AI for Marketing : Custom Modules

A Major Project Report (Project Work -II)

Submitted in partial fulfillment of requirement of the

Degree of

BACHELOR OF TECHNOLOGY

in

INFORMATION TECHNOLOGY

BY

Dheeraj Shah
EN18IT301036

Under the Guidance of
Mr. Dinesh Kumar Bhayal (Internal)
Mr. Irfan Khan (External)

Department of Information Technology
Faculty of Engineering
MEDI-CAPS UNIVERSITY, INDORE- 453331

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Report Approval

The project work **"AI for Marketing : Custom Modules"** is hereby approved as a creditable study of an engineering subject carried out and presented in a manner satisfactory to warrant its acceptance as prerequisite for the Degree for which it has been submitted.

It is to be understood that by this approval the undersigned do not endorse or approved any statement made, opinion expressed, or conclusion drawn there in; but approve the "Project Report" only for the purpose for which it has been submitted.

Internal Examiner

Name: Mr. Dinesh Kumar Bhayal

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External Examiner

Name: ____________________________

Designation: ____________________________

Affiliation: ____________________________

<u>Declaration</u>

I hereby declare that the project entitled **"AI for Marketing : Custom Modules"** submitted in partial fulfillment for the award of the degree of Bachelor of Technology in 'Information Technology' completed under the supervision of **Mr. Dinesh Kumar Bhayal, Assistant Professor, Department of Information Technology,** Faculty of Engineering, Medi-Caps University Indore and **Mr. Irfan Khan, Chief Technology Officer**, Intelli AiTrillion Technologies Private Limited is an authentic work.

Further, we declare that the content of this Project work, in full or in parts, have neither been taken from any other source nor have been submitted to any other Institute or University for the award of any degree or diploma.

Dheeraj Shah
(EN18IT301036)

Certificate

We, **Dinesh Kumar Bhayal** and **Irfan Khan** certify that the project entitled **"AI for Marketing: Custom Modules"** submitted in partial fulfillment for the award of the degree of Bachelor of Technology by **Dheeraj Shah (EN18IT301036)** is the record carried out by him under our guidance and that the work has not formed the basis of award of any other degree elsewhere.

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Abstract

Artificial Intelligence in Marketing is now one of the most prominent examples. AI is helping marketers predict what their customers want and is a key contributor to more seamless customer experiences. AI is often used where speed plays an important role and is essential in marketing efforts. To best communicate with customers and then serve them tailored messages at the right time, ensuring the maximum efficiency possible and without intervention from marketing team members, data and customer profiles are used by AI tools. In today's customer-driven market ,complexities involved in decision making is increasing every day. This includes understanding customer needs and desires and aligning products to those needs and desires. A handle on changing customer behaviour is vital to make the best marketing decisions. AI marketing uses artificial intelligence and machine learning technologies to make decisions based on data collection ,data analysis and additional observations of trends that may impact marketing efforts. "*AI is not just heading for our industry and it will radically change the use of machinery we use in marketing*" said by **Tim Berners Lee**. There are numerous ways businesses can take advantage of Artificial Intelligence and Machine Learning to create a more comprehensive marketing plan. With that things keeping in mind, This project is based on custom modules such as Sales Forecasting, Product Demand Forecasting and Content Generation.

Keywords: Deep Learning, Time-Series, Forecasting, Generation

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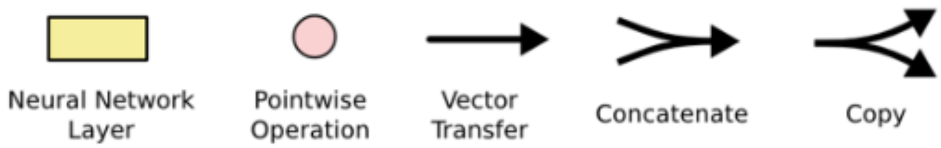
Abbreviations

Abbreviations	Explanation
ML	Machine Learning
NLP	Natural Language Processing
RNN	Recurrent Neural Network
LSTM	Long Short Term Memory
ARMA	Autoregressive Moving Average
ARIMA	Autoregressive Integrated Moving Average
SARIMA	Seasonal Autoregressive Integrated Moving Average
TSA	Time Series Analysis
API	Application Programming Interface
WS	Whole System
SF	Sales Forecasting
PDF	Product Demand Forecasting
CG	Content Generation

Notations & Symbols



LSTM SYMBOL

CHAPTER 1
INTRODUCTION

1.1 Introduction

AI marketing solutions optimize and streamline campaigns while eliminating risk for human error. Marketers can leverage AI to build marketing analytics techniques for targeting the customers which are potential and create customized experiences for their customers. For many of today's marketers, AI is used to perform more tactical tasks that require less human nuance and to augment marketing teams. AI is able to conduct tactical data analysis faster than its human counterparts and come to fast conclusions based on campaign and customer context. It helps the team members of the organization, give time to focus on strategic initiatives that can then inform AI-enabled campaigns. With the advent of AI and its growth at a high rate, marketers currently have to no longer wait until the end of a campaign to make the decisions, but they can make use of real-time analytics to make better media choices. In a multitude of use cases, AI is being used in marketing initiatives across a broad array of industries including financial services, healthcare, government, retail, entertainment, and more. Different results are shown or offered by each use case, from improvements to campaign performance, to enhanced customer experience or greater efficiency in marketing operations.

With huge amount of data coming every second, marketing teams have a hard time analysing and deriving insights from it. AI allows marketing teams to make the most of the data using predictive analytics, which leverages an assortment of machine learning algorithms, models and datasets to predict the future behaviour. This can be a great help for marketing teams to understand the types of products a consumer will be looking for and when and then allowing them to position campaigns more accurately. Predictive Marketing Analytics help marketers know what exactly consumers are thinking, saying and feeling in real time about the products and brand. AI marketing helps organizations understand who their target audience will be and so that they can create a personalized experience for each of their customers as consumers expect companies to understand and meet their needs and expectations. AI helps conduct data much faster than human intervention, guarantees the accuracy, security and enables team to focus on strategic initiatives to make effective AI-powered campaigns. AI is able to collect and track real-time tactical data so that marketers can make decisions right at the moment without having to wait until the campaigns end. They can determine what to do next based on the data-driven reports so that the decisions will be smarter and more objective.

Content Generation AI-powered tools can help the works of content creators much more efficiently and easily. Though the core of the content is routed from human creativity, you can use AI tools to maximize your content team's efficiency by automating specific tasks such as email content, personalized reports/messages or social media content curation. **Sales forecasting** knowing what to do next and doing it right is what every business should aim to meet customer's expectations and earn more sales. The application of AI in marketing makes it easier for marketers to understand customers and participate in their actions based on the data collected on their contacts and past purchases. Through this system, you can predict what customers will buy next and the quantity of a product sold. It helps you define what product to promote and promote to whom to drive higher sales. This way of creating business intelligence also enables you to avoid overselling or selling out-of-stock products by balancing your inventory. **Product Demand Forecasting,** Traditionally, demand forecasting is a form of predictive analytics, where the process of estimating customer demand is analysed using historical data. Using AI, organisations can make use of Machine Learning algorithms to predict changes in consumer demand as accurately as possible. These algorithms can automatically recognise patterns, identify complicated relationships in large datasets and capture signals for demand fluctuation by which errors in supply chain networks can be reduced with 30 to 50% with AI-powered demand forecasting and warehousing costs decrease with around 10 to 40%.

1.2 Literature Review

- **Survey 1**

Kumar, Priyanka. (2021). Role of Artificial Intelligence (AI) in Marketing. This article has put lights on how Artificial Intelligence has made leaps and bounds since a long time ago, and it already shapes the future of marketing. It also showed different areas in which AI integrating with the marketing thus it concluded that a successful online business can be enhanced by the AI-powered tools.

- **Survey 2**

Yau, Kok-Lim A., Norizan M. Saad, and Yung-Wey Chong. 2021. "Artificial Intelligence Marketing (AIM) for Enhancing Customer Relationships" Applied Sciences 11, no. 18: 8562. https://doi.org/10.3390/app11188562. This paper has develop the AIM framework, which bring together and curate a wide range of relevant literatures including real-life examples and cases, and then understand how these literatures contribute to the framework in this research topic. The AIM framework includes three main components, including the pre-processor, the main processor, and the memory storage. The main processor, which is the key component, uses AI to process structured data processed by pre-processor in order to make real-time decisions and reasonings.

- **Survey 3**

Armstrong, J.. (1999). Sales Forecasting. SSRN Electronic Journal. 10.2139/ssrn.1164602. This paper shredded lights on sales forecasting and Extrapolations of sales which are inexpensive and often adequate for the decisions that need to be made. In situations where large changes are expected or where one would like to examine alternative strategies, causal approaches are recommended. Key findings are: Methods should be selected on the basis of empirically-tested theories, not statistically based theories, Domain knowledge should be used, Complex models have not proven to be more accurate than relatively simple models. Given their added cost and the reduced understanding among users, highly complex procedures cannot be justified at the present time.

- **Survey 4**

Smirnov, P & Sudakov, Vladimir. (2021). Forecasting new product demand using machine learning. Journal of Physics: Conference Series. 1925. 012033. 10.1088/1742-6596/1925/1/012033. This paper proposes the use of machine learning methods. We used data about new product demand from the Ozon online store. The input data of the algorithm are characteristics such as the price, name, category and text description of the product. To solve the regression problem, various implementations of the gradient boosting algorithm were used, such as XGBoost, LightGBM, CatBoost. The forecast accuracy is now about 4.00. The proposed system can be used both independently and as part of another more complex system.

