

ABSTRACT

In the world of business, the ability to predict customer revenue is crucial for driving sales and improving profitability. One of the most effective ways to do this is through the use of machine learning algorithms, which can analyze customer data and identify patterns that can be used to make accurate revenue predictions. In this paper, we explore the use of the Light Gradient Boosting Machine (LGBM) algorithm for customer revenue prediction.

Then introduce the LGBM algorithm, explaining its advantages over other machine learning algorithms in terms of speed and accuracy. Next, we describe the dataset we used for our experiments, which contains customer data from an e-commerce company.

We preprocess the data using techniques such as feature engineering and normalization, before training the LGBM model. We then evaluate the model's performance using various metrics such as accuracy, and compare it to other popular machine learning algorithms. Our results show that the LGBM algorithm outperforms other models in terms of accuracy and efficiency. We also perform feature importance analysis to identify the most significant factors that contribute to revenue prediction. Our findings indicate that customer demographics, purchase history, and website behavior are the most important factors in predicting revenue.

Finally, we discuss the practical applications of our model, such as personalized marketing and product recommendations, and the potential for future research in this area. Overall, our study demonstrates the effectiveness of LGBM in customer revenue prediction and its potential for driving business growth and improving customer experiences.

TABLE OF CONTENTS

S.NO	TITLE	PAGENO
1	INTRODUCTION	
1.1	CONCEPT AN OVERVIEW	11
1.2	EXISTING SYSTEM	11
1.3	PROPOSED SYSTEM	12
2	METHODOLOGY	
2.1	PROBLEM DEFINITION	13
2.2	OBJECTIVE OF THE PROJECT	13
2.3	MODULE REQUIREMENTS	16
2.4	MACHINE LEARNING	18
2.5	ALGORITHMS	21
3	LANGUAGES/TOOLS,DATASETS	

3.1	LANGUAGE/TOOL DESCRIPTION	28
3.2	PACKAGES,FUNCTIONS	32
3.3	DATASETS	34
3.4	DATA STORAGE	37
3.5	DATA CLEANING	38
4	MODULE DESCRIPTION	
4.1	COLLECTION OF DATASET	39
4.2	SELECTION ATTRIBUTES	39
4.3	DATA PRE-PROCESSING	39
4.5	LightGBM MODEL	41
4.4	PREDICTION	41
5	RESULTS/DISCUSSIONS	
5.1	INPUTS & OUTPUT SCREENS	42

5.2	DATA VISUALIZATION	47
6	CONCLUSION	
6.1	CONCLUSION	48
6.2	FUTURE ENHANCEMENT	48
7	REFERENCES	
7.1	BOOK REFERENCES	49
7.2	WEB REFERENCES	50

TABLE OF FIGURE

S.NO	TITLE	PAGE NO.
1	Figure 2.1. Workflow of a customer revenue prediction model	14
2	Figure 2.2. Block diagram of customer revenue Prediction	15
3	Figure 2.3. Deep learning is a type of machine learning	18
4	Figure 2.4. The distinction between a XGBoost and a LightGBM	22
5	Figure 2.5. LightGBM	23
6	Figure 2.6. Level-wise growth	24
7	Figure 2.7. Leaf-wise growth	25
8	Figure 2.8. How does LGBM work	27
9	Figure 3.1. Steps involved in Data Cleaning	38
10	Figure 3.2.Data Preparation	40
11	Figure 3.3. Prediction of Stock	41

1. Introduction

Introduction

In today's highly competitive business landscape, companies are constantly searching for new ways to drive sales and improve profitability. One key strategy for achieving these goals is by accurately predicting customer behavior and preferences, particularly in terms of revenue generation. By identifying which customers are likely to spend more and when, businesses can optimize their marketing efforts and improve the overall customer experience. Machine learning algorithms have emerged as a powerful tool for customer revenue prediction, with the ability to analyze large amounts of data and identify patterns that may be missed by traditional statistical methods. One such algorithm is the Light Gradient Boosting Machine (LGBM), which has gained popularity in recent years due to its speed and accuracy. In this paper, we investigate the effectiveness of LGBM in predicting customer revenue. We begin by providing an overview of the importance of customer revenue prediction for businesses, and the challenges involved in accurately predicting customer behavior. We then introduce the LGBM algorithm, explaining its underlying principles and how it differs from other machine learning algorithms. Next, we describe the dataset we used for our experiments, which includes customer data from an e-commerce company. We discuss the steps we took to preprocess the data, including feature engineering and normalization, before training the LGBM model. We then evaluate the performance of the LGBM model using various metrics, such as accuracy and compare it to other popular machine learning algorithms. We also perform feature importance analysis to identify the most significant factors that contribute to revenue prediction. Finally, we discuss the practical applications of our model, such as personalized marketing and product recommendations, and the potential for future research in this area. Overall, the results of our study demonstrate the effectiveness of LGBM in customer revenue prediction, highlighting its potential to drive business growth and improve the customer experience. The insights gained from our analysis may also inform the development of more targeted marketing strategies and personalized recommendations for individual customers.

1.2. Concept an Overview

Customer revenue prediction using LGBM machine learning algorithm is a data-driven approach to predicting the revenue generated by individual customers. The Light Gradient Boosting Machine (LGBM) is a machine learning algorithm that is particularly well-suited for this task, as it can efficiently handle large amounts of data and identify complex patterns that may not be immediately apparent. This approach involves preprocessing the data, including feature engineering and normalization, before training the LGBM model. The model can then be used to make accurate revenue predictions based on customer demographics, purchase history, and website behavior.

1.3. EXISTING SYSTEM

Customer revenue prediction using Random Forest and Linear Regression is a widely used machine learning approach for businesses to predict the revenue generated by individual customers. The system involves the collection and preprocessing of customer data, followed by the training of a Random Forest or Linear Regression model to predict the revenue generated by individual customers. The data collected includes demographic information, customer behavior data, purchase history, and other relevant data points. This data is preprocessed to remove any irrelevant or redundant features, and to transform the data into a suitable format for the machine learning model. Random Forest is an ensemble learning algorithm that works by combining multiple decision trees to generate more accurate predictions. In this approach, multiple decision trees are trained on different subsets of the data, and their predictions are combined to make a final prediction. Linear Regression, on the other hand, is a statistical method that models the relationship between two or more variables. It works by fitting a linear equation to the data, which can then be used to make predictions.

DISADVANTAGE

One of the main disadvantages of using Random Forest and Linear Regression for customer revenue prediction is their limited ability to handle complex and non-linear relationships between variables. These algorithms assume that there is a linear relationship between the input features and the output variable, which may not always be the case in real-world scenarios. This can lead to inaccurate predictions and suboptimal marketing strategies.

1.4.PROPOSED SYSTEM

In this proposed system, Customer revenue prediction using LGBM (Light Gradient Boosting Machine) is a proposed machine learning approach for businesses to predict the revenue generated by individual customers. LGBM is a gradient boosting framework that uses tree-based learning algorithms, making it highly accurate and efficient for large datasets.

The proposed system involves the collection and preprocessing of customer data, followed by the training of an LGBM model to predict the revenue generated by individual customers. The data collected includes demographic information, customer behavior data, purchase history, and other relevant data points. This data is preprocessed to remove any irrelevant or redundant features, and to transform the data into a suitable format for the machine learning model.

LGBM works by combining multiple weak models to generate more accurate predictions. In this approach, multiple decision trees are trained on different subsets of the data, and their predictions are combined to make a final prediction. This allows LGBM to handle complex and non-linear relationships between variables, making it highly accurate for a wide range of datasets.

ADVANTAGE

One of the advantages of using LGBM for customer revenue prediction is its ability to handle both categorical and continuous data, making it a versatile algorithm for a wide range of datasets. Additionally, it is highly efficient and can be trained on large datasets with relatively low computational cost.

Another advantage of LGBM is its interpretability. LGBM provides feature importance scores, which can be used to understand which features are most important for predicting revenue and can help businesses identify areas for improvement in marketing strategies.

2.METHODOLOGY

2.1.PROBLEM DEFINITION

The problem that customer revenue prediction using LGBM machine learning algorithm aims to address is the difficulty that businesses face in predicting the revenue generated by individual customers. Accurately predicting customer revenue is essential for businesses to optimize their marketing strategies, increase customer engagement, and maximize revenue.

2.2.OBJECTIVE OF THE PROJECT

The objective of this project is to develop a customer revenue prediction model using the LGBM machine learning algorithm. The model aims to accurately predict the revenue generated by individual customers based on their demographic information, customer behavior data, and purchase history. The project also aims to provide interpretable insights into customer behavior and revenue generation using feature importance scores and visualization techniques.

Technical Objectives:

- To collect and preprocess customer data to prepare it for use in training the LGBM model.
- To develop an LGBM model for predicting customer revenue based on demographic information, customer behavior data, and purchase history.
- To optimize the LGBM model by tuning hyperparameters and selecting relevant features to improve prediction accuracy.

Experimental Objectives:

- To compare the performance of the LGBM model with other machine learning algorithms such as linear regression and random forest for customer revenue prediction.
- To assess the effect of different feature engineering techniques on the performance of the LGBM model.
- To investigate the impact of imputing missing data on the accuracy of the LGBM model.

