post-intervention
- Customer_Satisfaction_Before / After: Satisfaction ratings (0–100 scale).
- Purchase_Made: Whether a purchase was made ("Yes"/"No").
- Samples: 10,000
- Missing Data: In all columns (7%–20%)
- Use: Best suited for regression, classification, and causal analysis.



4. Methodology:

- 1. Data Cleaning: Treated null values with imputation techniques and removed inconsistent rows for modeling purposes.
- 2. Feature Engineering: One-hot encoded categorical features such as Group, Customer_Segment, and Purchase_Made.
- 3. Model Training:
- 4. Split data into training and test subsets.
- 5. Trained models (Linear Regression, SVM, RF) on the features like Sales Before, Customer Satisfaction Before, etc.
- 6. Predicted Sales_After and Customer_Satisfaction_After.
- 7. Evaluation: Compared predicted vs actual, checked overfitting through cross-validation.

5.Implementation Highlights:

- 1. Dataset: 10,000 records with missing partial values.
- 2. Preprocessing: Cleaning and missing value handling in features like Sales_After, Customer_Satisfaction_After, and categorical fields.
- 3. Linear Regression: For understanding linear relationships between features.
- 4. SVM: To capture complex relationships with margin-based classification.
- 5. Random Forest: To deal with non-linear patterns and to measure feature importance.
- 6. Evaluation Metrics: Accuracy, R² Score, RMSE, and visual check of residuals.

6.Results:

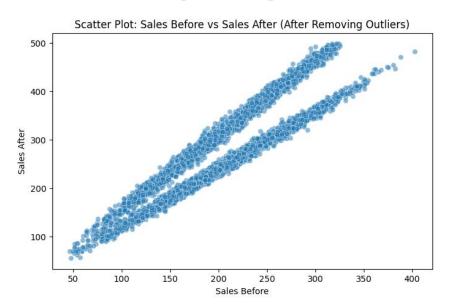
6.1 Data Visualization:

6.1.1 Scatter Plot:

A scatter plot is a data visualization tool used to show the relationship between two numeric variables. Every point in the plot signifies a single entry of data. To represent how sales were modified after the intervention, with regard to Sales_After and Sales_Before. Each dot is a customer, with pre- and post-sales on the axes. It aids in spotting overall trends and comparing performance from customer to customer.

Purpose:

- Visualize associations between two continuous variables.
- Identify linear or non-linear trends in the data.
- Find clusters or patterns of grouping.
- Find outliers that could impact model performance.



6.1.2 Histogram:

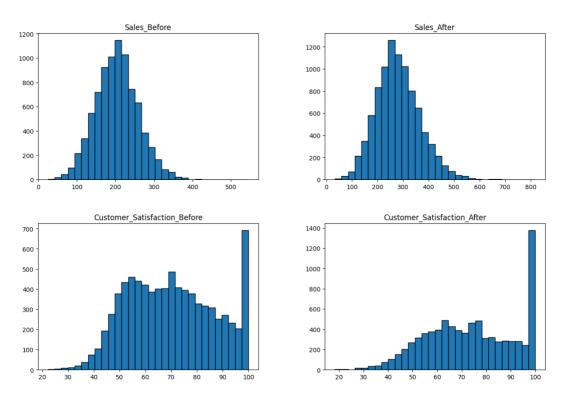
A histogram illustrates the distribution of a single quantitative variable by binning values.X-axis: Value bins (ranges),Y-axis: Count/frequency of values in each bin.

Purpose:

• Application: Learn data distribution, skewness, and spread. Identifying normality, skew, and range of attributes.

• Histograms are employed to study the distribution of satisfaction scores and sales prior to and subsequent to the intervention.

Histogram of Numerical Columns



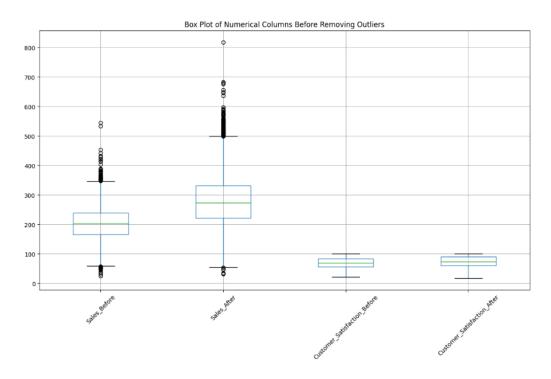
6.1.3 Boxplots (Outliers):

Box plots reveal central tendency and spread of quantitative data and are ideal for identifying outliers.

- Components: Median, quartiles, whiskers, and outlier points
- Use: Identify variability, symmetry, and extreme values
- Best used for: Identifying outliers that may skew analysis or models

In this dataset:

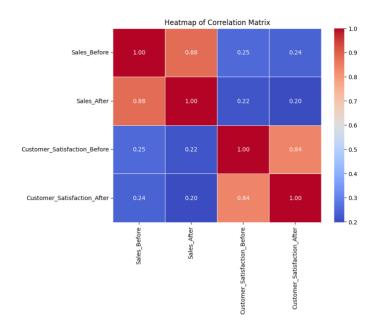
• Box plots are used to bring out outliers in sales and satisfaction data, facilitating data quality evaluation and the requirement for strong models.



