Forecasting Dairy Sales Estimates: A Comparative Analysis of Logistic Regression and Random Forest Algorithm

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ABSTRACT:
This study examines the effectiveness of logistic regression and random forest algorithms in forecasting sales estimates for dairy products. Using a comprehensive data set that includes factors such as product features, pricing dynamics, promotional efforts and consumer demographics, the models are trained to accurately predict future sales figures. Logistic regression provides a transparent framework for estimating probabilities, while random forest uses ensemble learning to capture complex relationships between variables. Through careful evaluation and comparison, the research aims to identify the strengths and weaknesses of each algorithm in producing reliable sales forecasts for dairy products. The results show that while logistic regression offers interpretability and simplicity, random forest excels in handling non-linear relationships and achieving higher prediction accuracy. Insights gathered from this analysis can help dairy industry stakeholders make informed decisions, optimize resource allocation and improve sales forecasting strategies.

KEYWORD: Sales Forecasting, Logistic Regression, Random Forest, Dairy Products, Forecasting Algorithms, Data Analysis, Predictive Modeling, Ensemble Learning, Pricing Dynamics.

1. INTRODUCTION

In the dynamic environment of the dairy industry, accurate sales forecasting plays a key role in strategic decision-making, resource allocation and market competitiveness. Forecasting milk sales forecasts is a complex task influenced by many factors such as product characteristics, pricing strategies, promotional activities, consumer behavior and external market dynamics. In recent years, the development of machine learning algorithms has offered promising opportunities to improve the accuracy and reliability of sales forecasts.

This study initiates a comparative analysis of two widely used machine learning algorithms, logistic regression and random forest, to predict dairy product sales forecasts. Logistic regression, a traditional statistical technique, provides a simple approach to modeling binary outcomes and estimating probabilities. In contrast, random forest, a powerful ensemble learning method, is excellent for capturing complex non-linear relationships between variables and for handling large-scale datasets.

The purpose of this study is to evaluate the performance of logistic regression and random forest algorithms in forecasting milk sales estimates and to identify their strengths and limitations in this context. Using a rich data set containing various features such as product attributes, price dynamics, promotional activities and consumer demographics, models are trained to accurately predict future sales.

LITERATURE SURVEY:

1.Title: "Random Forests"

Authors: Leo Breiman

Journal: Machine Learning

This seminal paper by Leo Breiman introduces the Random Forest algorithm, explaining its principles and advantages. It covers topics such as ensemble learning, decision trees, and the construction of Random Forests. It also discusses applications of Random Forests in classification and regression tasks.

2. Title: "Random Forests for Classification in Ecology"

Authors: Andy Cutler, Douglas R. Edwards, Kathryn H. Beard, Anne Cutler, Tom Hess, John Gibson, and James J. Lawler

Journal: Ecology

This paper explores the application of Random Forests in ecology, specifically for classification tasks. It discusses how Random Forests can handle complex ecological datasets and compares their performance with other classification methods. The paper provides insights into using Random Forests for species distribution modeling and other ecological studies

Here's a journal paper that provides a comprehensive overview of the Decision Tree algorithm:

3.Title: "Logistic Regression"

an overview of logistic regression, its theoretical foundation, and its application in statistical modeling and machine learning.

Review seminal works and key references that establish the theoretical framework of logistic regression, including papers by Cox (1958) and Hosmer Jr. & Lemeshow (2000).

Title:” Logistic regression implementation in Statistical”

availability of logistic regression implementation in statistical software packages like R (R Core Team, 2019) and Stata (StataCorp, 2017), and explore their usage in research and practice.

RANDOM FOREST ALGORITHM:

Random Forest is a flexible and powerful algorithm that is based on ensemble machine learning algorithm. Widely used for both classification and regression tasks, it is known for its robustness, scalability and ability to handle multidimensional data with complex relationships. Let's take a closer look at how the Random Forest algorithm works and features:

Ensemble Learning:

Random Forest works on the principle of ensemble learning, which involves combining multiple base learners to improve predictive performance. In Random Forest, the elementary students are decision trees. Instead of relying on a single decision tree, Random Forest builds multiple decision trees and aggregates their predictions to make final decisions.