BLOCK DIAGRAM OF THE PROJECT

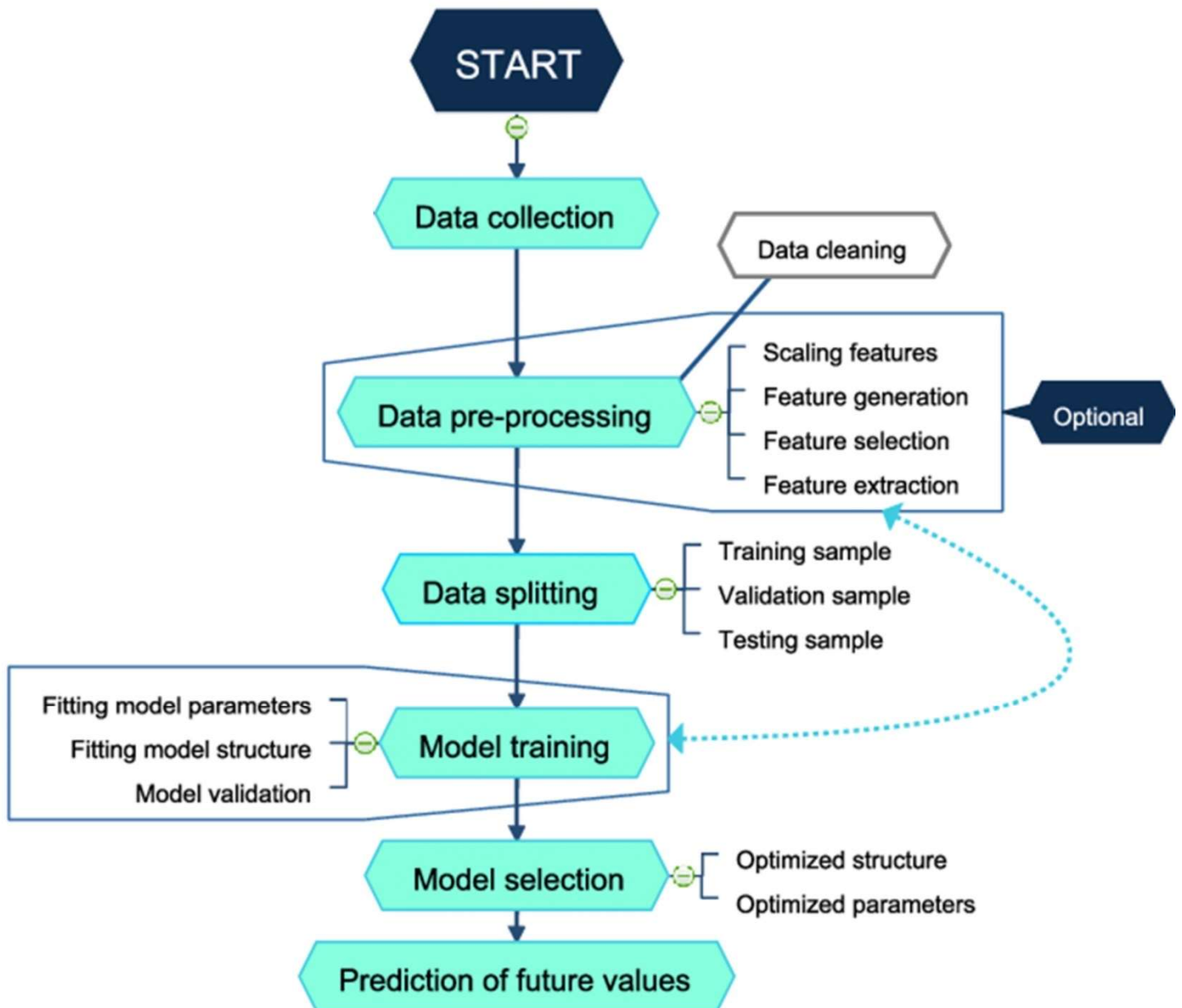


Figure 2.1. Workflow of a customer revenue prediction model

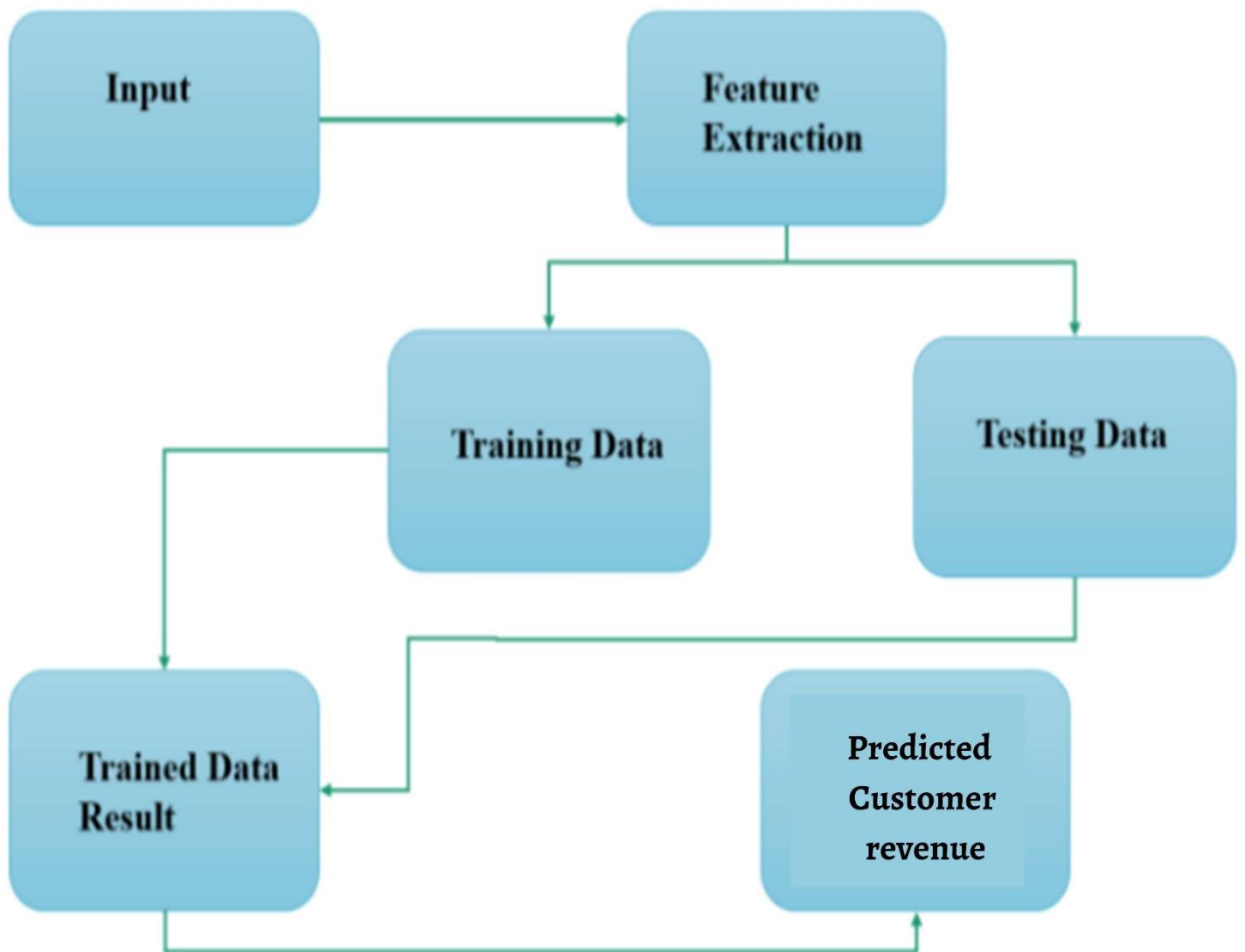


Figure 2.2. Block diagram of customer revenue Prediction

2.3.MODULE REQUIREMENTS

- COLLECTION OF DATASET
- SELECTION OF ATTRIBUTES
- DATA PRE-PROCESSING
- DATA VISUALIZATION
- X train Y train
- LGBM Model
- PREDICT

COLLECTION OF DATASET

A data set is a collection of data and it is a structured collection of data generally associated with a unique body of work. Dataset is a collection of various types of data stored in a digital format. Data is the key component of any Machine Learning project. Datasets primarily consist of images, texts, audio, videos, numerical data points

SELECTION OF ATTRIBUTES

Attribute selection is the process of identifying relevant information and removing as much of the irrelevant and redundant information as possible .Attribute selection is also defined as “the process of finding a best subset of features, from the original set of features in a given data set, optimal according to the defined goal

DATA PRE-PROCESSING

Data preprocessing is a data mining technique which is used to transform the raw data in a useful and efficient format and a component of data preparation, describes any type of processing performed on raw data.

DATA VISUALIZATION

Data visualization is the representation of data through use of common graphics, such as charts, plots, infographics, and even animations. These visual displays of information communicate complex data relationships and data-driven insights in a way that is easy to understand.

X train Y train

The train-test split procedure is used to estimate the performance of machine learning algorithms when they are used to make predictions on data not used to train the model. It is a fast and easy procedure to perform, the results of which allow you to compare the performance of machine learning algorithms for your predictive modeling problem.

LGBM Model

The LGBM (Light Gradient Boosting Machine) Model is a powerful machine learning algorithm that utilizes gradient boosting techniques to make accurate predictions. LGBM is known for its fast and scalable performance, making it ideal for large and complex datasets. It is designed to work well with both categorical and numerical data, enabling it to handle a wide range of data types and formats.

PREDICT

Predictive modeling is a commonly used statistical technique to predict future behavior. Predictive modeling solutions are a form of analyse that works by analyzing historical and current data and generating a model to help predict future outcomes.

2.4.MACHINE LEARNING

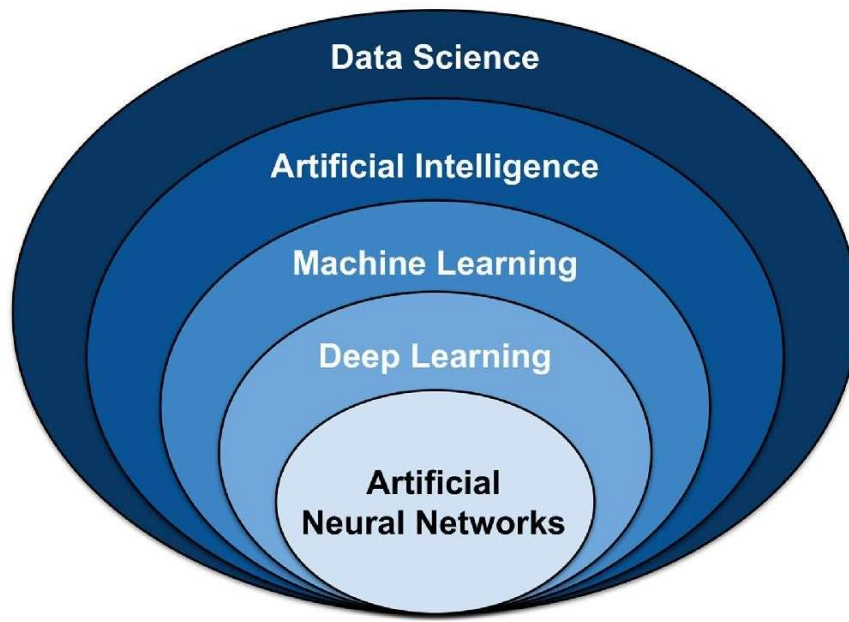


Figure 2.3. Deep learning is a type of machine learning

MACHINE LEARNING:

Machine learning, classification refers to a predictive modelling problem where a class label is predicted for a given example of input data. 10 Supervised Learning Supervised learning is the type of machine learning in which machines are trained using well "labelled" training data, and on the basis of that data, machines predict the output. The labelled data means some input data is already tagged with the correct output. In supervised learning, the training data provided to the machines work as the supervisor that teaches the machines to predict the output correctly. It applies the same concept as a student learns in the supervision of the teacher.

SUPERVISED LEARNING:

Supervised learning is a process of providing input data as well as correct output data to the machine learning model. The aim of a supervised learning algorithm is to find a mapping function to map the input variable(x) with the output variable(y). Unsupervised learning cannot be directly applied to a regression or classification problem because unlike supervised learning, we have the input data but no corresponding output data. The goal of unsupervised learning is to find the underlying structure of dataset, group that data according to similarities, and represent that dataset in a compressed format. Unsupervised learning is helpful for finding useful insights from the data.

UNSUPERVISED LEARNING

Unsupervised learning is much similar to how a human learns to think by their own experiences, which makes it closer to the real AI. Unsupervised learning works on unlabelled and uncategorized data which make unsupervised learning more important. In real-world, we do not always have input data with the corresponding output so to solve such cases, we need unsupervised learning. Reinforcement learning.

REINFORCEMENT LEARNING

Reinforcement learning is an area of Machine Learning. It is about taking suitable action to maximize reward in a particular situation. It is employed by various software and machines to find the best possible behaviour or path it should take in a specific situation. Reinforcement learning differs from supervised learning in a way that in supervised learning the training data has the answer key with it so the model is trained with the correct answer itself whereas in reinforcement learning, there is no answer but the reinforcement agent decides what to do to perform the given task. In the absence of a training dataset, it is bound to learn from its experience.

DEEP LEARNING:

Deep learning is a subset of machine learning, which is essentially a neural network with three or more layers. Deep Learning is a subfield of machine learning concerned with algorithms inspired by the structure and function of the brain called artificial neural networks. deep learning works with artificial neural networks, which are designed to imitate how humans think and learn.

Neural Network

A neural network is a series of algorithms that endeavors to recognize underlying relationships in a set of data through a process that mimics the way the human brain operates. In this sense, neural networks refer to systems of neurons, either organic or artificial in nature. Neural networks can adapt to changing input; so the network generates the best possible result without needing to redesign the output criteria. The concept of neural networks, which has its roots in artificial intelligence, is swiftly gaining popularity in the development of trading systems. They are used in a variety of applications in financial services, from forecasting and marketing research to fraud detection and risk assessment. Neural networks with several process layers are known as "deep" networks and are used for deep learning algorithms. The success of neural networks for stock market price prediction varies.

2.5.ALGORITHM

LightGBM (Light Gradient Boosting Machine)

Light GBM is a gradient boosting framework that uses tree based learning algorithm.LightGBM is a versatile machine learning algorithm that can be applied to a wide range of business problems.