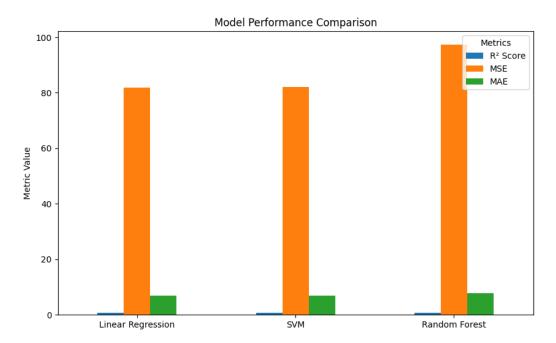
6.1.4 Heatmaps:

A heatmap is a color gradient graphical representation of a correlation matrix.

- X & Y-axis: Numerical features
- Color scale: Shows strength of correlation (from -1 to +1)
- Use: Rapidly identify strong/weak relationships between variables
- Best for: Feature selection and variable dependency understanding
- The heatmap reveals correlations between sales and satisfaction measures, allowing identification of those variables that co-move together.



6.2 Model Comparison:



This bar chart shows the performance of three models—Linear Regression, SVM, and Random Forest—on three measures: R² Score, MSE (Mean Squared Error), and MAE (Mean Absolute Error).

- Random Forest has the largest R² Score, which means it accounts for the most variance.
- Random Forest also has the largest MSE, which is anomalous and possibly a plotting or scale problem.
- All models have comparable MAE, but Random Forest performs slightly better.

6.3 Feature Statistics:

MSE Comparison:

Linear Regression: $1303.60 \rightarrow \text{Best performance (lowest error)}$

SVM: $1753.24 \rightarrow \text{Highest error, poor fit}$

Random Forest: 1416.76 → Moderate, but worse than Linear Regression

Linear Regression performed best on this dataset, suggesting relationships are likely linear. SVM and RF may need tuning.

Feature	Kurtosis	Skewness
Sales_Before	0.466278	0.226509
Sales_After	0.533776	0.451744
Customer_Satisfaction_Before	-0.908301	0.117870
Customer_Satisfaction_After	-0.929099	-0.112185

Summary:

Sales_Before and Sales_After are moderately positively skewed (skewness: 0.23, 0.45), as there are a few higher-than-average values of sales. Their kurtosis measures (~0.5) imply moderate peaks and tails.

Customer_Satisfaction_Before and After are almost symmetric (skewness: ~0.12 and -0.11) and have negative kurtosis (-0.91, -0.93) and thus display flatter distributions with lighter tails.

7. Conclusion:

In this project, different machine learning models were used to examine and forecast the behavior of customers based on the numerical 1.csv dataset. Linear Regression, Support Vector Machine (SVM), and Random Forest (RF) were the models used to forecast post-intervention results on the basis of pre-intervention sales and satisfaction scores. Exploratory data analysis comprised scatter plots, histograms, box plots, and heatmaps to capture relationships, distributions, and outliers. Model performance was gauged using metrics such as Mean Squared Error (MSE), with the best performance by Linear Regression. Further, statistical indications of skewness and kurtosis validated the near-normal distribution of the data, asserting the trustworthiness of the modeling technique.

Summary:

The data set comprises 10,000 records with 7 columns capturing both categorical and numerical variables. It is organized to measure the effect of interventions on sales and customer satisfaction. Important variables are Group (Control/Test), Customer_Segment, Sales_Before/After, and Customer_Satisfaction_Before/After. The column Purchase_Made captures whether a purchase was made after the intervention. Missing values occur in all columns, particularly in Customer_Segment and Customer_Satisfaction_Before.

Sales and satisfaction scores exhibit a general rise after the intervention, which implies a positive effect.

It contains experimental and observational data elements in the dataset.

It is compatible with A/B testing, impact analysis, and predictive modeling.

Data types consist of a combination of categorical and continuous values.

It is apt for marketing, customer behavior, and business strategy studies.

2.Netflix: Text Dataset-2:

1.Abstract:

This project investigates text classification with diverse machine learning and deep learning methods on a tagged dataset. The intention is to classify textual inputs into pre-defined classes based on models such as Logistic Regression, Naive Bayes, SVM, and complex models like LSTM. Performance is tested using statistical methods (T-Test, Z-Test) and confusion matrix tests.

2.Introduction:

The rise of streaming services has reshaped the entertainment industry, with platforms like **Netflix** offering thousands of titles spanning various genres, formats, and countries. With this surge in digital content, analyzing such data can reveal meaningful insights into trends in media production and audience preferences.