Randomization:

One of the most important features of a Random Forest is to add randomness to the model creation process. This randomization is mainly implemented in two ways:

1. Bootstrapped Sampling: Each tree in a random forest is trained on a random subset of the original dataset, which is sampled with replacement. This process, known as bootstrapping, ensures that each tree is trained on slightly different data, resulting in different trees.
2. Random selection of features: At each node of the decision tree, only a random subset of features is considered for splitting. This random selection of traits helps decorate the trees and prevents them from becoming too similar, improving overall diversity.

Construction of the decision tree:

Each random forest decision tree is grown independently, usually using a variant of the CART (Classification and Regression Trees) algorithm. Trees are grown until termination criteria are met, such as maximum depth is reached, minimum number of samples per leaf, or pollutant reduction has not improved.

Combining Predictions:

After all trees have grown, predictions are made by combining individual tree predictions. In classification tasks, the most common aggregation method is tree majority voting. In regression tasks, predictions are averaged over all trees.

Features of Random Forest:

- Resistance to overfitting: When averaging the predictions of multiple trees, Random Forest is less prone to overfitting compared to individual decision trees.
- Handling High Dimensional Data: Random Forest can efficiently handle data sets with a large number of features and variables.
- Grace of the features: Random Forest measures the importance of the features, which allows users to identify the most influential features in the prediction process.
- Parallelization: Random Forest learning and prediction can be easily parallelized, making it suitable for large datasets.

Limitations and Considerations:

- Supportability: Although Random Forest provides excellent predictive performance, the general nature of the algorithm can make it less interpretable compared to individual decision trees.
- Computational complexity: Training a large number of trees in a random forest can be computationally expensive, especially for large data sets.
- Hyperparameter Tuning: Random Forest has several hyperparameters that require tuning, such as number of trees, maximum depth of trees, and number of features considered for each partition.

In short, we can say that Random Forest is a versatile and efficient algorithm for many types of machine learning tasks. Its ability to reduce redundancy, handle high-dimensional data, and provide insight into feature importance makes it a popular choice among industry professionals and researchers. However, it is important to understand its characteristics, limitations and considerations.