Here are some examples:

- Customer churn prediction: LightGBM can be used to predict which customers are likely to churn, based on their past behavior and demographic information.
- Fraud detection: LightGBM can help detect fraudulent transactions by identifying patterns in the data that are indicative of fraud.
- Image recognition: LightGBM can be used to train models for image classification and recognition, enabling applications such as facial recognition and object detection.
- Credit risk assessment: LightGBM can help assess the creditworthiness of loan applicants, based on their financial history and other relevant factors.
- Forecasting: LightGBM can be used to predict future trends and patterns in time-series data, such as sales forecasts or stock price predictions.
- Recommendation systems: LightGBM can help build recommendation systems that suggest products or services to customers based on their past behavior and preferences.
- Natural Language Processing (NLP): LightGBM can be used in NLP applications such as sentiment analysis, topic modeling, and text classification.
- Supply chain optimization: LightGBM can help optimize supply chain operations by predicting demand for products, identifying areas for cost reduction, and improving logistics planning.
- Medical diagnosis: LightGBM can be used to diagnose medical conditions based on patient symptoms and medical history.
- Energy consumption forecasting: LightGBM can help forecast energy consumption and optimize energy usage in buildings, factories, and other facilities.

LightGBM

LightGBM is a gradient boosting framework that uses decision trees to model the relationship between the input features and the target variable. It works by iteratively adding decision trees to the model, each one correcting the errors made by the previous trees. Unlike traditional gradient boosting algorithms, which grow the decision trees in a depth-first manner, LightGBM uses a leaf-wise approach. This means that it grows the tree by choosing the split that yields the greatest reduction in the loss function, rather than splitting each node equally. This approach can result in faster training times and better accuracy on large datasets. LightGBM also features several optimization techniques, such as data parallelism, histogram-based gradient estimation, and feature bundling, which further improve its speed and accuracy. Overall, LightGBM is a powerful and efficient machine learning algorithm

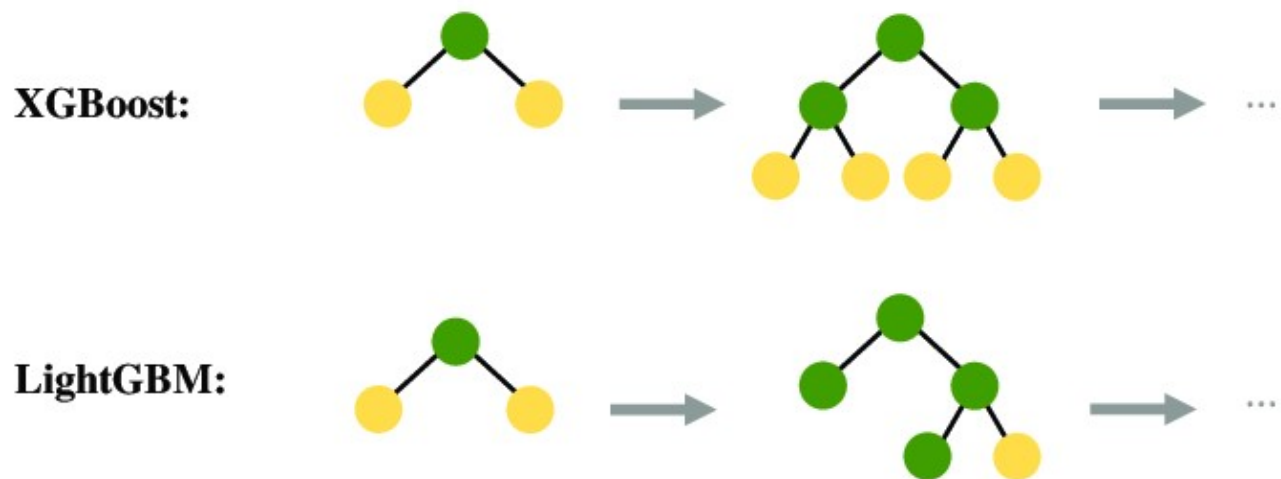


Figure 2.4. The distinction between a XGBoost and a LightGBM

Light GBM

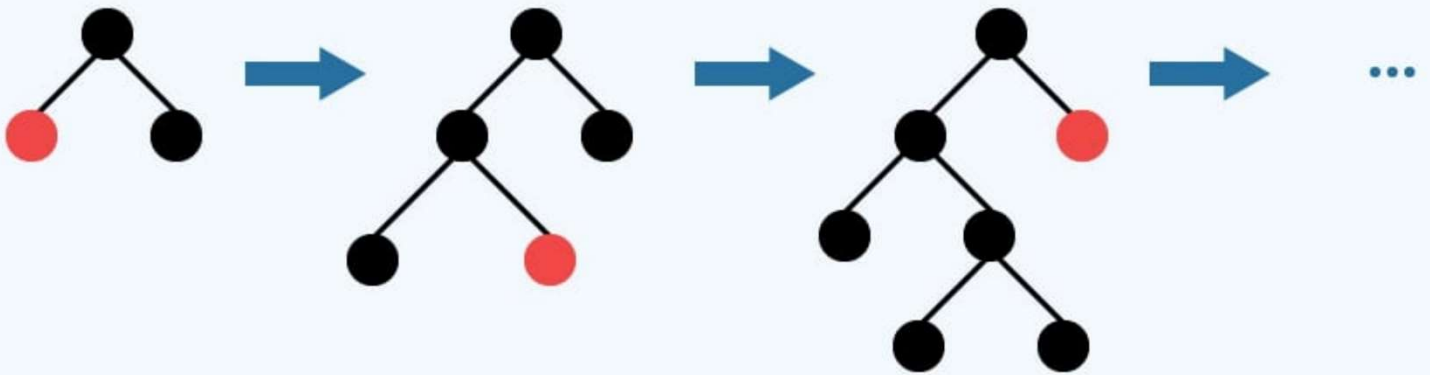


Figure 2.5. LightGBM

LightGBM is a gradient boosting framework that uses tree-based models to solve machine learning problems. One of the key differences between LightGBM and other gradient boosting frameworks like XGBoost is the way that LightGBM grows decision trees. Specifically, LightGBM can grow trees in one of two ways:

Level-wise Growth: This is the default method used in LightGBM, where the tree is grown level by level, similar to how a breadth-first search algorithm works. In this method, all nodes at a particular level of the tree are expanded before moving on to the next level. This approach can be more memory-efficient than leaf-wise growth, but it may result in a suboptimal tree structure.

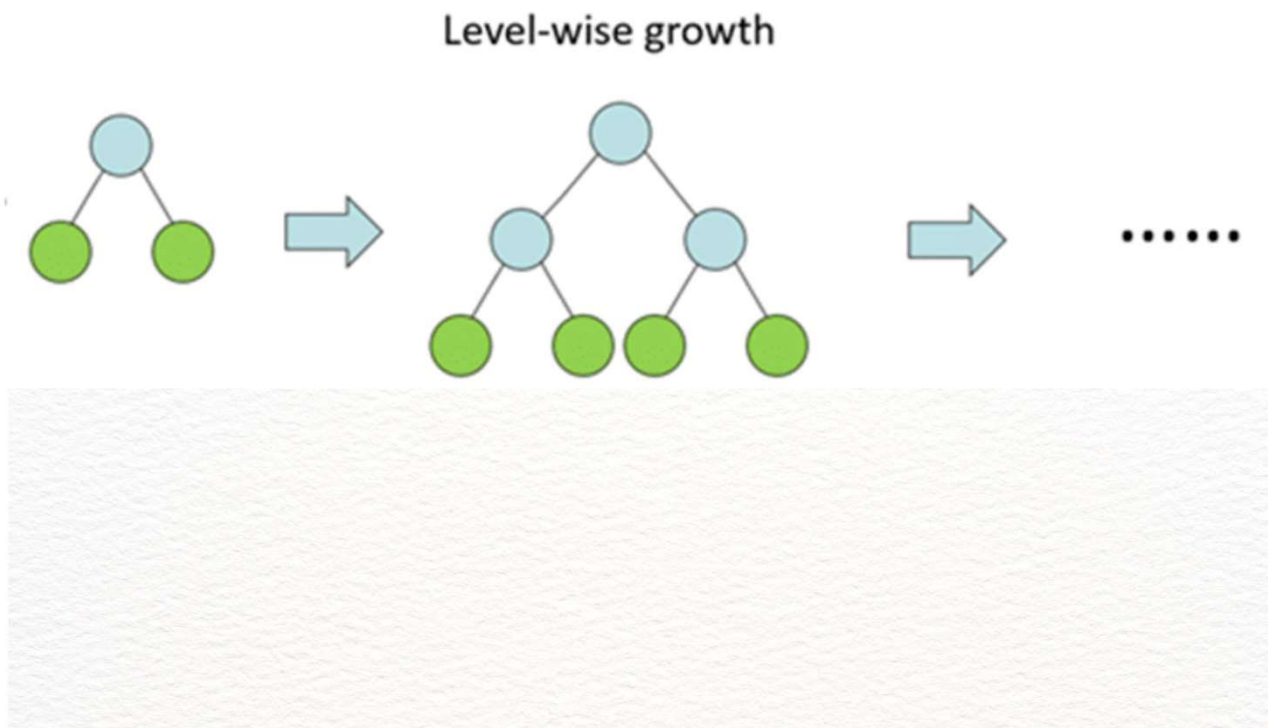


Figure 2.6. Level-wise growth

Leaf-wise Growth: This is an alternative method that LightGBM can use to grow decision trees. In this method, the tree is grown by splitting the node that results in the largest reduction in the objective function, rather than expanding all nodes at a particular level. This approach can lead to faster training times and better accuracy, but it can also be more memory-intensive.

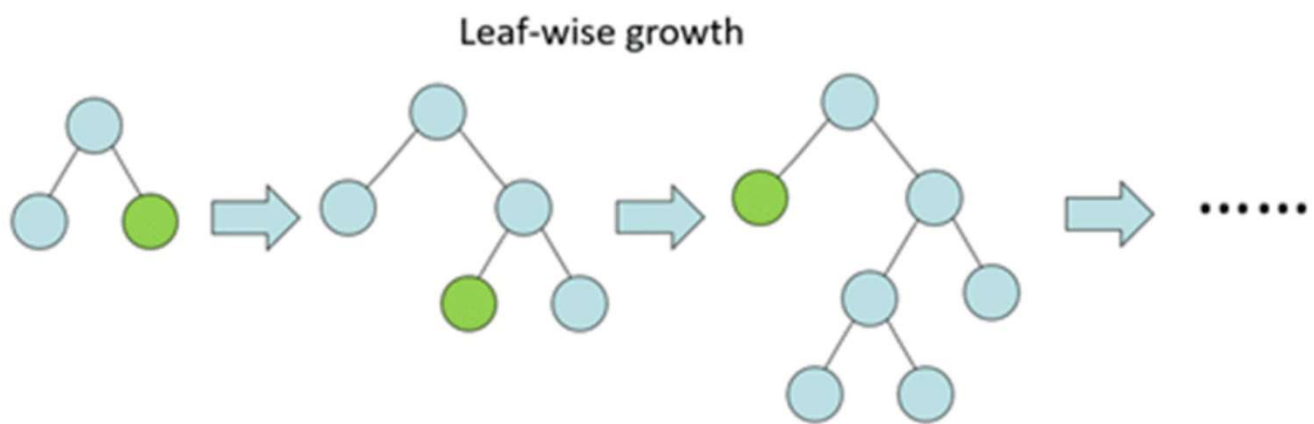


Figure 2.7. Leaf-wise Growth

Why LightGBM?

There are several reasons why LGBM has become a popular algorithm in the machine learning community:

- **Speed:** LGBM is designed to be fast and can handle large datasets with millions of samples and features. It uses a leaf-wise approach to build decision trees, which allows it to achieve high accuracy with fewer trees than other gradient boosting algorithms.

- **Accuracy:** LGBM is known for its high accuracy and ability to handle complex data structures. It uses a combination of gradient boosting and feature splitting to create a model that can accurately predict outcomes.
- **Flexibility:** LGBM can be used for both classification and regression tasks and can handle both continuous and categorical variables. It also has several parameters that can be adjusted to optimize the model for different types of data.