- **Survey 5**

ONikolaev, Evgeny & Dvoryaninov, Pavel & Drozdovsky, Nikita & Lensky, Yaroslav. (2017). An intelligent system for content generation. Here they introduce an artificial system based on a Deep Neural Network that creates images, audio or 3D-content. In this work, they propose an content generative system for producing content by using pre-trained Deep Neural Network. This is made possible mainly two technical innovations. First, they propose to use different pre-trained neural networks, so that generative system can use optimized network parameters to produce new images. Content generative system and core Deep Neural Network are weakly bound components and we can obtain different system output by core replacement. Second, proposed artificial system can be used not only for image generation, but also for producing audio content and generation 3D-models with target style.

1.3 Objective

AiTrillion is an Intelligent Marketing Cloud, built for the e-commerce world. With AiTrillion, companies can orchestrate campaigns across channels like push, email, in-app messaging, and, with auto-optimization towards higher conversions powered by machine learning. AiTrillion aims to simplify the nuances of technology and create a simple yet powerful Ai-powered eCommerce platform. Using the power of crowdsourcing and technology.

Different modules for **AI Custom Prediction:** Product Demand Forecasting, Customer Experience (CX), AiTrillion Sales Dashboard, Email Schedular, Membership Plan, Personalize recommendations based on customer history. Specific modules were finalized those are **Sales forecasting** using ARIMA, short for ‘Auto Regressive Integrated Moving Average’ is actually a class of models that ‘explains’ a given time series based on its own past values, that is, its own lags and the lagged forecast errors. **Content Generation** using LSTM recurrent neural networks in Python with Keras. KerasLSTM model to make predictions is to first start off with a seed sequence as input, generate the next character then update the seed sequence to add the generated character on the end and trim off the first character. **Product Demand Forecasting**

1.4 Significance

In uncertain times like these, business leaders would kill to have predictable revenue. Many of them are still grappling with how to forecast revenue for the next year, which is often the starting point for drawing up annual budgets for the organization. With distributed sales teams, businesses are now relying on their ability to forecast, now more than ever, to drive their entire growth strategy. Sales forecasting is both a science and an art. Decision makers rely on these forecasts to plan for business expansion and to determine how to fuel the company's growth. So, in many ways, sales forecasting affects everyone in the organization.

AI content generator has provided support for many copywriters by helping to speed up the process and increase the quality of output. It has already been used for many years for various different tasks. However, not for content writing – until now. The reason for this is that the AI was not reliable and trustworthy yet to produce creative high performing content. With artificial intelligence marketers can automatically generate content for simple stories such as stock updates and sports reports. You've probably even read content written by an algorithm without noticing it.

Demand Forecasting is an important activity that influences companies from different segments, such as: retail, consumer goods, pharmaceutical industry, automotive electronics, heavy machinery among others. Demand forecasting is used for business planning, as every plan involves estimates about this type of forecast. Thus, the predictions are of importance, as they enable managers to plan more assertive activities toward the strategic goals of the business. It is also useful for the tactical and strategic process of companies. Managers and decision makers utilize demand forecasts on their daily activities. These predictions can also be used as inputs for the sales and marketing teams to create insights into demand generation and organize their actions.

1.5 Module Description

1.5.1 Dataset Source

This is the fundamental module before starting of the project. The dataset is a group of data that are mended together to show the data variations in a time span to undergo further estimation and the source of the resources and its outcome for the later time of evaluation. It generates the result optimization and gives a feasible time period to customize and get the flow to the derivation.

This increases and are used in the level of research and finding the best suitable resource out of the same the resources has to be finely estimated and derived for the best possible outcome and the finest the value become the better is the level of extraction and closure is the best yield values that needs to be considered. Product Demand Forecasting dataset is from Kaggle "Forecast Order Demand and Visualization" Source1. For Sales Forecasting dataset is from Jason Browlee demo dataset Source2. For Content Generation dataset is from famous article Beyond good and evil uploaded on AWS Source3.

1.5.2 Time Series Analysis

A time-series model is one which postulates a relationship amongst a number of temporal sequences or time series. An example is provided by the simple regression model (1)

$$y(t) = x(t)\beta + \varepsilon(t),$$

where y(t) = {yt; t = 0, ±1, ±2, . . .} is a sequence, indexed by the time subscript t, which is a combination of an observable signal sequence x(t) = {xt} and an unobservable white-noise sequence ε(t) = {εt} of independently and identically distributed random variables.
A more general model, which we shall call the general temporal regression model, is one which postulates a relationship comprising any number of consecutive elements of x(t), y(t) and ε(t). The model may be represented by the equation below (2)

$$\sum_{i=0}^{p} \alpha_i y(t-i) = \sum_{i=0}^{k} \beta_i x(t-i) + \sum_{i=0}^{q} \mu_i \varepsilon(t-i),$$

where it is usually taken for granted that α0 = 1. This normalisation of the leading coefficient on the LHS identifies y(t) as the output sequence. Any of the sums in the equation can be infinite, but if the model is to be viable, the sequences of coefficients {αi}, {βi} and {μi} can depend on only a limited number of parameters.

Although it is convenient to write the general model in the form of (2), it is also common to represent it by the equation below (3)

$$y(t) = \sum_{i=1}^{p} \phi_i y(t-i) + \sum_{i=0}^{k} \beta_i x(t-i) + \sum_{i=0}^{q} \mu_i \varepsilon(t-i),$$

where $\varphi i = -\alpha i$ for $i = 1,...,p$. This places the lagged versions of the sequence y(t) on the RHS in the company of the input sequence x(t) and its lags.

Whereas engineers are liable to describe this as a feedback model, economists are more likely to describe it as a model with lagged dependent variables.

The foregoing models are termed regression models by virtue of the inclusion of the observable explanatory sequence x(t). When x(t) is deleted, we obtain a simpler unconditional linear stochastic model:

$$\sum_{i=0}^{p} \alpha_i y(t-i) = \sum_{i=0}^{q} \mu_i \varepsilon(t-i).$$

This is the autoregressive moving-average (ARIMA) model. A time-series model can often assume a variety of forms. Consider a simple dynamic regression model of the form (5)

$$y(t) = \phi y(t-1) + x(t)\beta + \varepsilon(t),$$

where there is a single lagged dependent variable. By repeated substitution, we obtain

$$\begin{aligned} y(t) &= \phi y(t-1) + \beta x(t) + \varepsilon(t) \\ &= \phi^2 y(t-2) + \beta\{x(t) + \phi x(t-1)\} + \varepsilon(t) + \phi\varepsilon(t-1) \\ &\vdots \\ &= \phi^n y(t-n) + \beta\{x(t) + \phi x(t-1) + \cdots + \phi^{n-1}x(t-n+1)\} \\ &\qquad + \varepsilon(t) + \phi\varepsilon(t-1) + \cdots + \phi^{n-1}\varepsilon(t-n+1). \end{aligned}$$

If $|\varphi| < 1$, then $\lim(n \to \infty)\varphi n = 0$; and it follows that, if x(t) and ε(t) are bounded sequences, then, as the number of repeated substitutions increases indefinitely, the equation will tend to the limiting form of

$$y(t) = \beta \sum_{i=0}^{\infty} \phi^i x(t-i) + \sum_{i=0}^{\infty} \phi^i \varepsilon(t-i).$$

It is notable that, by this process of repeated substitution, the feedback structure has been eliminated from the model. As a result, it becomes easier to assess the impact upon the output sequence of changes in the values of the input sequence. The direct mapping from the input sequence to the output sequence is described by engineers as a transfer function or as a filter.

For models more complicated than the one above, the method of repeated substitution, if pursued directly, becomes intractable. Thus we are motivated to use more powerful algebraic methods to effect the transformation of the equation. This leads us to consider the use of the so-called lag operator. A proper understanding of the lag operator depends upon a knowledge of the algebra of polynomials and of rational functions.

1.5.3 Method used to convert non-stationary data into stationary data

In machine learning, when the data is not in a Gaussian distribution we typically employ transformations like BOX-COX, or LOG. Similarly, when we have non-stationary time series data, there are two types of techniques to convert into stationary time series:

Differencing: Differencing is one of the most important strategies to make a time series stationary

$$y' = y_t - y_{t-1}$$

Differencing says instead of predicting yt directly try to predict the gap between yt and yt-1:

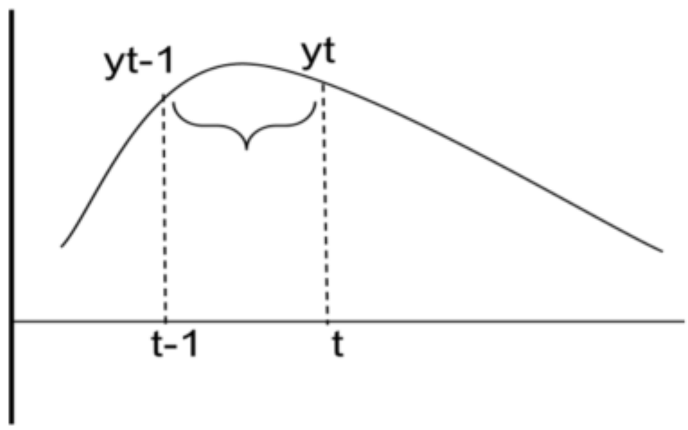


Figure 1.1: Converting non-stationary to stationary

Transformations: Differencing works very well with practical time series data. But it can't be applied to all time series. There are other methods, like Log transform, just like there are different methods to convert data into a Gaussian distribution. Log transforms are some of the most popular transforms used. In Log transforms, instead of modeling **yt** points, try to apply the logarithmic function to a point, and model the time series with the new log-transformed data. Let's called the new point **ỹt**(y Tilda)

$$\tilde{y_t} = log(y_t)$$

1.5.4 Arima & Sarima

Autoregressive Integrated Moving Average, or ARIMA, is a forecasting method for univariate time series data. As its name suggests, it supports both an autoregressive and moving average elements. The integrated element refers to differencing allowing the method to support time series data with a trend. A problem with ARIMA is that it does not support seasonal data. That is a time series with a repeating cycle.