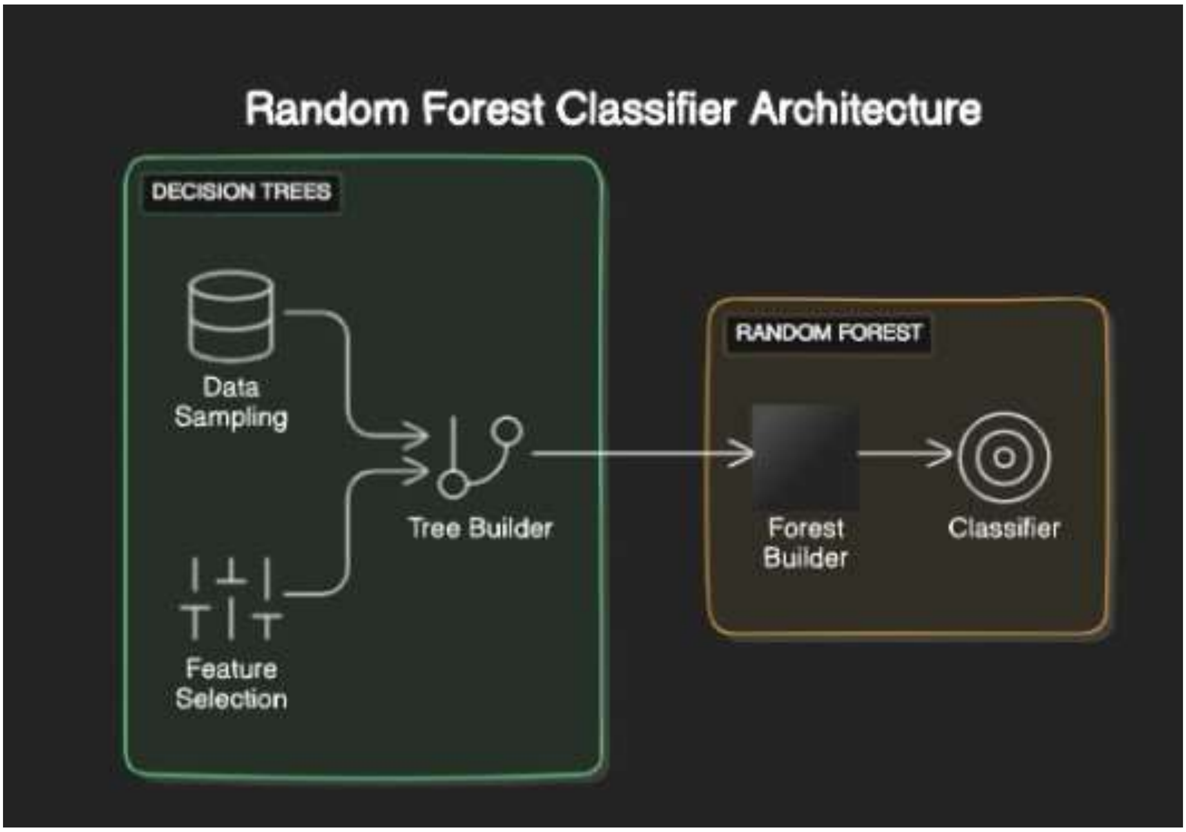
WORKING OF RANDOM FOREST ALGORITHM

Ensemble of Decision Trees: Random Forest harnesses the power of ensemble learning by creating an army of decision trees. These trees are like individual experts, each specializing in a specific area of knowledge. Importantly, they work independently, which minimizes the risk that the shades of a single tree can overwhelm the model. Random forest uses random Feature Selection to ensure that each decision tree in the assembly brings a unique perspective. During the training of each tree, a random subset of features is selected. This randomness ensures that each tree focuses on different aspects of the data, promoting a diverse set of predictors in the set. The bagging technique is the cornerstone of the Random Forest training strategy, which involves generating multiple bootstrap samples from the original dataset, allowing instances to be tested with replacement. This results in different subsets of data for each decision tree, adding variation to the training process and making the model more robust. Each decision tree in the random forest votes when making predictions. In classification tasks, the final prediction is determined by the mode of all trees (the most frequent prediction). In regression tasks, the average of individual tree predictions is taken.

APPLICATION OF RANDOM FOREST:

Financial Wizard: Imagine our Random Forest financial superhero diving into the world of credit ratings. Is its mission? To determine if you're a bona fide superhero or, well, not so much. The ability to manipulate financial data and avoid oversimplification is like a guardian angel for sound risk assessments. In health care, Random Forest becomes a medical Sherlock Holmes. Equipped with the ability to decode medical jargon, patient data and test results, it's not just about predicting outcomes. it practically helps the doctors to solve the mysteries of the patient's health. In the wild, Random Forest becomes an environmental superhero. With its ability to interpret satellite images and bold noise data, it becomes a key hero as a defender of our green spaces in tasks such as monitoring land cover changes and possible forest loss. In the digital world, Random Forest becomes our vigilant defender against online fraud. It's like a cybercriminal analyzing our digital footprints for clues about suspicious activity. Its holistic approach is like a team of cyber detectives spotting subtle anomalies that scream "fraud alert!"