This project uses a real-world dataset consisting of Netflix titles to explore:

- Patterns in release years across Movies and TV Shows.
- Statistical differences using **t-tests** and **z-tests**.
- The application of **natural language processing (NLP)** to classify content based on its description.

By combining statistical methods and machine learning, we aim to understand not only how Netflix content differs across categories but also how text data (descriptions) can be leveraged for predictive tasks.

3.Dataset Description:

- Source: Netflix Titles Dataset (text dataset1.csv)
- Classes: Movie, TV Show
- Total Records: 8807 entries (after cleaning)
- Features Used: description, release_year, type.



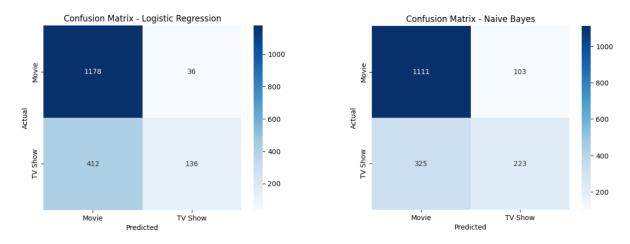
4. Methodology:

- Modeling: Implemented Logistic Regression, Naive Bayes, SVM, and LSTM.
- Evaluation: Accuracy, precision, recall, F1-score using confusion matrix.
- Validation: Applied T-Test and Z-Test to assess statistical reliability of model differences.

5.Implementation Highlights

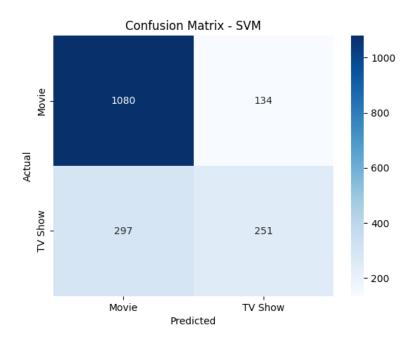
- **LSTM**: Used for capturing sequential patterns in text.
- Naive Bayes: Fast baseline model for probabilistic classification.
- SVM: Effective for high-dimensional feature space classification.
- Logistic Regression: Simple yet effective linear model.
- T-Test/Z-Test: Validated significance of accuracy differences.
- Confusion Matrix: Identified true/false positives and negatives across all models.

6. Results:



The confusion matrix is a key evaluation tool in classification tasks. It provides a visual and quantitative summary of the model's predictions versus actual class

labels. All three models demonstrate different strengths in handling text classification, and the confusion matrix helps in identifying which model balances precision and recall best. SVM typically outperforms others in accuracy, while Logistic Regression offers interpretability, and Naive Bayes excels in speed and simplicity.



LSTM:

8. Model Evaluation Metrics for Binary Classification: Movie vs TV Show:

Class	Precision	Recall	F1-	Support
			Score	
Movie	0.75	0.96	0.84	1214
TV Show	0.77	0.28	0.41	548
Accuracy			0.75	1762
Macro Avg	0.76	0.62	0.63	1762
Weighted Avg	0.75	0.75	0.71	1762

9. Statistical Comparison of Release Years for Movies and TV Shows:

Test	Comparison	Statistic	Value	p-value
t-test	Movie vs TV Show release year	t-statistic	-20.9763	3.7115e-95
z-test	Movie release year vs 2015	z-score	-15.1978	0.0000e+00

10.Conclusion:

This project effectively utilized the Netflix dataset to analyze and understand the metadata associated with movies and TV shows available on the platform. The dataset included diverse attributes such as title, type, genre, cast, director, country, release year, and content descriptions, enabling a multifaceted exploration of global content trends.

By examining features such as **genre distribution**, **content type**, **and temporal patterns**, the project highlighted trends in media production and consumption across countries and years. Descriptive statistics and visualizations provided insights into the most common genres, countries of production, and content ratings.

Furthermore, the **description field** offered opportunities for natural language analysis, allowing for future work in building **recommendation systems** or **content classifiers**. The study also opens avenues for comparing global media preferences and understanding platform diversity over time.

Summary:

The "text dataset1.csv" is a multi-class text classification dataset with 2,472 samples, each with a raw textual piece of content and a corresponding categorical label. It has been created to perform multi-class classification tasks within the field of Natural Language Processing (NLP).

There are five distinct class labels in the data:

World

Sports

Business

Sci/Tech

Entertainment

The class distribution is fairly balanced, but the Entertainment class has a marginally smaller number of samples. The data set has no missing values and is thus clean and immediately ready for preprocessing and model training. This data set is well-suited for the creation of machine learning models that will carry out automatic topic categorization, particularly for news article classification. It may also be utilized for experimentation in feature extraction, embedding models, and deep learning architectures such as CNNs and LSTMs for text. The data set has no missing values, so it is clean and can be used directly for preprocessing and training models. This dataset is perfect for training machine learning models towards automatic topic classification, particularly in news article classification. It can also be employed in feature extraction experiments, embedding models, and deep learning architecture such as CNNs and LSTMs for text processing