How Does LightGBM Work?

Here's a step-by-step overview of how LGBM works:

- **Data preparation:** The first step is to prepare the data for training. This involves cleaning the data, converting categorical variables to numerical ones (if necessary), and splitting the data into training and validation sets.
- **Initialization:** The algorithm starts by initializing a model with a single decision tree. This tree predicts the target variable based on the input features.
- **Training:** The model is then trained using the training data. During training, the algorithm iteratively adds decision trees to the model, each one correcting the errors made by the previous tree. The algorithm uses a technique called gradient boosting to determine the direction and magnitude of the corrections.
- **Splitting:** When creating a new tree, LGBM chooses the best split point for each feature using a method called Leaf-wise Best-First Search. This method searches for the split that results in the largest reduction in the loss function.
- **Regularization:** To prevent overfitting, LGBM includes several regularization techniques. One of these techniques is called "gradient-based one-side sampling" (GOSS), which samples the data to prioritize examples with larger gradients.
- **Prediction:** Once the model is trained, it can be used to make predictions on new data. To make a prediction, the algorithm feeds the new data through the ensemble of decision trees and combines the results to produce a final prediction.

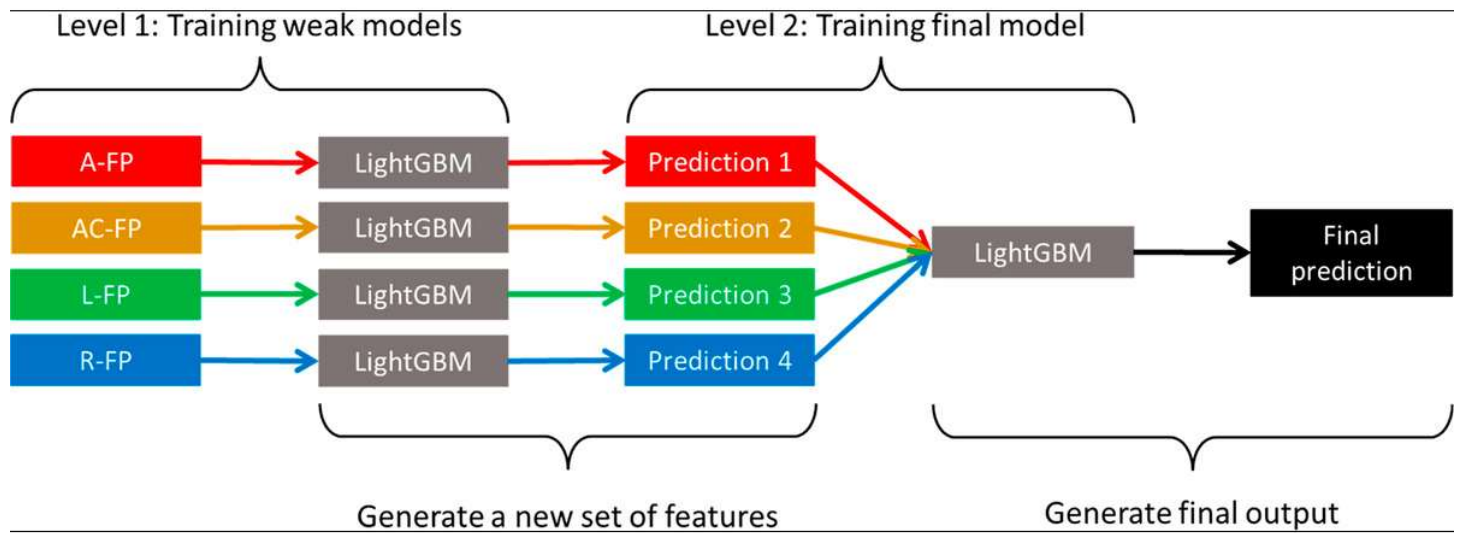


Figure 2.8. How Does LGBM Work

3.LANGUAGES/TOOLS, DATASET

3.1.LANGUAGES / TOOLS DESCRIPTION

HARDWARE REQUIREMENTS

Operating System	:	Windows 10
RAM	:	8.00GB
System Type	:	64-bit OS
Processor	:	Intel(R) core i5

SOFTWARE REQUIREMENTS

Front-End	:	Python
Tools	:	Google Colab

PYTHON

Python is an object-oriented, high level programming language with integrated dynamic semantics primarily for web and app development. It is extremely attractive in the field of Rapid Application Development because it offers dynamic typing and dynamic binding options. Developers can read and translate Python code much easier than other languages. In turn, this reduces the cost of program maintenance and development because it allows teams to work collaboratively without significant language and experience barriers. Additionally, Python supports the use of modules and packages, which means that programs can be designed in a modular style and code can be reused across a variety of projects. Once you've developed a module or package you need, it can be scaled for use in other projects, and it's easy to import or export these modules. Python is an open source community language.

Uses of Python

Python is a general-purpose programming language, which is another way to say that it can be used for nearly everything. Most importantly, it is an interpreted language. Which means that the written code is not actually translated to a computer-readable format at runtime. Whereas, most programming languages do this conversion before the program is even run. This type of language is also referred to as a "scripting language" because it was initially meant to be used for trivial projects.

PYTHON FEATURES

Easy-to-learn – Python has few keywords, simple structure, and a clearly defined syntax. This allows the student to pick up the language quickly.

Easy-to-read – Python code is more clearly defined and visible to the eyes.

Easy-to-maintain – Python's source code is fairly easy-to-maintain.

A broad standard library – Python's bulk of the library is very portable and cross- platform compatible on UNIX, Windows, and Macintosh.

Interactive Mode – Python has support for an interactive mode which allows interactive testing and debugging of snippets of code.

Portable – Python can run on a wide variety of hardware platforms and has the same interface on all platforms.

Extendable –You can add low-level modules to the Python interpreter. These modules enable programmers to add to or customize their tools to be more efficient.

Databases – Python provides interfaces to all major commercial databases.

GUI Programming – Python supports GUI applications that can be created and ported to many system calls, libraries and windows systems, such as Windows MFC, Macintosh, and the X Window system of Unix.

Scalable – Python provides a better structure and support for large programs than shell scripting

Import Important Packages

Sklearn

Scikit-learn (Sklearn) is the most useful and robust library for machine learning in Python. It provides a selection of efficient tools for machine learning and statistical modeling including classification, regression, clustering and dimensionality reduction via a consistence interface in Python. This library, which is largely written in Python, is built upon NumPy, SciPy and Matplotlib.

TensorFlow

TensorFlow is an open source machine learning framework for all developers. It is used for implementing machine learning and deep learning applications. To develop and research on fascinating ideas on artificial intelligence, Google team created TensorFlow. TensorFlow is designed in Python programming language, hence it is considered an easy to understand framework.

PyTorch

PyTorch is an open source machine learning (ML) framework based on the Python programming language and the Torch library. Torch is an open source ML library used for creating deep neural networks and is written in the Lua scripting language. It's one of the preferred platforms for deep learning research.

Keras

Keras is considered as one of the coolest machine learning libraries in Python. It provides an easier mechanism to express neural networks. Keras also provides some of the best utilities for compiling models, processing data-sets, visualization of graphs, and much more.

In the backend, Keras uses either Theano or TensorFlow internally. Some of the most popular neural networks like CNTK can also be used. Keras is comparatively slow when we compare it with other machine learning libraries. Because it creates a computational graph by using back-end infrastructure and then makes use of it to perform operations. All the models in Keras are portable.

3.2. PACKAGES, FUNCTIONS

Numpy

NumPy is the fundamental package for scientific computing in Python. It is a Python library that provides a multidimensional array object, various derived objects (such as masked arrays and matrices), and an assortment of routines for fast operations on arrays, including mathematical, logical, shape manipulation, sorting, selecting, I/O, discrete Fourier transforms, basic linear algebra, basic statistical operations, random simulation and much more.

At the core of the NumPy package, is the *ndarray* object. This encapsulates *n*- dimensional arrays of homogeneous data types, with many operations being performed in compiled code for performance. There are several important differences between NumPy arrays and the standard Python sequences:

- NumPy arrays have a fixed size at creation, unlike Python lists (which can grow dynamically). Changing the size of an *ndarray* will create a new array and delete the original.
- The elements in a NumPy array are all required to be of the same data type, and thus will be the same size in memory. The exception: one can have arrays of (Python, including NumPy) objects, thereby allowing for arrays of different sized elements.
- NumPy arrays facilitate advanced mathematical and other types of operations on large numbers of data. Typically, such operations are executed more efficiently and with less code than is possible using Python's built-in sequences.

Pandas

Pandas is an open source Python package that is most widely used for data science/data analysis and machine learning tasks. It is built on top of another package named Numpy, which provides support for multi-dimensional arrays. As one of the most popular data wrangling packages, Pandas works well with many other data science modules inside the Python ecosystem, and is typically included in every Python distribution, from those that come with your operating system to commercial vendor distributions like Active State's Active Python.

Pandas makes it simple to do many of the time consuming, repetitive tasks associated with working with data, including:

- Data cleansing
- Data fill
- Data normalization
- Merges and joins
- Data visualization
- Statistical analysis
- Data inspection

3.3. DATASET

TRAIN DATASET

- This training dataset has 12 rows and 903,654 columns with all values filled.

	A	B	C	D	E	F	G	H	I	J	K	L
1	channelGrouping	date	device	fullVisitorId	geoNetwork	sessionId	socialEngagementType	totals	trafficSource	visitId	visitNumber	visitStartTime
2	Organic Search	20160902	{"browser"	1.1317E+18	{"continent": "	1131660440785	Not Socially Engaged	{"visits": "1", "hits": "1" {"campaign":	1472830385		1	1472830385
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14	Organic Search	20160902	{"browser"	3.5766E+17	{"continent": "	3576598896008	Not Socially Engaged	{"visits": "1", "hits": "1" {"campaign":	1472839882		1	1472839882
15	Organic Search	20160902	{"browser"	1.4381E+18	{"continent": "	1438082600262	Not Socially Engaged	{"visits": "1", "hits": "1" {"campaign":	1472803483		1	1472803483
16	Organic Search	20160902	{"browser"	3.531E+18	{"continent": "	3531015320757	Not Socially Engaged	{"visits": "1", "hits": "1" {"campaign":	1472868337		1	1472868337
17	Organic Search	20160902	{"browser"	9.6382E+18	{"continent": "	9638207207743	Not Socially Engaged	{"visits": "1", "hits": "1" {"campaign":	1472824614		1	1472824614
18	Organic Search	20160902	{"browser"	9.8768E+18	{"continent": "	9876750586615	Not Socially Engaged	{"visits": "1", "hits": "1" {"campaign":	1472801099		1	1472801099
19	Organic Search	20160902	{"browser"	2.2223E+18	{"continent": "	2222266935962	Not Socially Engaged	{"visits": "1", "hits": "1" {"campaign":	1472826820		1	1472826820
20	Organic Search	20160902	{"browser"	9.6748E+18	{"continent": "	9674781571160	Not Socially Engaged	{"visits": "1", "hits": "1" {"campaign":	1472804607		1	1472804607
21	Organic Search	20160902	{"browser"	3.6969E+18	{"continent": "	3696906537737	Not Socially Engaged	{"visits": "1", "hits": "1" {"campaign":	1472856874		1	1472856874
22	Organic Search	20160902	{"browser"	4.4783E+18	{"continent": "	4478318070775	Not Socially Engaged	{"visits": "1", "hits": "1" {"campaign":	1472826420		1	1472826420
23	Organic Search	20160902	{"browser"	6.0982E+18	{"continent": "	6098154234696	Not Socially Engaged	{"visits": "1", "hits": "1" {"campaign":	1472863754		1	1472863754
24	Organic Search	20160902	{"browser"	3.3234E+18	{"continent": "	3323434834508	Not Socially Engaged	{"visits": "1", "hits": "1" {"campaign":	1472872530		1	1472872530
25	Organic Search	20160902	{"browser"	3.0536E+18	{"continent": "	3053576296023	Not Socially Engaged	{"visits": "1", "hits": "1" {"campaign":	1472808484		1	1472808484
26	Organic Search	20160902	{"browser"	7.0274E+17	{"continent": "	7027368264872	Not Socially Engaged	{"visits": "1", "hits": "1" {"campaign":	1472806593		1	1472806593
27	Organic Search	20160902	{"browser"	8.7946E+18	{"continent": "	8794587387581	Not Socially Engaged	{"visits": "1", "hits": "1" {"campaign":	1472816048		1	1472816048