ARIMA expects data that is either not seasonal or has the seasonal component removed, e.g. seasonally adjusted via methods such as seasonal differencing.

This acronym is descriptive, capturing the key aspects of the model itself. Briefly, they are:

- **AR**: *Autoregression*. A model that uses the dependent relationship between an observation and some number of lagged observations.
- **I**: *Integrated*. The use of differencing of raw observations (e.g. subtracting an observation from an observation at the previous time step) in order to make the time series stationary.
- **MA**: *Moving Average*. A model that uses the dependency between an observation and a residual error from a moving average model applied to lagged observations.

Each of these components are explicitly specified in the model as a parameter. A standard notation is used of ARIMA(p,d,q) where the parameters are substituted with integer values to quickly indicate the specific ARIMA model being used.

The parameters of the ARIMA model are defined as follows:

- **p**: The number of lag observations included in the model, also called the lag order.
- **d**: The number of times that the raw observations are differenced, also called the degree of differencing.
- **q**: The size of the moving average window, also called the order of moving average

A linear regression model is constructed including the specified number and type of terms, and the data is prepared by a degree of differencing in order to make it stationary, i.e. to remove trend and seasonal structures that negatively affect the regression model.

A value of 0 can be used for a parameter, which indicates to not use that element of the model. This way, the ARIMA model can be configured to perform the function of an ARMA model, and even a simple AR, I, or MA model.

Adopting an ARIMA model for a time series assumes that the underlying process that generated the observations is an ARIMA process. This may seem obvious, but helps to motivate the need to confirm the assumptions of the model in the raw observations and in the residual errors of forecasts from the model.

Seasonal Autoregressive Integrated Moving Average, SARIMA or Seasonal ARIMA, is an extension of ARIMA that explicitly supports univariate time series data with a seasonal component.

It adds three new hyperparameters to specify the autoregression (AR), differencing (I) and moving average (MA) for the seasonal component of the series, as well as an additional parameter for the period of the seasonality. Configuring a SARIMA requires selecting hyperparameters for both the trend and seasonal elements of the series

There are three trend elements that require configuration. They are the same as the ARIMA model; specifically:

- **p**: Trend autoregression order.
- **d**: Trend difference order.
- **q**: Trend moving average order.

There are four seasonal elements that are not part of ARIMA that must be configured; they are:

- **P**: Seasonal autoregressive order.
- **D**: Seasonal difference order.
- **Q**: Seasonal moving average order.
- **m**: The number of time steps for a single seasonal period

1.5.5 RNN:LSTM

One of the appeals of RNNs is the idea that they might be able to connect previous information to the present task, such as using previous video frames might inform the understanding of the present frame. If RNNs could do this, they'd be extremely useful. But can they? It depends.

Sometimes, we only need to look at recent information to perform the present task. For example, consider a language model trying to predict the next word based on the previous ones. If we are trying to predict the last word in "the clouds are in the *sky*," we don't need any further context – it's pretty obvious the next word is going to be sky. In such cases, where the gap between the relevant information and the place that it's needed is small, RNNs can learn to use the past information.

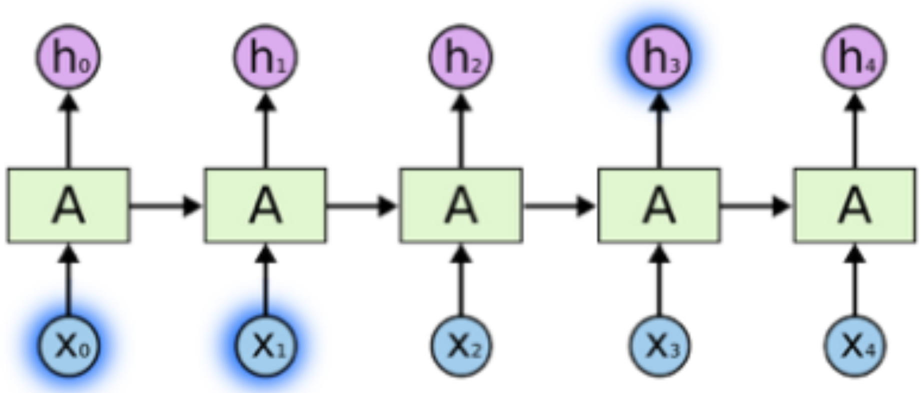


Figure 1.2: RNN-1

But there are also cases where we need more context. Consider trying to predict the last word in the text "I grew up in France… I speak fluent *French*." Recent information suggests that the next word is probably the name of a language, but if we want to narrow down which language, we need the context of France, from further back. It's entirely possible for the gap between the relevant information and the point where it is needed to become very large. Unfortunately, as that gap grows, RNNs become unable to learn to connect the information.

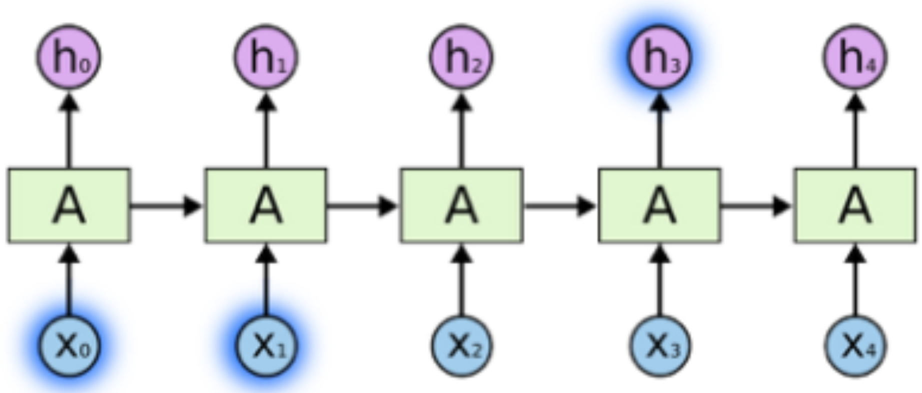


Figure 1.3: RNN-2

In theory, RNNs are absolutely capable of handling such "long-term dependencies." A human could carefully pick parameters for them to solve toy problems of this form. Sadly, in practice, RNNs don't seem to be able to learn them. The problem was explored in depth by Hochreiter (1991) [German] and Bengio, et al. (1994), who found some pretty fundamental reasons why it might be difficult. Thankfully, LSTMs don't have this problem!

Long Short Term Memory networks – usually just called "LSTMs" – are a special kind of RNN, capable of learning long-term dependencies. They were introduced by Hochreiter & Schmidhuber (1997), and were refined and popularized by many people in following work.[1] They work tremendously well on a large variety of problems, and are now widely used. LSTMs are explicitly designed to avoid the long-term dependency problem. Remembering information for long periods of time is practically their default behavior, not something they struggle to learn!

All recurrent neural networks have the form of a chain of repeating modules of neural network. In standard RNNs, this repeating module will have a very simple structure, such as a single tanh layer.

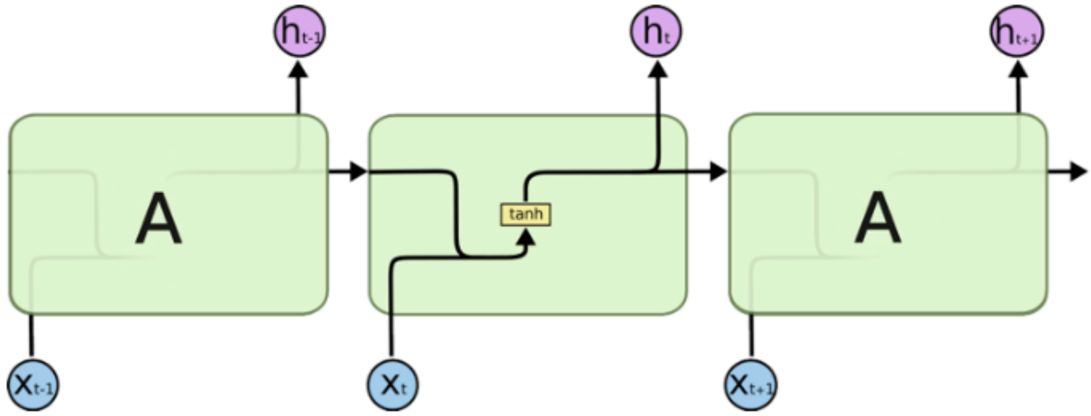


Figure 1.4: The repeating module in a standard RNN contains a single layer.

LSTMs also have this chain like structure, but the repeating module has a different structure. Instead of having a single neural network layer, there are four, interacting in a very special way.

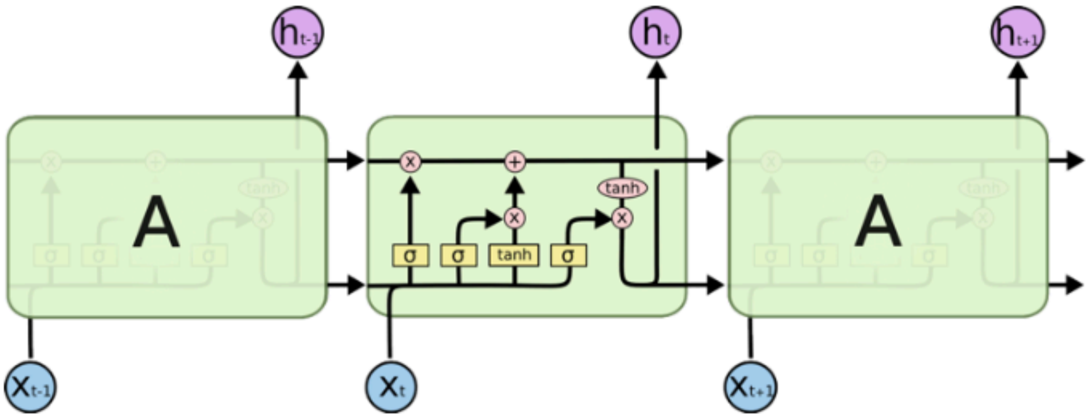


Figure 1.5: The repeating module in an LSTM contains four interacting layers.