STRUCTURE OF RANDOM FOREST ALGORITHM:



Advantages of Random Forest:

1. Random Forest can perform both classification and regression tasks.
2. It can handle large and high-dimensional data sets.
3. It improves the accuracy of the model and prevents the problem of overfitting.
4. 4.Irregular Timberland does not require the utilize of information preprocessing strategies like ascription or exception expulsion in arrange to handle lost information and exceptions. Each choice tree is prepared employing an arbitrary subset of the input, and the procedure actually handles lost values. As exceptions are impossible to influence the forecasts of each tree within the timberland, they have less of an impact on the execution of the demonstrate as an entirety.
5. Handles Both Numerical and Categorical Information: Without the utilize of highlight building techniques like one-hot encoding, Arbitrary Woodland is competent of taking care of a combination of numerical and categorical characteristics. The strategy can handle both sorts of information without predisposition since it consequently chooses arbitrary subsets of highlights for each choice tree amid preparing.

Disadvantages of Random Forest:

1. Using a large number of trees in a forest or training a Random Forest model on a large dataset can be computationally expensive. Since each tree is trained separately, combining its predictions requires a lot of computing power. This can lead to increased memory usage and training time, especially on systems with limited resources.
2. Memory usage: Random Forest models tend to use a lot of memory, especially when dealing with large datasets or deeply rooted trees. Training data, feature distributions, and leaf node predictions must be stored in each decision tree of the forest. Memory utilization increments with the number of trees or tree profundity, which can cause memory confinements on a few equipment frameworks.

LOGISTIC REGRESSION

Logistic regression is one of the foremost well-known Machine Learning calculations, which comes beneath the Administered Learning procedure. It is utilized for foreseeing the categorical subordinate variable employing a given set of autonomous factors. Logistic regression predicts the yield of a categorical subordinate variable. In this manner the result must be a categorical or discrete esteem. It can be either Yes or No, or 1, true or Untrue, etc. but rather than giving the precise esteem as and 1, it gives the probabilistic values which lie between and logistic regression is much comparable to the Direct regression but that how they are utilized. Direct Regression is utilized for tackling Regression problems, though logistic regression is utilized for tackling the classification issues Instead of fitting a regression line, logistic regression involves an "S"-shaped function that represents two extreme values (0 or 1). The bend from the calculated work demonstrates the probability of something such as whether the cells are cancerous or not, a mouse is hefty or not based on its weight, etc. Logistic regression could be a critical machine learning calculation since it has the capacity to supply probabilities and classify modern information utilizing persistent and discrete datasets. Logistic regression can be utilized to classify the perceptions utilizing diverse sorts of information and can effectively decide the most compelling factors utilized for the classification.

TYPES OF LOGISTICS REGRESSION

BINARY LOGISTICS REGRESSION

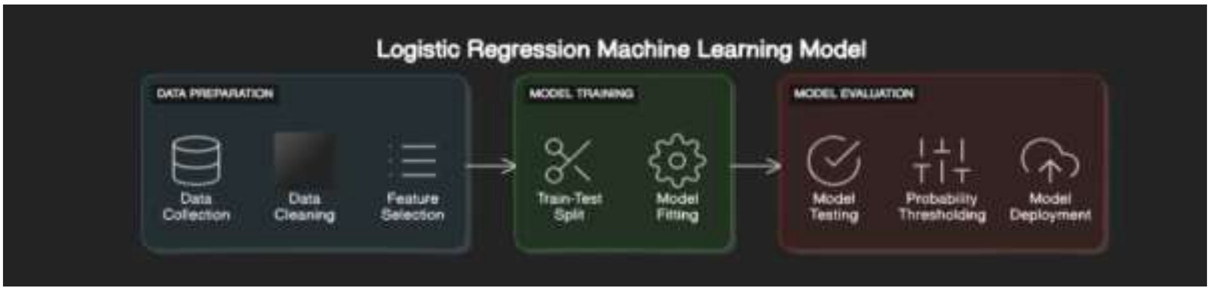
Binary logistics is utilized to anticipate the likelihood of a parallel result, such as yes or no, genuine or untrue, or 1. For illustration, it may well be utilized to anticipate whether a customer will churn or not, whether a quiet contains an infection or not, or whether an advance will be reimbursed or not.