TEST DATASET

- This test dataset has 12 rows and 804,685 columns with all values filled

	A	B	C	D	E	F	G	H	I	J	K	L
1	channelGrouping	date	device	fullVisitorId	geoNetwork	sessionId	socialEngagement	totals	trafficSource	visitId	visitNumber	visitStartTime
2	Organic Search	20171016	{\"browser\"}	6.16787E+18	{\"continent\": \"A 616787133061 Not Socially Engag	{\"visits\": \"\": {\"campaign\": \"(1.51E+09				2	1.51E+09
3	Organic Search	20171016	{\"browser\"}	6.43698E+17	{\"continent\": \"E 064369764097 Not Socially Engag	{\"visits\": \"\": {\"campaign\": \"(1.51E+09				1	1.51E+09
4	Organic Search	20171016	{\"browser\"}	6.05938E+18	{\"continent\": \"E 605938381096 Not Socially Engag	{\"visits\": \"\": {\"campaign\": \"(1.51E+09				1	1.51E+09
5	Organic Search	20171016	{\"browser\"}	2.37672E+18	{\"continent\": \"A 237672007856 Not Socially Engag	{\"visits\": \"\": {\"campaign\": \"(1.51E+09				1	1.51E+09
6	Organic Search	20171016	{\"browser\"}	2.31454E+18	{\"continent\": \"A 231454452079 Not Socially Engag	{\"visits\": \"\": {\"campaign\": \"(1.51E+09				1	1.51E+09
7	Organic Search	20171016	{\"browser\"}	4.13304E+18	{\"continent\": \"A 413303988410 Not Socially Engag	{\"visits\": \"\": {\"campaign\": \"(1.51E+09				1	1.51E+09
8	Organic Search	20171016	{\"browser\"}	4.32048E+18	{\"continent\": \"A 432047885020 Not Socially Engag	{\"visits\": \"\": {\"campaign\": \"(1.51E+09				1	1.51E+09
9	Organic Search	20171016	{\"browser\"}	5.87644E+18	{\"continent\": \"A 587643824759 Not Socially Engag	{\"visits\": \"\": {\"campaign\": \"(1.51E+09				1	1.51E+09
10	Organic Search	20171016	{\"browser\"}	5.14591E+17	{\"continent\": \"E 051459126873 Not Socially Engag	{\"visits\": \"\": {\"campaign\": \"(1.51E+09				6	1.51E+09
11	Organic Search	20171016	{\"browser\"}	6.43057E+18	{\"continent\": \"E 643056703153 Not Socially Engag	{\"visits\": \"\": {\"campaign\": \"(1.51E+09				1	1.51E+09
12	Organic Search	20171016	{\"browser\"}	7.02637E+18	{\"continent\": \"A 702637407015 Not Socially Engag	{\"visits\": \"\": {\"campaign\": \"(1.51E+09				1	1.51E+09
13	Paid Search	20171016	{\"browser\"}	2.86172E+18	{\"continent\": \"A 286172430413 Not Socially Engag	{\"visits\": \"\": {\"campaign\": \"(1.51E+09				1	1.51E+09
14	Display	20171016	{\"browser\"}	7.90825E+18	{\"continent\": \"A 790824711728 Not Socially Engag	{\"visits\": \"\": {\"campaign\": \"(1.51E+09				1	1.51E+09
15	Organic Search	20171016	{\"browser\"}	4.45213E+18	{\"continent\": \"A 445212795235 Not Socially Engag	{\"visits\": \"\": {\"campaign\": \"(1.51E+09				1	1.51E+09
16	Organic Search	20171016	{\"browser\"}	5.16468E+18	{\"continent\": \"A 516467745049 Not Socially Engag	{\"visits\": \"\": {\"campaign\": \"(1.51E+09				1	1.51E+09
17	Organic Search	20171016	{\"browser\"}	1.17274E+18	{\"continent\": \"E 117273669416 Not Socially Engag	{\"visits\": \"\": {\"campaign\": \"(1.51E+09				1	1.51E+09
18	Organic Search	20171016	{\"browser\"}	2.22728E+18	{\"continent\": \"E 222727609264 Not Socially Engag	{\"visits\": \"\": {\"campaign\": \"(1.51E+09				1	1.51E+09
19	Organic Search	20171016	{\"browser\"}	6.09791E+18	{\"continent\": \"A 609790536718 Not Socially Engag	{\"visits\": \"\": {\"campaign\": \"(1.51E+09				1	1.51E+09
20	Organic Search	20171016	{\"browser\"}	2.87575E+18	{\"continent\": \"A 287574841138 Not Socially Engag	{\"visits\": \"\": {\"campaign\": \"(1.51E+09				1	1.51E+09
21	Organic Search	20171016	{\"browser\"}	1.06322E+17	{\"continent\": \"A 106322241208 Not Socially Engag	{\"visits\": \"\": {\"campaign\": \"(1.51E+09				1	1.51E+09
22	Organic Search	20171016	{\"browser\"}	2.53915E+18	{\"continent\": \"A 253914623910 Not Socially Engag	{\"visits\": \"\": {\"campaign\": \"(1.51E+09				1	1.51E+09
23	Organic Search	20171016	{\"browser\"}	8.2923E+18	{\"continent\": \"E 829230297809 Not Socially Engag	{\"visits\": \"\": {\"campaign\": \"(1.51E+09				4	1.51E+09
24	Organic Search	20171016	{\"browser\"}	3.56809E+18	{\"continent\": \"A 356808759285 Not Socially Engag	{\"visits\": \"\": {\"campaign\": \"(1.51E+09				1	1.51E+09
25	Organic Search	20171016	{\"browser\"}	1.31486E+17	{\"continent\": \"A 013148598040 Not Socially Engag	{\"visits\": \"\": {\"campaign\": \"(1.51E+09				2	1.51E+09
26	Organic Search	20171016	{\"browser\"}	9.53429E+17	{\"continent\": \"A 095342909098 Not Socially Engag	{\"visits\": \"\": {\"campaign\": \"(1.51E+09				1	1.51E+09

Input dataset attributes

- ChannelGrouping
- Date
- Device
- FullVisitorId
- GeoNetwork
- SessionId
- SocialEngagementType
- Totals
- TrafficSource
- VisitId
- VisitNumber
- VisitStartTime

3.4. DATA STORAGE

DATA STORAGE DEFINITION

There are two types of digital information: input and output data. Users provide the input data. Computers provide output data. But a computer's CPU can't compute anything or produce output data without the user's input.

Users can enter the input data directly into a computer. However, they have found early on in the computer-era that continually entering data manually is time- and energy-prohibitive. One short-term solution is computer memory, also known as random access memory (RAM). But its storage capacity and memory retention are limited. Read-only memory (ROM) is, as the name suggests, the data can only be read but not necessarily edited. They control a computer's basic functionality.

Although advances have been made in computer memory with dynamic RAM (DRAM) and synchronous DRAM (SDRAM), they are still limited by cost, space and memory retention. When a computer powers down, so does the RAM's ability to retain data.

With data storage space, users can save data onto a device. And should the computer power down, the data is retained. And instead of manually entering data into a computer, users can instruct the computer to pull data from storage devices. Computers can read input data from various sources as needed, and it can then create and save the output to the same sources or other storage locations. Users can also share data storage with others.

Today, organizations and users require data storage to meet today's high-level computational needs like big data projects, artificial intelligence (AI), machine learning and the internet of things (IoT).

3.5. DATA CLEANING

Data cleaning is one of the important parts of machine learning. It plays a significant part in building a model. It surely isn't the fanciest part of machine learning and at the same time, there aren't any hidden tricks or secrets to uncover. However, the success or failure of a project relies on proper data cleaning. Professional data scientists usually invest a very large portion of their time in this step because of the belief that **"Better data beats fancier algorithms"**.

If we have a well-cleaned dataset, there are chances that we can get achieve good results with simple algorithms also, which can prove very beneficial at times especially in terms of computation when the dataset size is large. Obviously, different types of data will require different types of cleaning. However, this systematic approach can always serve as a good starting point.

Steps involved in Data Cleaning:

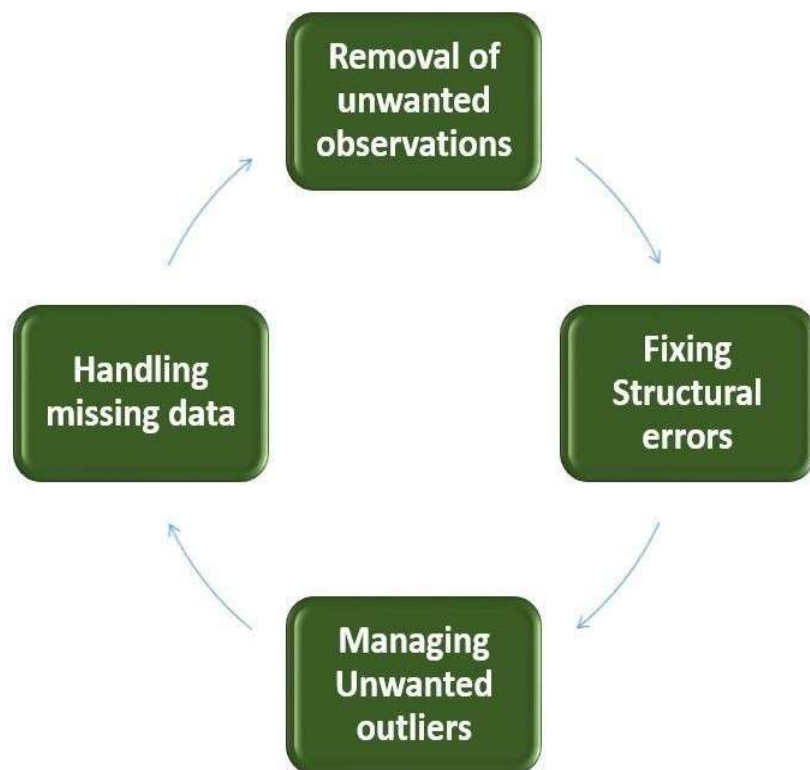


Figure 3.1. Steps involved in Data Cleaning

4. MODULE DESCRIPTION

4.1 COLLECTION OF DATASET

Initially, we collect a dataset for our Stock market prediction. After the collection of the dataset, we split the dataset into training data and testing data. The training dataset is used for prediction model learning and testing data is used for evaluating the prediction model. For this project, 70% of training data is used and 30% of data is used for testing. The dataset used for this project is Stock Price.