1.6 AiTrillion Product

At AiTrillion, it's our mission to help eCommerce sellers automate their marketing by targeting the right people with the right message using the right channel. We believe in providing customer-centric, result-oriented, cost-competitive, innovative, and functional business solutions to our clients around the globe. To learn more about our Shopify app, you can simply install it and start driving sales and increasing customer engagement with 11+ tools and actionable analytics.

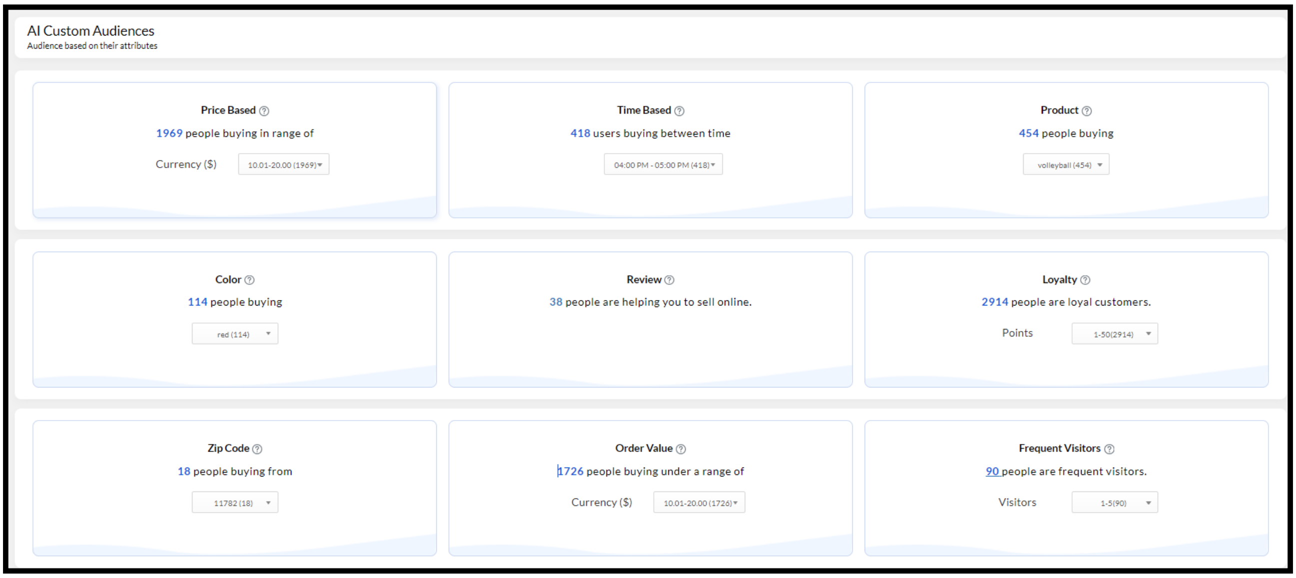


Figure 1.6: AiTrillion Custom Audiences

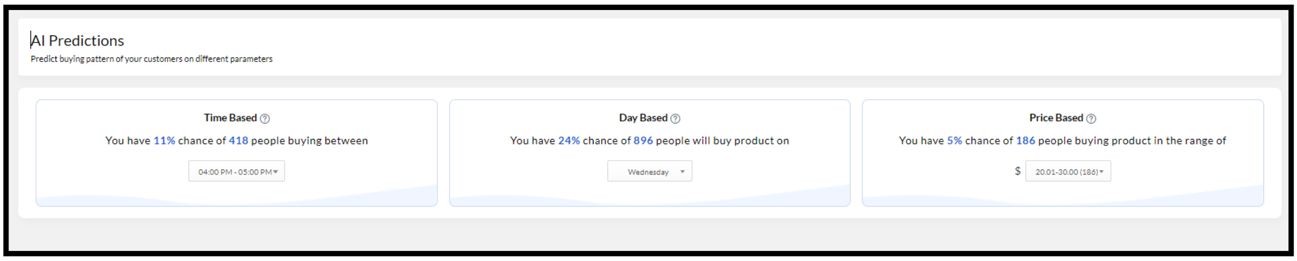


Figure 1.7: AiTrillion AI Predictions

1.7 Systems Description

- **Sales Forecasting**

Sales forecasting involves the determination of the expected levels of sales in the future, based on past and present sales data, the intentions of management and environmental influences upon the enterprise. The forecasting of sales can be regarded as a system having inputs, a process and an output.This may be a simplistic viewpoint, but it serves as a useful tool for the analysis of the true worth of sales forecasting as an aid to management