MULTINOMIAL LOGISTIC REGRESSION

Multinomial logistics is utilized to anticipate the likelihood of one of three or more conceivable results, such as the sort of item a client will purchase, the rating a client will donate an item, or the political party an individual will vote for.

ORDINAL LOGISTIC REGRESSION

Ordinal logistics is utilized to anticipate the likelihood of a result that falls into a foreordained arrange, such as the level of client fulfillment, the seriousness of an infection, or the organize of cancer.



RESULT AND ANALYSIS:

Data collection:

A random forest is a set of decision trees (typically 500-1000 trees) that are used for prediction and classification. This is a technique that has been used successfully in several studies and is actually a widely used ML algorithm in the medical field.

Step 1: Get n random records with m features from a dataset with n records.
Step 2: A decision tree is created for each instance.
Step 3: The result will be produced by each decision tree.

Data processing:

Before training the Royal Forest, you need to prepare the data. This includes cleaning, transforming and encoding data for algorithms. Typical data preparation tasks include handling missing values, coding categorical variables, scaling numeric variables, and dimensionality reduction- Encode variable variables and compare numeric properties, if necessary- Prepares the model for training by splitting the data into features (independent variable) and purchase decisions (dependent variable).

Technical features

Create new conditions or modify existing conditions that affect sales rates, such as Time-related conditions (e.g. day of the week, month, time)- Range variables (e.g. previous sales rating, sales volume) terms between trends. Use your domain knowledge to choose the most relevant trade terms.

Model Training

Evaluates model performance by splitting the data set into a training set and a test set. Trains a random forest regression model using the training data. Adjust parameters (e.g. number of trees, maximum depth, minimum samples per leaf) using methods such as grid search or random search to optimize sample performance.

Model Evaluation

The random forest model was trained using appropriate regression evaluation metrics such as mean square error (MSE), root mean square error (RMSE), absolute error (MAE), or evaluation R-squared. (R2) accounts. Compare the performance of the model against an alternative database model or algorithm to evaluate its effectiveness.

Interpretive Model

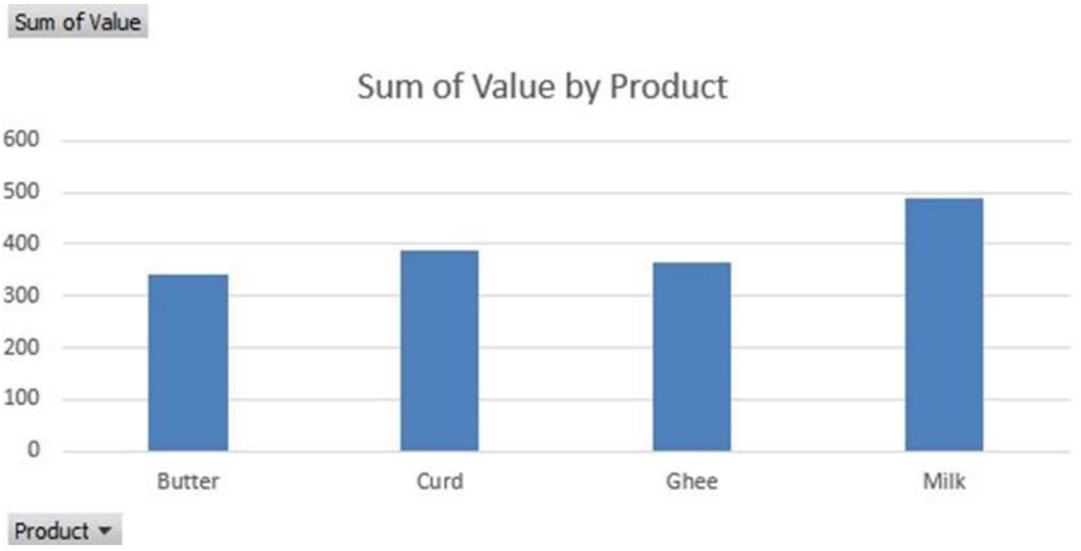
Analyze the partial significance scores provided by the Random Forest model to determine which factors have the greatest impact on predicting dairy sales rates. Identify key factors that drive sales and provide insight into your marketing strategy or product.