4.2 SELECTION OF ATTRIBUTES

Attribute or Feature selection includes the selection of appropriate attributes for the prediction system. This is used to increase the efficiency of the system. Attribute selection is the process of identifying relevant information and removing as much of the irrelevant and redundant information as possible. Attribute selection is also defined as “the process of finding a best subset of features, from the original set of features in a given data set, optimal according to the defined goal

4.3 PRE-PROCESSING OF DATA

Data pre-processing is an important step for the creation of a machine learning model. Initially, data may not be clean or in the required format for the model which can cause misleading outcomes. In pre-processing of data, we transform data into our required format. It is used to deal with noises, duplicates, and missing values of the dataset. Data pre-processing has the activities like importing datasets, splitting datasets, attribute scaling, etc. Preprocessing of data is required for improving the accuracy of the model

Data Preparation

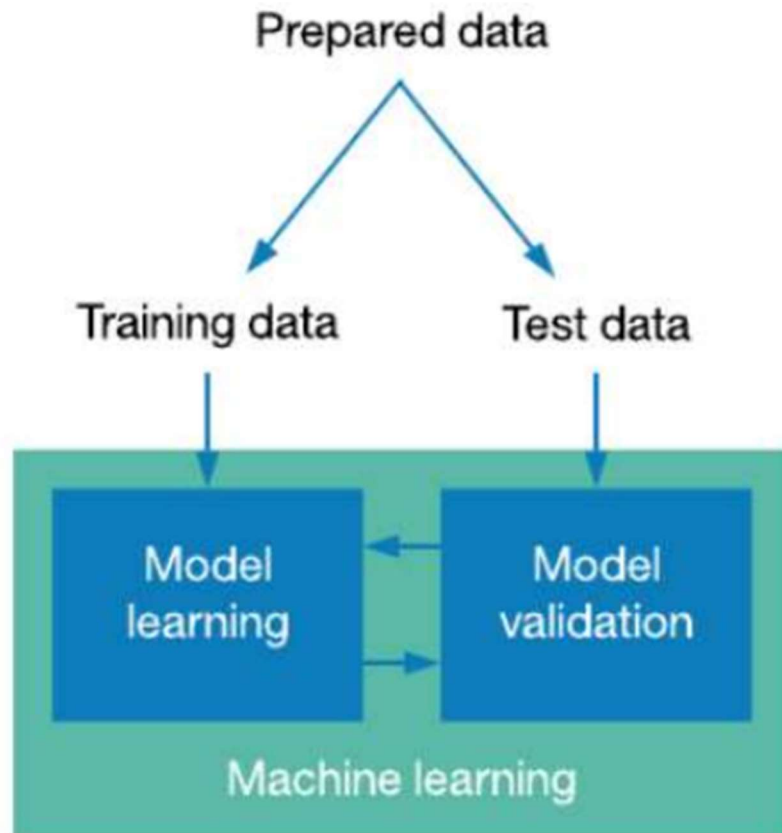


Figure 3.2. Data Preparation

4.4 DATA VISUALIZATION

Data visualization is a technique used to represent data in a visual form such as charts, graphs, and maps. The goal of data visualization is to communicate information clearly and effectively through graphical means. It is an important tool in data analysis as it helps to identify trends, patterns, and relationships in data that may not be apparent from numerical or text-based representations. With the increasing amount of data being generated by businesses and individuals, data visualization has become a crucial aspect of modern data analysis. It allows stakeholders to quickly and easily understand complex data, make informed decisions, and communicate insights to others.

4.5 LightGBM Model

The LightGBM model is particularly well-suited for dealing with large datasets with high-dimensional features. LightGBM uses a histogram-based approach for faster training and a leaf-wise approach to grow the trees, which leads to better accuracy with fewer trees.

4.6 PREDICTION

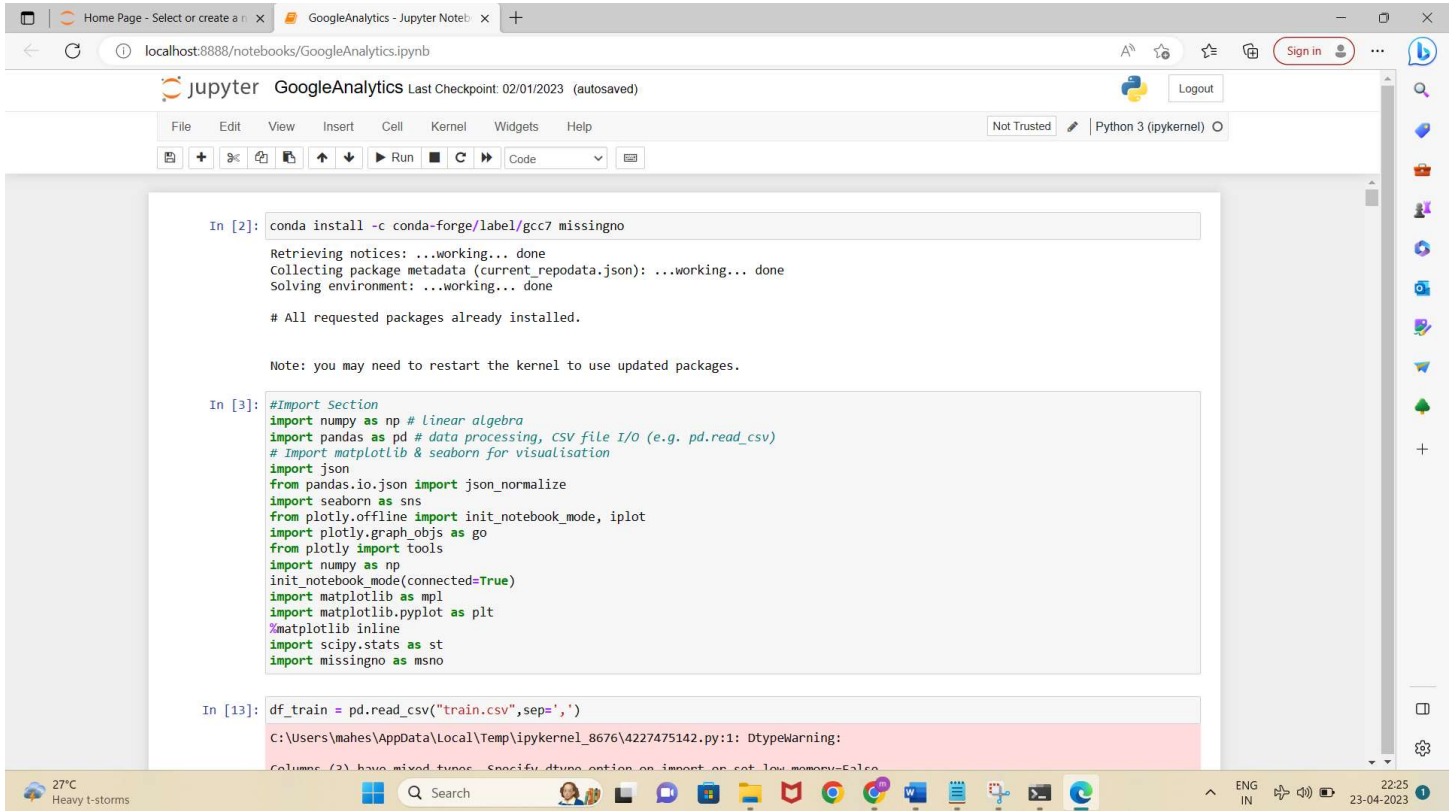
	fullVisitorId	PredictedLogRevenue
0	0000000259678714014	0.053754
1	0000049363351866189	0.000121
2	0000053049821714864	0.000000
3	0000059488412965267	0.002343
4	0000085840370633780	0.018547

Figure 3.3.Prediction of Revenue

Predictive modeling is a commonly used statistical technique to predict future behavior. Predictive modeling solutions are a form of analyse that works by analyzing historical and current data and generating a model to help predict future outcomes.

5. RESULTS AND DISCUSSION

5.1. INPUT AND OUTPUT SCREENS



The screenshot shows a Jupyter Notebook interface with the following code and output:

```
In [2]: conda install -c conda-forge/label/gcc7 missingno
```

Retrieving notices: ...working... done
Collecting package metadata (current_repodata.json): ...working... done
Solving environment: ...working... done

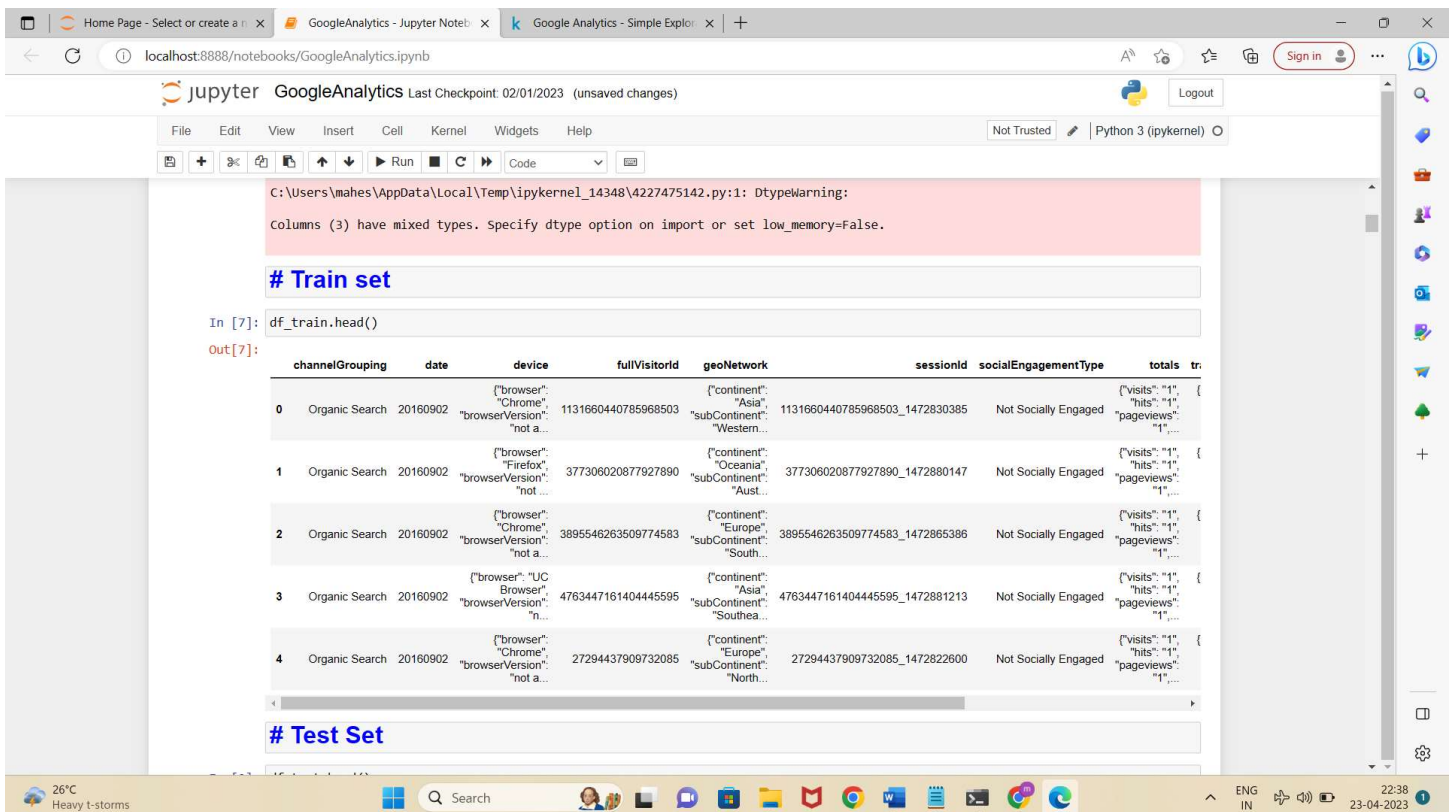
All requested packages already installed.

Note: you may need to restart the kernel to use updated packages.

```
In [3]: #Import Section
import numpy as np # linear algebra
import pandas as pd # data processing, CSV file I/O (e.g. pd.read_csv)
# Import matplotlib & seaborn for visualisation
import json
from pandas.io.json import json_normalize
import seaborn as sns
from plotly.offline import init_notebook_mode, iplot
import plotly.graph_objs as go
from plotly import tools
import numpy as np
init_notebook_mode(connected=True)
import matplotlib as mpl
import matplotlib.pyplot as plt
%matplotlib inline
import scipy.stats as st
import missingno as msno
```

```
In [13]: df_train = pd.read_csv("train.csv", sep=',')
```

C:\Users\mahes\AppData\Local\Temp\ipykernel_8676\4227475142.py:1: DtypeWarning:
Columns (3) have mixed types. Specify dtype option on import or set low_memory=False.