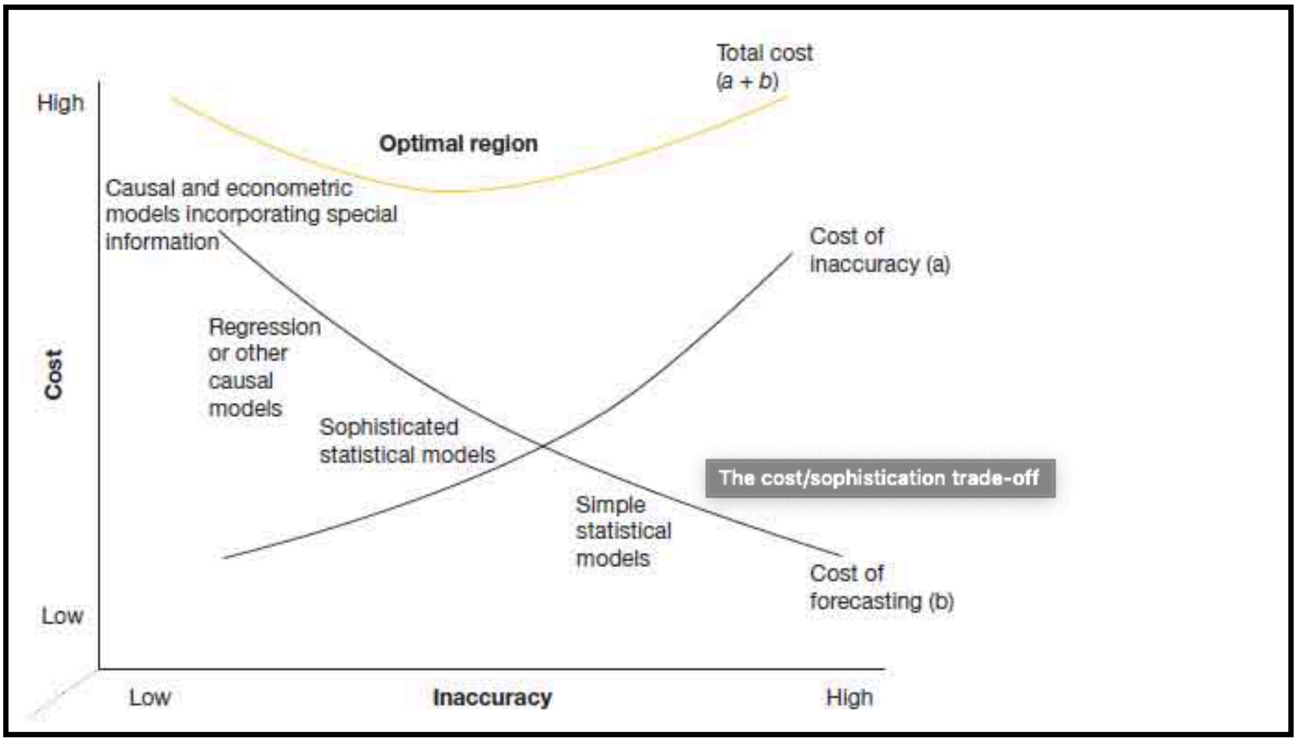


Figure 1.8: The cost/sophistication trade-off

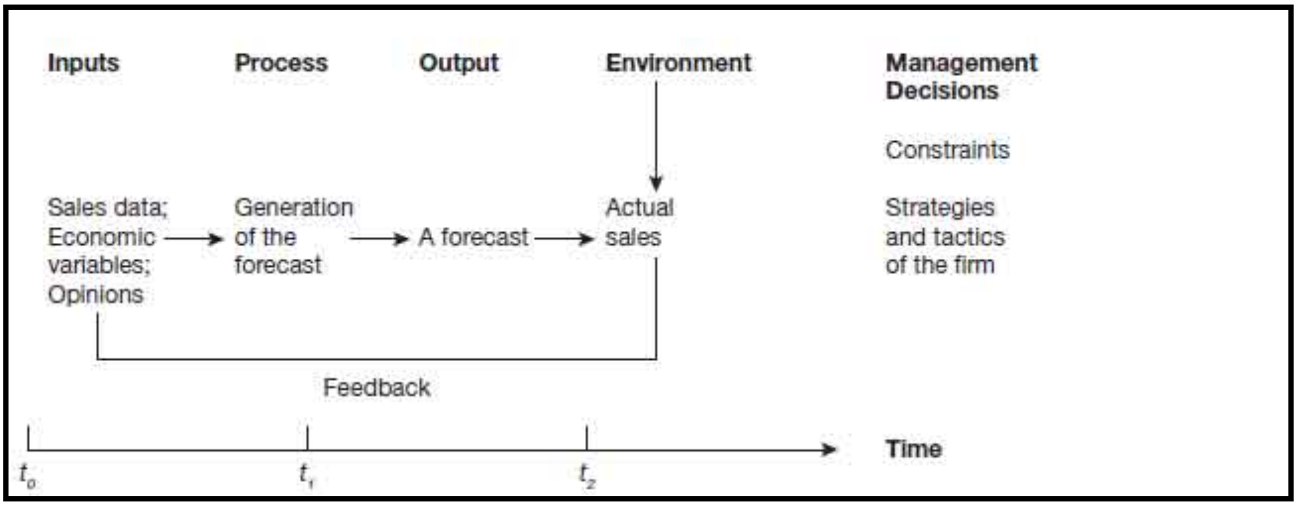


Figure 1.9: Sales Forecasting System

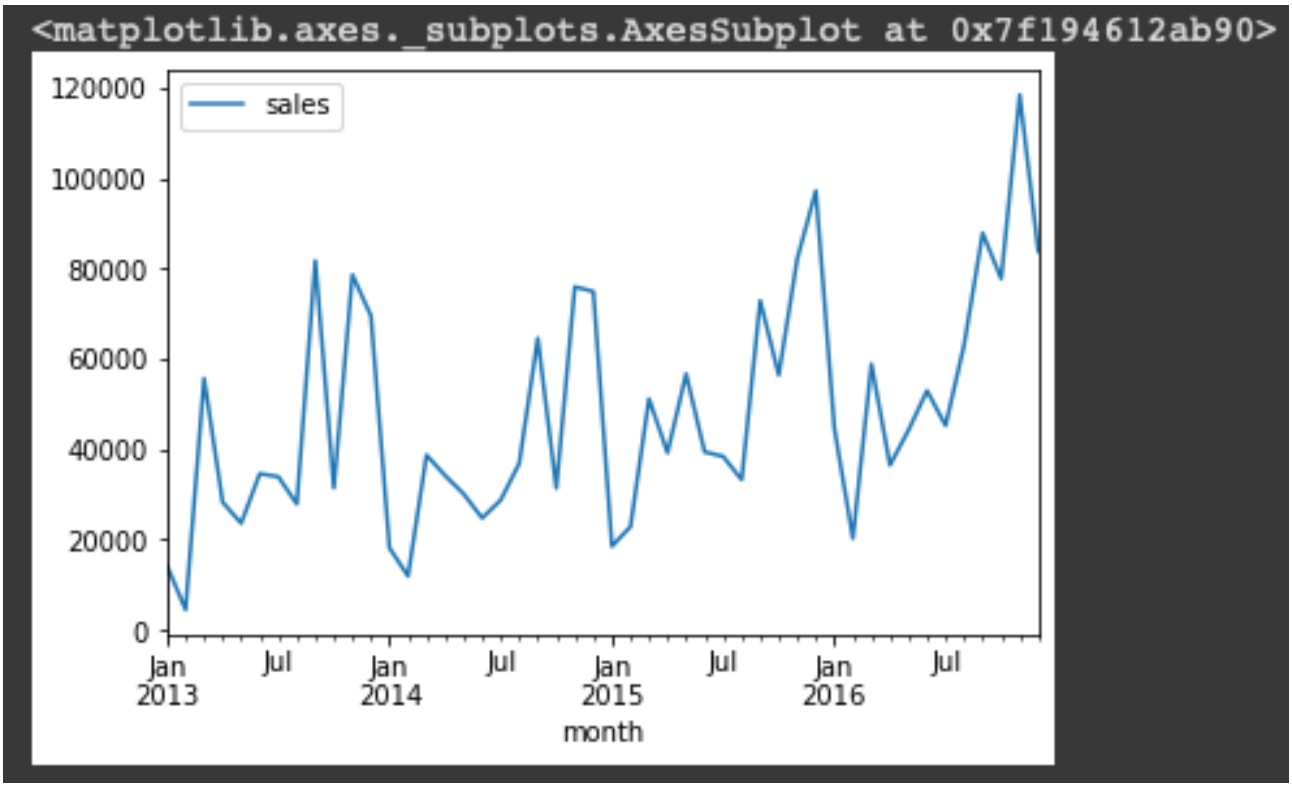


Figure 1.10: Demo Sales Graph

- **Product Demand Forecasting**

Reliable demand forecasts are integral to the health of retail operations because, simply put, they reduce uncertainty. With an accurate calculation of how many items they will sell at any given time, retailers can order, allocate, and replenish those items accordingly. Beyond supply chain and inventory management, though, an accurate forecast in a unified retail planning environment can be used to optimize capacity management, workforce scheduling, planograms, and more. In short, the demand

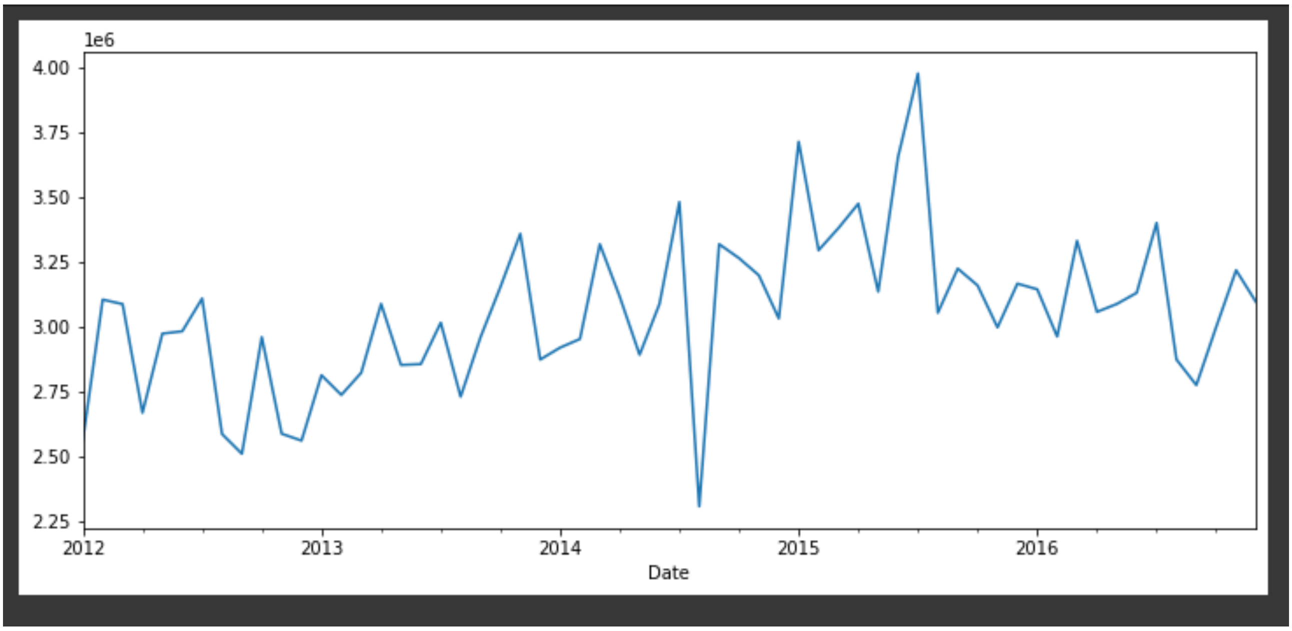


Figure 1.11: Order Demand Graph

forecast is the foundation from which retailers can drive a wide range of benefits across retail functions.

Machine learning not only increases the accuracy of demand forecasts, it also automates large amounts of planner work and can process enormous data sets—far more than any human planner would be capable of. To generate an accurate demand forecast, a system must be able to process an enormous amount of data on the wide range of variables that can potentially impact demand. With advancements in large-scale data processing and in-memory computing, modern demand planning systems can make millions of forecast calculations within a minute's time, taking into consideration more variables than ever before possible.

Consider the three broad areas of variability that continuously impact demand: recurring variations in baseline demand patterns, your own internal business decisions, and external factors such as weather or local events.

- **Content Generation**

Long short-term memory(LSTM) units on sequence-based models are being used in translation, question-answering systems, classification tasks due to their capability of learning long-term dependencies. In Natural language generation, LSTM networks are providing impressive results on text generation models by learning language models with grammatically stable syntaxes. But the downside is that the network does not learn about the context. The network only learns the input-output function and generates text given a set of input words irrespective of pragmatics. As the model is trained without any such context, there is no semantic consistency among the generated sentences.

```
----- diversity: 0.2
----- Generating with seed: "creature, in order to render his own pow"
creature, in order to render his own powerful and with the stand and are and and and the strength and the the same stand the form of the s
----- diversity: 0.5
----- Generating with seed: "creature, in order to render his own pow"
creature, in order to render his own power which the present by the world, and so fully and that it will a matter to the speaks and all po
----- diversity: 1.0
----- Generating with seed: "creature, in order to render his own pow"
creature, in order to render his own power tyrrong no leasty feectangent, the own merely
seed they so his finere and and de dread. he hatible to powen that the how
omeoming. the tegitue, every bad morals and anmortifelly about a than that cueture such ascorpors. oppeeve feeldness we have ni-having the
the kni:k the restricts of schoolerhe class:
perstition, and and against
negerable; is back bit means of notic
----- diversity: 1.2
----- Generating with seed: "creature, in order to render his own pow"
creature, in order to render his own power toroitue
cannon its
complete.
lirldy,
```

Figure 1.12: Content Generation Epochs

CHAPTER 2

SYSTEM REQUIREMENT ANALYSIS

2.1 Product Perspective

The product is supposed to be a premium source. It is a web based system implementing client-server model. AiTrillion product is cross platform for e-commerce and artificial intelligence which provides solutions in email marketing also AI related prediction, which is a SAAS.