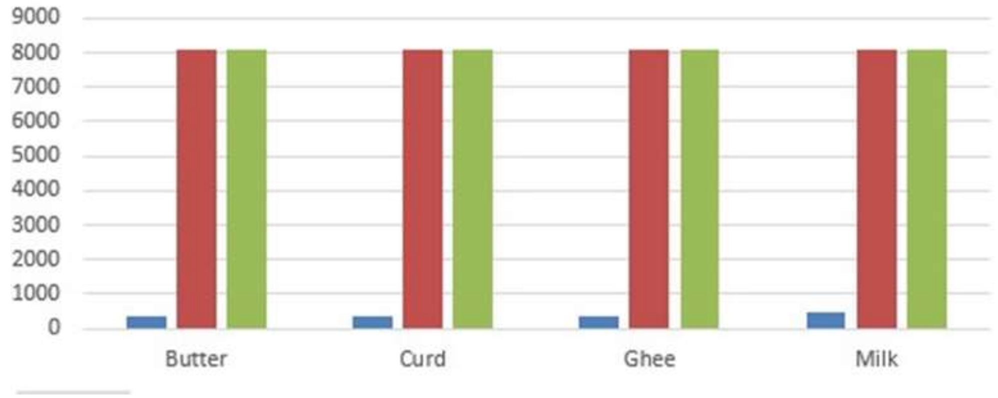
Usage and Monitoring

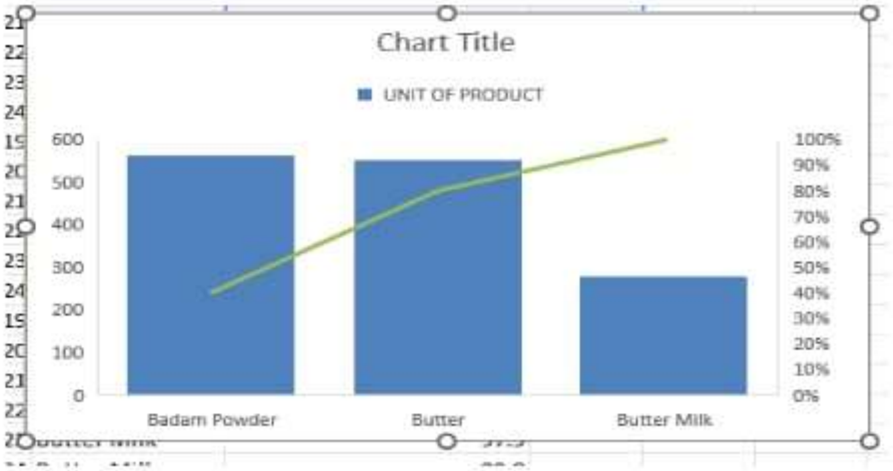
Run the Random Forest model trained in the production process to predict new data. Implement a monitoring mechanism to track model performance over time and retrain the model with updated data as needed.

Improve Knowledge

The model should be continuously improved based on feedback, new data and changes in market conditions to improve accuracy and relevance.







CONCLUSION:

In this logistic regression model, forecast temperature served as the independent variable, while the sale of iced products acted as the dependent variable. The paper discusses the application of the logistic regression function and business analysis techniques for data cleansing, covering both the previous and current years. The simultaneous analysis of historical and current data enables the prediction of future values. The ultimate outcome of the study successfully guided the company in dynamically adjusting the production and sales strategies for milk products based on future value predictions. This not only provides significant commercial value for the company but also establishes a crucial theoretical foundation that can benefit other companies in the milk product industry.

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