The screenshot shows a Jupyter Notebook interface with the following code and output:

```
C:\Users\mahes\AppData\Local\Temp\ipykernel_14348\4227475142.py:1: DtypeWarning:
Columns (3) have mixed types. Specify dtype option on import or set low_memory=False.
```

```
# Train set

In [7]: df_train.head()
```

Out[7]:

	channelGrouping	date	device	fullVisitorId	geoNetwork	sessionId	socialEngagementType	totals	tr
0	Organic Search	20160902	{ "browser": "Chrome", "browserVersion": "not a ..."	1131660440785968503	{ "continent": "Asia", "subContinent": "Western..."	1131660440785968503_1472830385	Not Socially Engaged	{ "visits": "1", "hits": "1", "pageviews": "1",...	{
1	Organic Search	20160902	{ "browser": "Firefox", "browserVersion": "not a ..."	377306020877927890	{ "continent": "Oceania", "subContinent": "Aust..."	377306020877927890_1472880147	Not Socially Engaged	{ "visits": "1", "hits": "1", "pageviews": "1",...	{
2	Organic Search	20160902	{ "browser": "Chrome", "browserVersion": "not a ..."	3895546263509774583	{ "continent": "Europe", "subContinent": "South..."	3895546263509774583_1472865386	Not Socially Engaged	{ "visits": "1", "hits": "1", "pageviews": "1",...	{
3	Organic Search	20160902	{ "browser": "UC Browser", "browserVersion": "n..."	4763447161404445595	{ "continent": "Asia", "subContinent": "Southea..."	4763447161404445595_1472881213	Not Socially Engaged	{ "visits": "1", "hits": "1", "pageviews": "1",...	{
4	Organic Search	20160902	{ "browser": "Chrome", "browserVersion": "not a ..."	27294437909732085	{ "continent": "Europe", "subContinent": "North..."	27294437909732085_1472822600	Not Socially Engaged	{ "visits": "1", "hits": "1", "pageviews": "1",...	{

```
# Test Set
```

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Not Trusted Python 3 (ipykernel)

Test Set

```
In [9]: df_test.head()
```

```
Out[9]:
```

	channelGrouping	date	device	fullVisitorId	geoNetwork	sessionId	socialEngagementType	totals	tr
0	Organic Search	20171016	{\"browser\": \"Chrome\", \"browserVersion\": \"not a ...\"}	6167871330617112363	{\"continent\": \"Asia\", \"subContinent\": \"Southea...	6167871330617112363_1508151024	Not Socially Engaged	{\"visits\": \"1\", \"hits\": \"4\", \"pageviews\": \"4\"}	{
1	Organic Search	20171016	{\"browser\": \"Chrome\", \"browserVersion\": \"not a ...\"}	0643697640977915618	{\"continent\": \"Europe\", \"subContinent\": \"South...	0643697640977915618_1508175522	Not Socially Engaged	{\"visits\": \"1\", \"hits\": \"5\", \"pageviews\": \"5\"}	{
2	Organic Search	20171016	{\"browser\": \"Chrome\", \"browserVersion\": \"not a ...\"}	6059383810968229466	{\"continent\": \"Europe\", \"subContinent\": \"Weste...	6059383810968229466_1508143220	Not Socially Engaged	{\"visits\": \"1\", \"hits\": \"7\", \"pageviews\": \"7\"}	{
3	Organic Search	20171016	{\"browser\": \"Safari\", \"browserVersion\": \"not a ...\"}	2376720078563423631	{\"continent\": \"Americas\", \"subContinent\": \"Nor...	2376720078563423631_1508193530	Not Socially Engaged	{\"visits\": \"1\", \"hits\": \"0\", \"pageviews\": \"4\"}	{
4	Organic Search	20171016	{\"browser\": \"Safari\", \"browserVersion\": \"not a ...\"}	2314544520795440038	{\"continent\": \"Americas\", \"subContinent\": \"Nor...	2314544520795440038_1508217442	Not Socially Engaged	{\"visits\": \"1\", \"hits\": \"9\", \"pageviews\": \"4\"}	{

```
In [10]: json_columns = ['device', 'geoNetwork', 'totals', 'trafficSource']
def load_dataframe(filename):
    #path = \"../input/\" + filename
    df = pd.read_csv(filename, converters={column: json.loads for column in json_columns},
                    dtype={'fullVisitorId': 'str'})

    for column in json_columns:
        column_as_df = json_normalize(df[column])
```

26°C Heavy t-storms

Search

ENG IN 22:38 23-04-2023

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```
In [24]: numeric_features_train = train.select_dtypes(include=[np.number])
numeric_features_train.columns
```

```
Out[24]: Index(['date', 'visitId', 'visitNumber', 'visitStartTime'], dtype='object')
```

```
In [25]: numeric_features_test = test.select_dtypes(include=[np.number])
numeric_features_test.columns
```

```
Out[25]: Index(['date', 'visitId', 'visitNumber', 'visitStartTime'], dtype='object')
```

```
In [26]: categorical_features_train = train.select_dtypes(include=[np.object])
categorical_features_train.columns
```

C:\Users\mahes\AppData\Local\Temp\ipykernel_8676\2131648654.py:1: DeprecationWarning:

'np.object' is a deprecated alias for the builtin 'object'. To silence this warning, use 'object' by itself. Doing this will not modify any behavior and is safe.

Deprecated in NumPy 1.20; for more details and guidance: <https://numpy.org/devdocs/release/1.20.0-notes.html#deprecations>

```
Out[26]: Index(['channelGrouping', 'fullVisitorId', 'sessionId', 'socialEngagementType',
'device browser', 'device browserVersion', 'device browserSize',
'device operatingSystem', 'device operatingSystemVersion',
'device mobileDeviceBranding', 'device mobileDeviceModel',
'device mobileInputSelector', 'device mobileDeviceInfo',
'device mobileDeviceMarketingName', 'device flashVersion',
'device language', 'device screenColors', 'device screenResolution',
'device deviceCategory', 'geoNetwork continent',
'geoNetwork subContinent', 'geoNetwork country', 'geoNetwork region',
'geoNetwork metro', 'geoNetwork city', 'geoNetwork cityId',
'geoNetwork networkDomain', 'geoNetwork latitude',
'geoNetwork longitude', 'geoNetwork networkLocation', 'totals_visits',
'totals hits', 'totals_pageviews', 'totals_bounces', 'totals_newVisits',
'totals_transactionRevenue', 'trafficSource campaign',
'trafficSource source', 'trafficSource medium', 'trafficSource keyword',
'trafficSource adwordsClickInfo.criteriaParameters'], dtype='object')
```

26°C Heavy t-storms

Search

ENG IN 22:39 23-04-2023

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Before removing constant columns - shape of train & test datasets: (903653, 55) (804684, 53)
 After Removing Constant Columns - shape of train & test datasets: (903653, 36) (804684, 34)

```
In [29]: total_test = categorical_features_train.isnull().sum().sort_values(ascending=False)
percent = (categorical_features_train.isnull().sum() / categorical_features_train.isnull().count()).sort_values(ascending=False)
missing_data = pd.concat([total_test, percent], axis=1, join='outer', keys=['Total Missing Count', '% of Total Observations'])
missing_data.index.name = 'Feature'
missing_data.head(14)
```

Out[29]:

Feature	Total Missing Count	% of Total Observations
trafficSource_campaignCode	903652	99.999889
trafficSource_adContent	892707	98.788694
totals_transactionRevenue	892138	98.725728
trafficSource_adwordsClickInfo.isVideoAd	882193	97.625195
trafficSource_adwordsClickInfo.adNetworkType	882193	97.625195
trafficSource_adwordsClickInfo.slot	882193	97.625195
trafficSource_adwordsClickInfo.page	882193	97.625195
trafficSource_adwordsClickInfo.gclid	882092	97.614018
trafficSource_isTrueDirect	629648	69.678073
trafficSource_referralPath	572712	63.377425
trafficSource_keyword	502929	55.655102
totals_bounces	453023	50.132407
totals_newVisits	200593	22.198012
totals_pageviews	100	0.011066

In []:

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```
In [43]: import warnings
warnings.simplefilter(action='ignore', category=FutureWarning)

agg_dict = {}
for col in ["totals_bounces", "totals_hits", "totals_newVisits", "totals_pageviews", "totals_transactionRevenue"]:
    train[col] = train[col].astype('float')
    agg_dict[col] = "sum"
tmp = train.groupby("fullVisitorId").agg(agg_dict).reset_index()
tmp.head()
```