2.1.1 Product Function

- Highly accurate
- Cloud based – scalable, anytime, and anywhere access
- Store data on Amazon AWS.
- Visualization in the form of chart, map graph for better understanding.

2.1.2 User Classes and Characteristics

- In my system it has mainly two, first is the who uses a system, second is the administrator.
- **User:** User who can use application to predict: sales price, product demand forecasting, personalised recommendation, content generation.
- **Admin:** These users has an authority to update, schedule and Configure a system.

2.1.3 Operating Environment

Our project is based on cloud and user application runs on all platforms. So, we need any device like mobile, tablet, desktop to run the application.

2.1.4 Design and Implementation Constraints

There are three major components for our system are client App, cloud, modules(backend).

2.1.5 Assumptions and Dependencies

Only assumptions in the system is that user has knowledge of smartphone and internet.

2.2 External Interface Requirements

2.2.1 User Interfaces

The user of the system must have a device with working internet connection to access application.

2.2.2 Hardware Interfaces

Processor	Intel i5 or above
RAM	Minimum 225MB or more.
Hard Disk	Minimum 2 GB of space
Input Device	Keyboard & Mouse
Output Device	Screens of Monitor or a Laptop

2.2.3 Software Interfaces

Operating system	Windows & Linux
IDE	Jupiter Notebook or Pycharm
Data Set	.csv file(Kaggle and Dummy Data)
Visualization	matplotlib, ML library
Server	Streamlit with HTTP process.

2.2.4 Communications Interfaces

The system can be worked in only online mode hence, communication interfaces are compulsory.

2.3. System Features

2.3.1 Functional Requirement

- Collecting accurate data from the Kaggle/dummy in consistent manner.
- Option to select any prediction i.e sales forecast, product demand forecast and content generation.
- Different interaction charts to increase understanding of respective modules.
- Can look previous data information which was collected.
- Prediction functionality, respectively to every modules in the form of forecasting sales price next months, Demand forecasting and content generation.

2.3.2 Non-Functional Requirement

Performance Requirements: The system should take immediate action and show result as fast as possible.

Safety Requirements: The system/application is currently in developing phase so, don’t use for legal purpose.

Security Requirements: Here the system works in online mode so, there is a need of security mechanism**.**

Software Quality Attributes:

Reliability: The reliability that user can easily use module to ger sales forecast, demand of the product and content generation for marketing.

Availability: These Modules will deployed on a product AiTrillion E-commerce Platform so there is 99.9% availability.

Maintainability: Our system usually will require maintenance every day.

Portability: The application works on all platforms.

CHAPTER 3
SYSTEM ANALYSIS

3.1 Information Flow Representation

3.1.1 Use Case Diagram (WS)

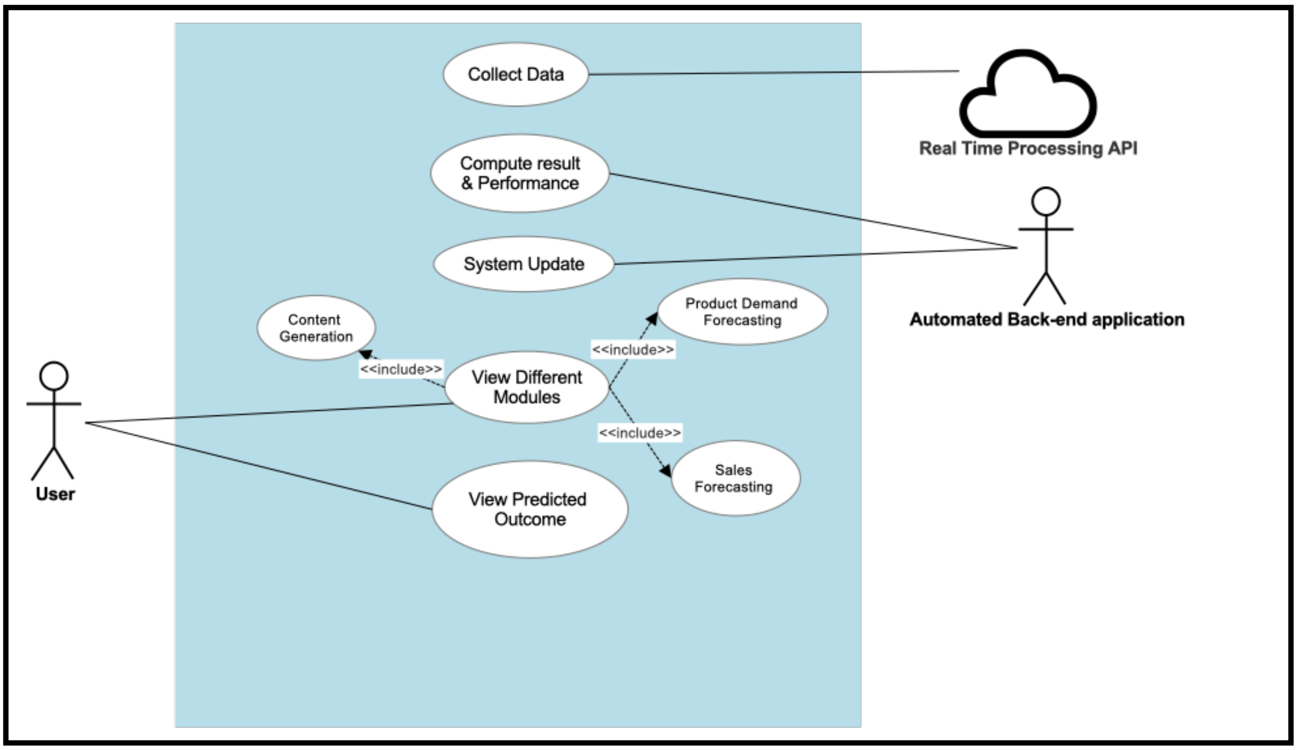


Figure 3.1: Use Case Diagram(WS)

Use Case Index

Table 3.1 Use Case Index (WS)

Use Case ID	Use Case Name	Primary actor	Scope	Complexity	Priority
1	Collect Data	Automated UI App Backend	In	High	1
2	Compute result & Performance	Automated UI App Backend	In	High	1
3	System Update	Automated UI App Backend	In	High	1
4	View Different Modules	User	In	Medium	2
5	Content Generation	User	In	Medium	1
6	Product Demand Forecasting	User	In	Medium	1
7	Sales Forecasting	User	In	Medium	1

Use Case ID	Use Case Name	Primary actor	Scope	Complexity	Priority
8	View Predicted Outcome	User	In	High	1

Use Case Description

Use case ID: 1

Use case name: Collect Data

Description: Every module required data will be fetched from the source. Automated User Interface Application Backend will be able to collect the data for system.

Use case ID: 2

Use case name: Compute result and performance

Description: Prediction result will be handled and generated by Automated User Interface Application Backend. The system will be built, through which the result of prediction and system performance will be analyzed.

Use case ID: 3

Use case name: System update

Description: With the change of module and technology regular update of system is required. The predicted result of every module will be auto-updated by the Automated User Interface Application Backend on regular basis

Use case ID: 4

Use case name: View different modules

Description: Three Different modules can be viewed by user.

Use Case ID: 5

Use Case Name: Content Generation

Description: It is Content Generation feature which predict the content using the at least 1000 word article.

Use Case ID: 6

Use Case Name: Product Demand Forecasting

Description: It is a feature used to predict the inventory (warehouse) demand forecasting

Use Case ID: 7

Use Case Name: Sales Forecasting

Description: It predict the sales for the store for next months and years.

3.1.2 Use Case Diagram (SF)

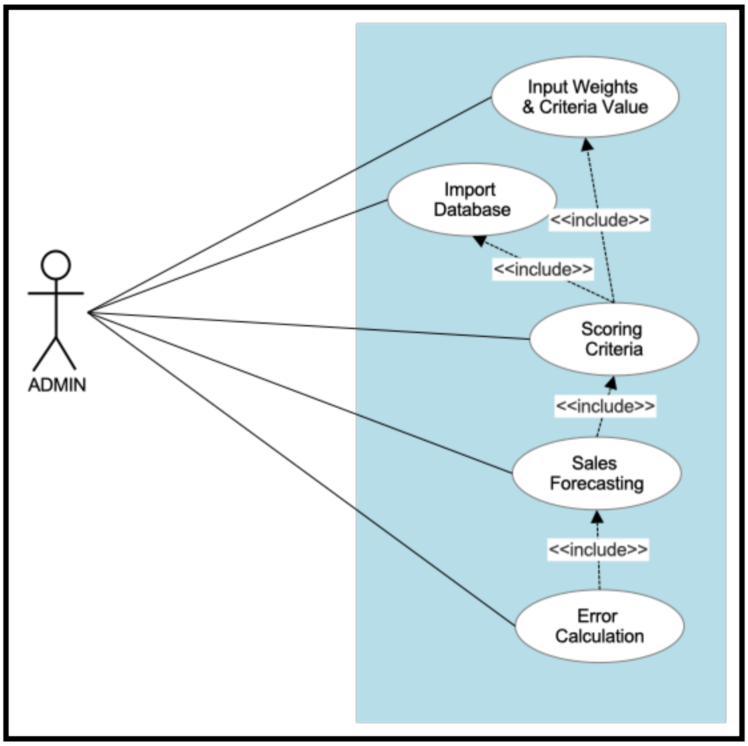


Figure 3.2: Use Case Diagram(SF)

Use Case Index

Table 3.2: Use Case Diagram(SF)

Use Case ID	Use Case Name	Primary actor	Scope	Complexity	Priority
1	Input Weights & Criteria Value	Admin	In	High	1
2	Import Database	Admin	In	High	1
3	Scoring Criteria	Admin	In	High	1
4	Sales Forecasting	Admin	In	High	1
5	Error Calculation	Admin	In	High	1

Use Case Description

Use case ID: 1

Use case name: Input Weights & Criteria Value

Description: This function to input the value of each weight and criteria that most influence the sales volume based on the evaluation of the best-worst method.