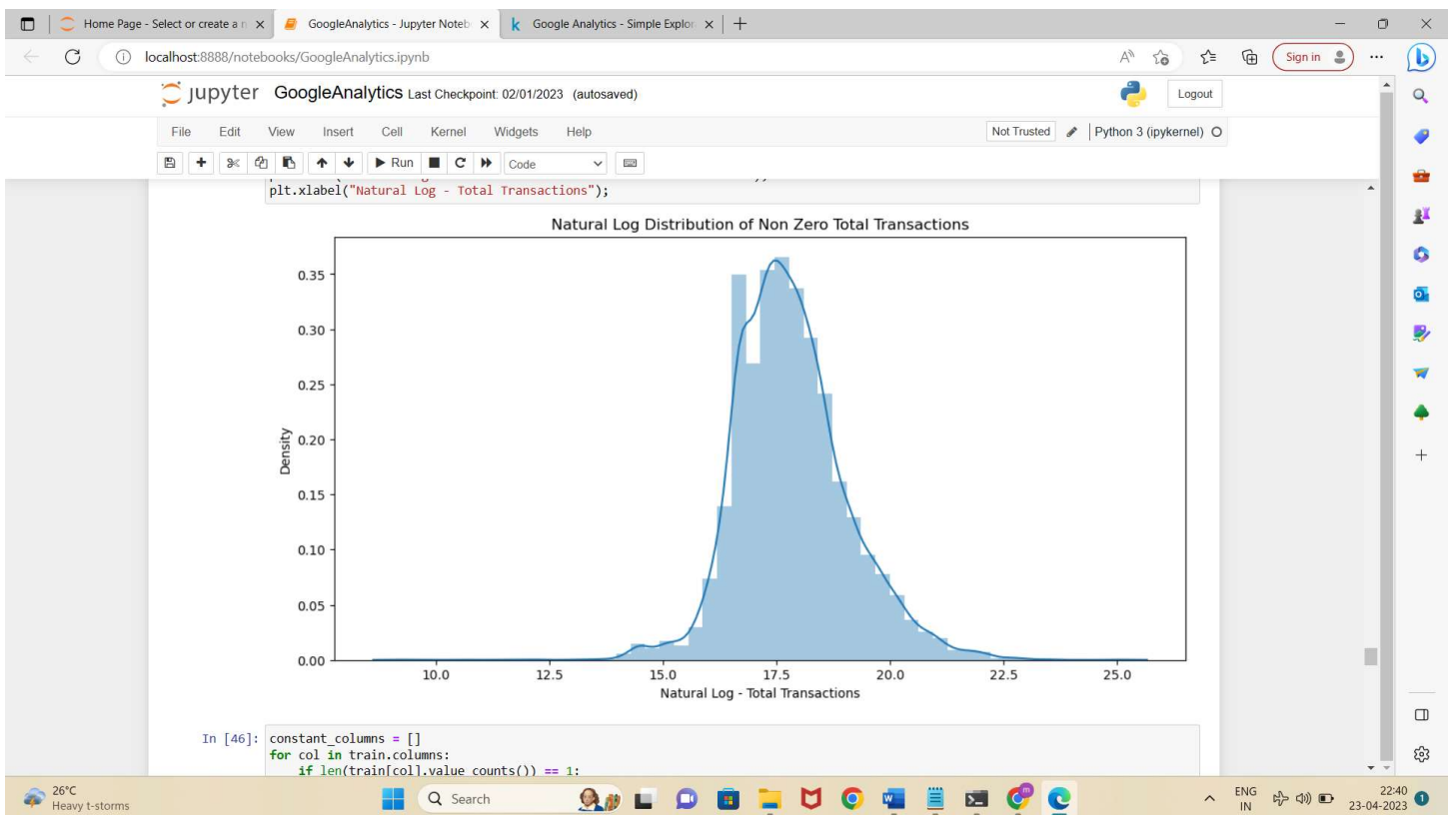
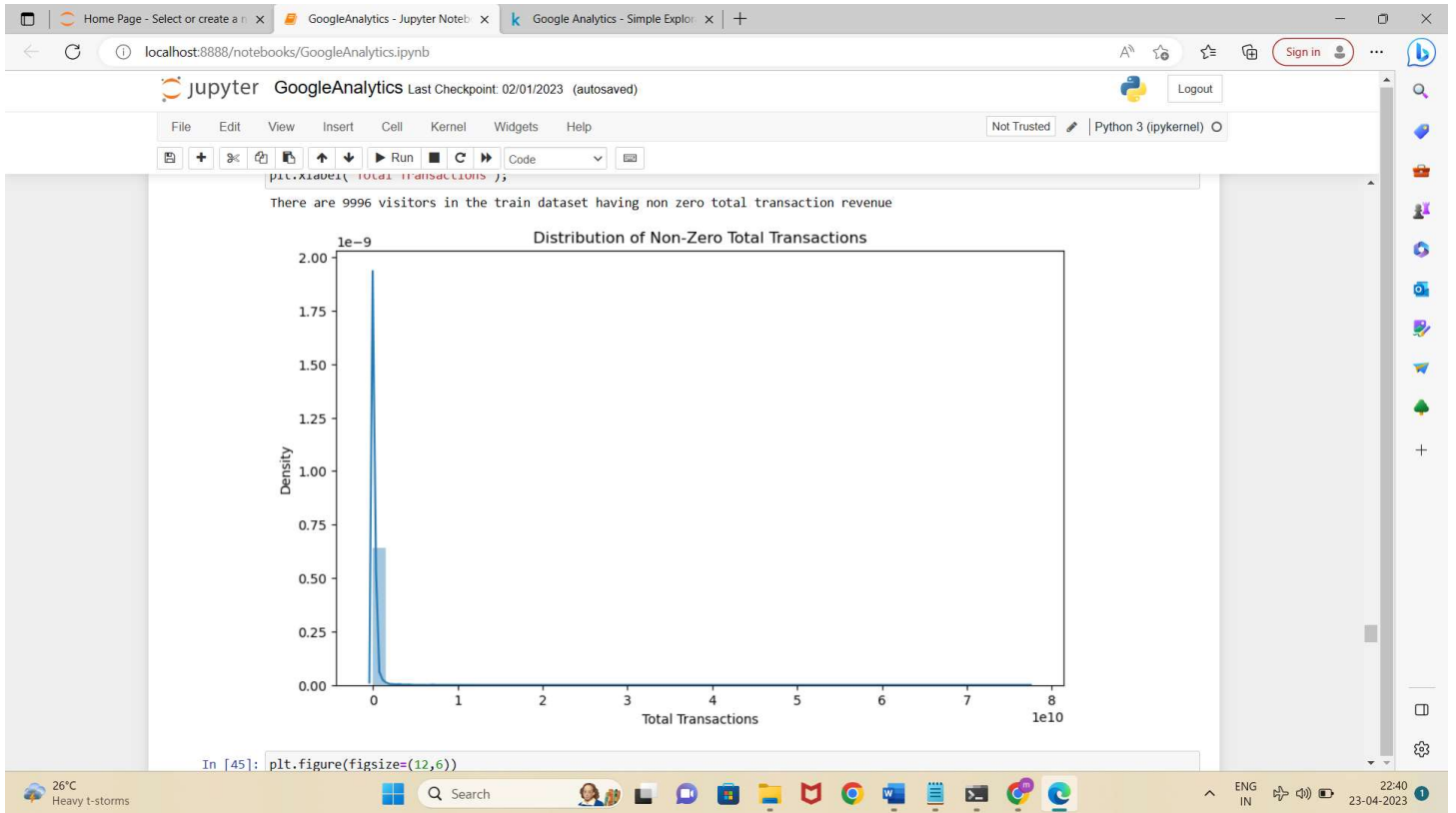
Out[43]:

	fullVisitorId	totals_bounces	totals_hits	totals_newVisits	totals_pageviews	totals_transactionRevenue
0	0000010278554503158	0.0	11.0	1.0	8.0	0.0
1	0000020424342248747	0.0	17.0	1.0	13.0	0.0
2	0000027376579751715	0.0	6.0	1.0	5.0	0.0
3	0000039460501403861	0.0	2.0	1.0	2.0	0.0
4	0000040862739425590	0.0	5.0	1.0	5.0	0.0

```
In [44]: non_zero = tmp[tmp["totals_transactionRevenue"] > 0]["totals_transactionRevenue"]
print("There are " + str(len(non_zero)) + " visitors in the train dataset having non zero total transaction revenue")

plt.figure(figsize=(10,6))
sns.distplot(non_zero)
plt.title("Distribution of Non-Zero Total Transactions");
plt.xlabel("Total Transactions");
```

There are 9996 visitors in the train dataset having non zero total transaction revenue



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Not Trusted Python 3 (ipykernel)

```
In [54]: import lightgbm as lgb

lgb_params = {"objective": "regression", "metric": "rmse",
              "num_leaves": 50, "learning_rate": 0.02,
              "bagging_fraction": 0.75, "feature_fraction": 0.8, "bagging_frequency": 9}

lgb_train = lgb.Dataset(train_x, label=train_y)
lgb_val = lgb.Dataset(valid_x, label=valid_y)
model = lgb.train(lgb_params, lgb_train, 700, valid_sets=[lgb_val], early_stopping_rounds=150, verbose_eval=20)

[LightGBM] [Warning] Unknown parameter: bagging_frequency
[LightGBM] [Warning] Unknown parameter: bagging_frequency
[LightGBM] [Warning] Auto-choosing row-wise multi-threading, the overhead of testing was 0.026752 seconds.
You can set 'force_row_wise=true' to remove the overhead.
And if memory is not enough, you can set 'force_col_wise=true'.
[LightGBM] [Info] Total Bins 2081
[LightGBM] [Info] Number of data points in the train set: 677739, number of used features: 27
[LightGBM] [Warning] Unknown parameter: bagging_frequency
[LightGBM] [Info] Start training from score 0.226447
Training until validation scores don't improve for 150 rounds
[20] valid_0's rmse: 1.84338
[40] valid_0's rmse: 1.75602
[60] valid_0's rmse: 1.71234
[80] valid_0's rmse: 1.68674
[100] valid_0's rmse: 1.67271
[120] valid_0's rmse: 1.66383
[140] valid_0's rmse: 1.65795
[160] valid_0's rmse: 1.65311
[180] valid_0's rmse: 1.65015
[200] valid_0's rmse: 1.64766
[220] valid_0's rmse: 1.64585
[240] valid_0's rmse: 1.64443
[260] valid_0's rmse: 1.64358
[280] valid_0's rmse: 1.64279
[300] valid_0's rmse: 1.64219
[320] valid_0's rmse: 1.64165
[340] valid_0's rmse: 1.6414
```

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Not Trusted Python 3 (ipykernel)

```
[360] valid_0's rmse: 1.63962
[580] valid_0's rmse: 1.63958
[600] valid_0's rmse: 1.63953
[620] valid_0's rmse: 1.63958
[640] valid_0's rmse: 1.63932
[660] valid_0's rmse: 1.63938
[680] valid_0's rmse: 1.6394
[700] valid_0's rmse: 1.63949
Did not meet early stopping. Best iteration is:
[638] valid_0's rmse: 1.6393

In [55]: preds = model.predict(test[features], num_iteration=model.best_iteration)
test["PredictedLogRevenue"] = np.expml(preds)
submission = test.groupby("fullVisitorId").agg({"PredictedLogRevenue": "sum"}).reset_index()
submission["PredictedLogRevenue"] = np.log1p(submission["PredictedLogRevenue"])
submission["PredictedLogRevenue"] = submission["PredictedLogRevenue"].apply(lambda x: 0.0 if x < 0 else x)
submission.to_csv("baseline.csv", index=False)
submission.head()
```

C:\Users\mahes\anaconda3\lib\site-packages\pandas\core\arraylike.py:397: RuntimeWarning:
invalid value encountered in log1p

```
Out[55]:
```

	fullVisitorId	PredictedLogRevenue
0	0000000259678714014	0.053754
1	0000049363351866189	0.000121
2	0000053049821714864	0.000000
3	0000059488412965267	0.002343
4	0000085840370633780	0.018547

```
In [ ]:
```

```
In [ ]:
```

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5.2. DATA VISUALIZATION

Data visualization is the representation of data through use of common graphics, such as charts, plots, info graphics, and even animations. These visual displays of information communicate complex data relationships and data-driven insights in a way that is easy to understand.

Data visualization can be utilized for a variety of purposes, and it's important to note that is not only reserved for use by data teams. Management also leverages it to convey organizational structure and hierarchy while data analysts and data scientists use it to discover and explain patterns and trends. Harvard Business Review (link resides outside IBM) categorizes data visualization into four key purposes: idea generation, idea illustration, visual discovery.

TYPES OF DATA VISUALIZATION

- **Tables:** This consists of rows and columns used to compare variables. Tables can show a great deal of information in a structured way, but they can also overwhelm users that are simply looking for high-level trends.
- **Pie charts and stacked bar charts:** These graphs are divided into sections that represent parts of a whole. They provide a simple way to organize data and compare the size of each component to one other.
- **Line charts and area charts:** These visuals show change in one or more quantities by plotting a series of data points over time and are frequently used within predictive analytics. Line graphs utilize lines to demonstrate these changes while area charts connect data points with line segments, stacking variables on top of one another and using color to distinguish between variables.
- **Scatter plots:** These visuals are beneficial in revealing the relationship between two variables, and they are commonly used within regression data analysis. However, these can sometimes be confused with bubble charts, which are used to visualize three variables via the x-axis, the y-axis, and the size of the bubble.
- **Heat maps:** These graphical representation displays are helpful in visualizing behavioral data by location. This can be a location on a map, or even a webpage.

6. CONCLUSION AND FUTURE ENHANCEMENT

6.1. CONCLUSION

In conclusion, the customer revenue prediction model using LGBM machine learning algorithm has shown promising results in accurately predicting customer revenue. The model was trained on a dataset consisting of various customer attributes such as age, gender, purchase history, and website interactions. The model was able to predict customer revenue with a high degree of accuracy, which can help businesses make informed decisions about marketing, sales, and customer engagement strategies.

The performance of the LGBM model was compared with other popular machine learning algorithms such as Random Forest and Linear Regression, and it outperformed them in terms of accuracy and speed. The LGBM model is capable of handling large datasets with millions of rows and columns, making it a suitable choice for enterprise-level applications.

However, there is still room for improvement in the model. Feature engineering, ensemble learning, and online learning techniques can be explored to improve the model's accuracy and performance further. In addition, the model can be deployed in real-time applications to provide businesses with up-to-date customer revenue predictions.

Overall, the customer revenue prediction model using LGBM machine learning algorithm is a valuable tool for businesses looking to improve their customer engagement and revenue generation strategies. It is a versatile and efficient algorithm that can be tailored to fit the unique needs of any business.

6.2. FUTURE ENHANCEMENT

Customer revenue prediction could be enhanced by integrating data from various sources, such as social media, customer feedback, and economic indicators. This would provide a more comprehensive view of customer behavior and improve the accuracy of the predictions.

Additionally, the LGBM model's hyperparameters could be fine-tuned to improve its performance. The number of estimators, learning rate, and maximum depth of the tree are all hyperparameters that significantly impact the model's performance. Future research could explore different combinations of hyperparameters to optimize the model's accuracy.

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