Use case ID: 2

Use case name: Import Database

Description: It is the function to import data from the database of a case company.

Use case ID: 3

Use case name: Scoring Criteria

Description: It is the function for projecting the customer value into numbers.

Use case ID: 4

Use case name: Sales Forecasting

Description: It is sales forecasting that serves to forecast the sales volume of each product for the coming month.

Use case ID: 5

Use case name: Error Calculation

Description: It is a case of calculation of sales forecasting errors (accuracy)

3.1.3 Data Flow Diagram

A data flow diagram shows the way information flows through a process or system. It includes data inputs and outputs, data stores, and the various sub processes the data moves through. DFDs are built using standardized symbols and notation to describe various entities and their relationships.

Data flow diagram levels:

Data flow diagrams are also categorized by level. Starting with the most basic, level 0, DFDs get increasingly complex as the level increases.

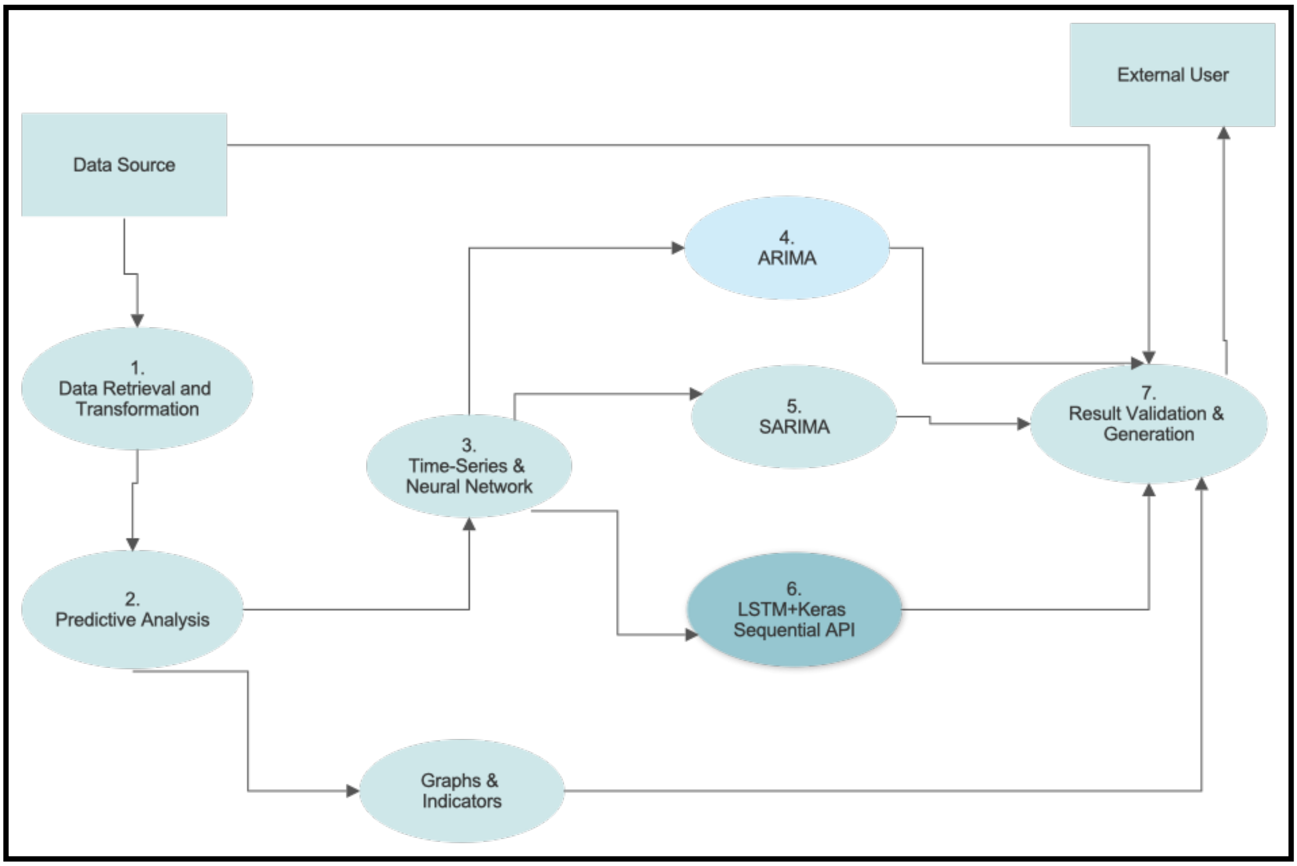


Figure 3.3: Data Flow Diagram(level-1)

Context Diagrams/Level 0 DFDs are the most basic data flow diagrams. They provide a broad view that is easily digestible but offers little detail. Level 1 DFDs go into more detail than a Level 0 DFD. In a level 1 data flow diagram, the single process node from the context diagram is broken down into sub processes. As these processes are added, the diagram will need additional data flows and data stores to link them together.

3.1.4 System Flow Diagram

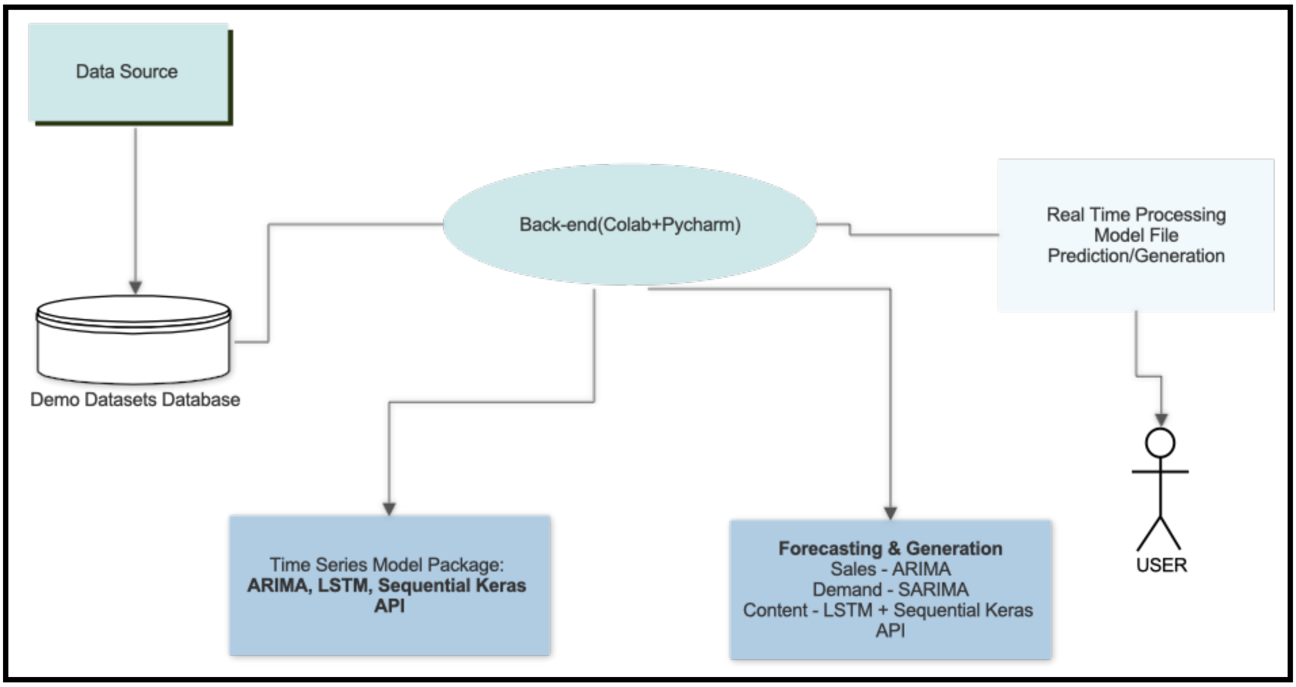


Figure 3.4: System Flow Diagram

CHAPTER 4

Design

4.1 Algorithm Snapshot for operations

- **Product Demand Forecasting**

```
[ ] for param in pdq:
        for param_seasonal in seasonal_pdq:
            try:
                mod = sm.tsa.statespace.SARIMAX(y,
                                                order=param,
                                                seasonal_order=param_seasonal,
                                                enforce_stationarity=False,
                                                enforce_invertibility=False)

                results = mod.fit()

                print('SARIMA{}x{}12 - AIC:{}'.format(param, param_seasonal, results.aic))
            except:
                continue
```

Figure 4.4: Adfuller Test

Figure 4.1: SARIMA - Parameters

```
[ ] from statsmodels.tsa.statespace.sarimax import SARIMAX
    mod = sm.tsa.statespace.SARIMAX(y,
                                    order=(1, 1, 1),
                                    seasonal_order=(1, 1, 0, 12),
                                    enforce_stationarity=False,
                                    enforce_invertibility=False)
    results = mod.fit()
    print(results.summary().tables[1])
```

	coef	std err	z	P>|z|	[0.025	0.975]
ar.L1	-0.2450	0.368	-0.666	0.505	-0.966	0.476
ma.L1	-0.4385	0.325	-1.348	0.178	-1.076	0.199
ar.S.L12	-0.4568	0.208	-2.192	0.028	-0.865	-0.048
sigma2	1.018e+11	9.55e-13	1.06e+23	0.000	1.02e+11	1.02e+11

Figure 4.2: SARIMA - Stats

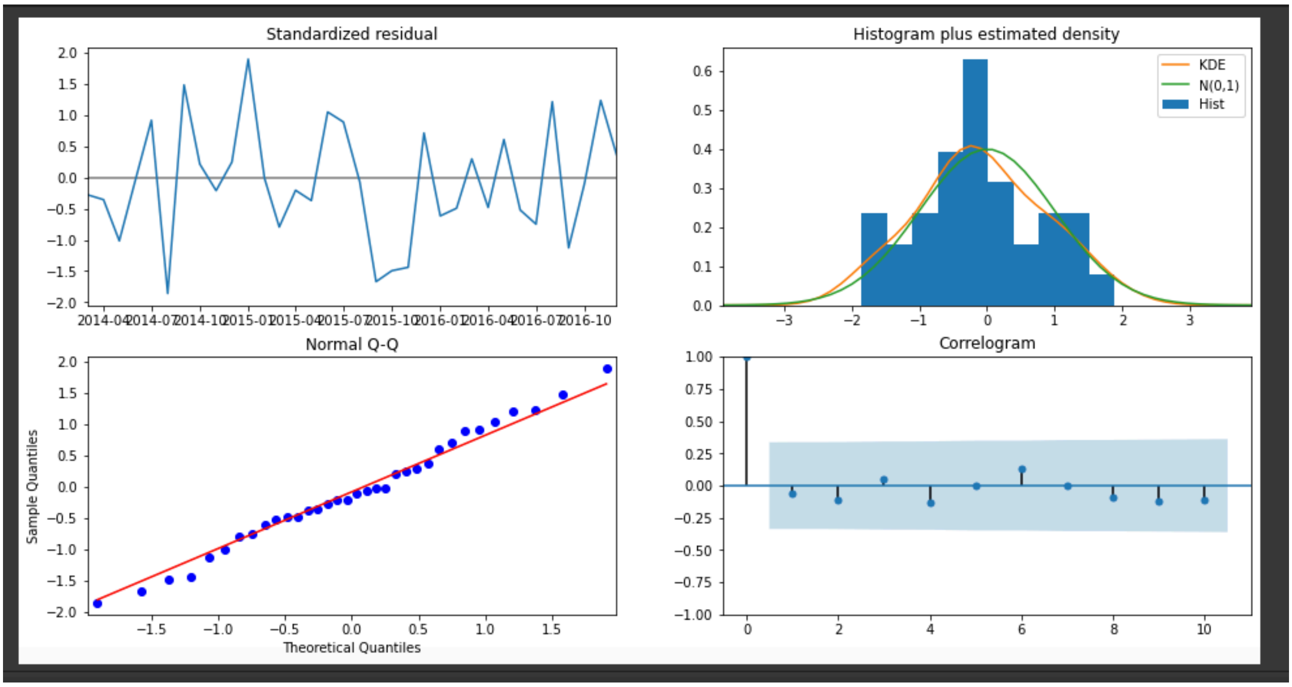


Figure 4.3: SARIMA - Diagnostics Plot

- **Sales Forecasting**

```python
def adfuller_test(sales):
  result = adfuller(sales)
  labels = ['ADF Test Statistic','p-value','Lags used','Number of Observation used']
  for value,label in zip(result,labels):
    print(label+' : '+str(value))
    if result[1] <= 0.05:
      print("Data is stationary")
    else:
      print("Data is not stationary")
```

Figure 4.4: Adfuller Test

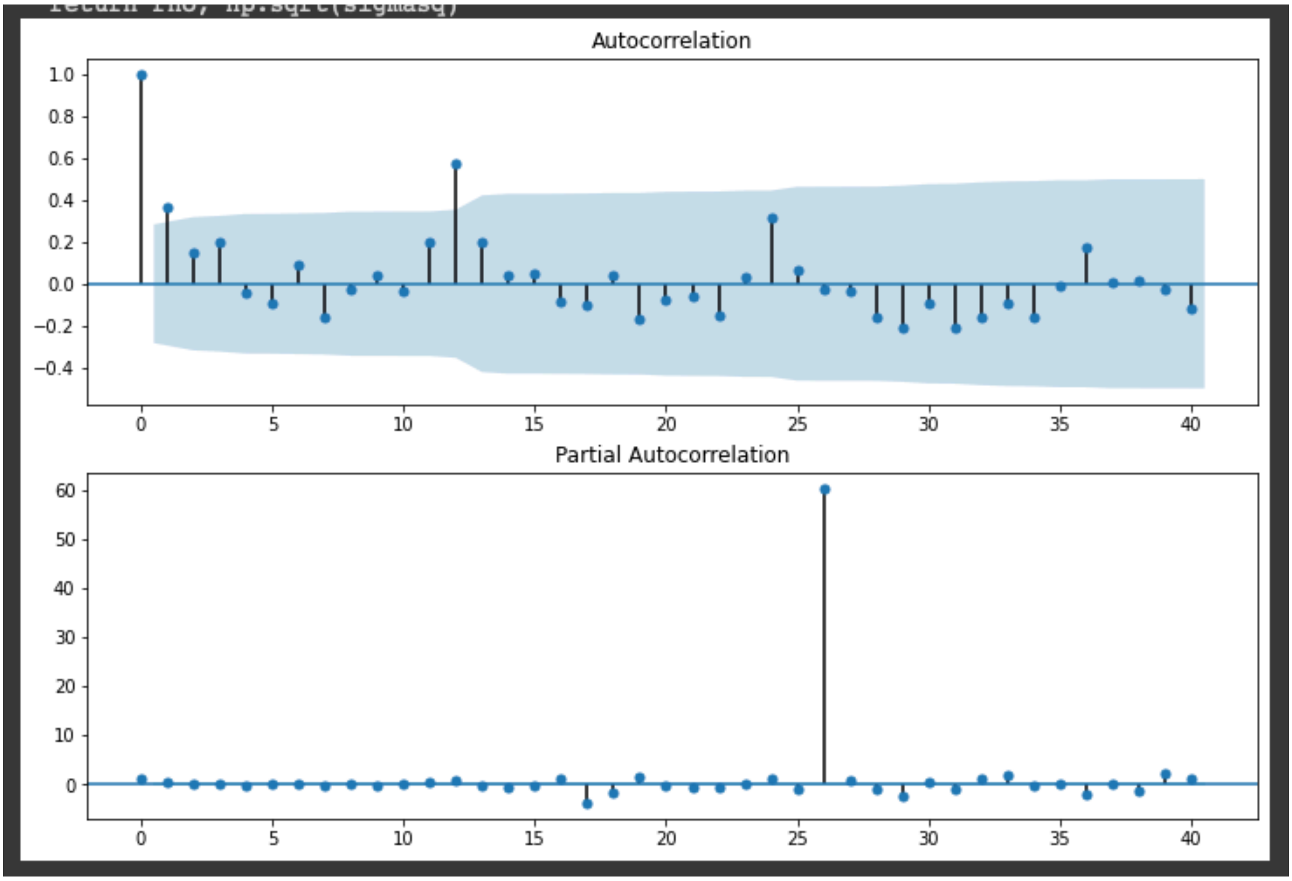


Figure 4.5: ACF & PACF Plot

```python
[ ]  model=sm.tsa.statespace.SARIMAX(df['sales'],order=(1, 1, 1),seasonal_order=(1,1,1,10))
     results=model.fit()
```

Figure 4.6: Sales Forecasting - SARIMA

Statespace Model Results

Dep. Variable:	sales	No. Observations:	48
Model:	SARIMAX(1, 1, 1)x(1, 1, 1, 10)	Log Likelihood	-432.803
Date:	Mon, 31 Jan 2022	AIC	875.606
Time:	10:36:56	BIC	883.660
Sample:	01-01-2013	HQIC	878.445
	- 12-01-2016		
Covariance Type:	opg		

	coef	std err	z	P>|z|	[0.025	0.975]
ar.L1	0.4577	0.771	0.594	0.553	-1.054	1.969
ma.L1	-0.8720	0.580	-1.503	0.133	-2.009	0.265
ar.S.L10	-0.4778	0.494	-0.967	0.334	-1.446	0.491
ma.S.L10	-0.4844	0.767	-0.632	0.527	-1.987	1.018
sigma2	1.539e+09	2.85e-10	5.4e+18	0.000	1.54e+09	1.54e+09

Ljung-Box (Q):	nan	Jarque-Bera (JB):	0.20
Prob(Q):	nan	Prob(JB):	0.91
Heteroskedasticity (H):	1.62	Skew:	-0.03
Prob(H) (two-sided):	0.41	Kurtosis:	2.65

Figure 4.7: Statespace Model Results

- **Content Generation**

```
print('Build model...')
model = Sequential()
model.add(LSTM(128, input_shape=(maxlen, len(chars))))
model.add(Dense(len(chars)))
model.add(Activation('softmax'))

optimizer = RMSprop(lr=0.01)
model.compile(loss='categorical_crossentropy', optimizer=optimizer)
```

Figure 4.8: Content Generation: LSTM

CHAPTER 5

Testing

5.1 Testing Plan

Table 5.1 Testing Plan

Type of Test	Will Test be Performed	Comment/Explanation	Software Component
Requirement Testing	Yes	The tester should look at the project from organization perspective and make sure it defines and reflects what customers have in mind. It should align with client's goals without being biased towards technicalities.	Does input and output meet the requirements, i.e. input output synchronization according to the proposed algorithm.
Unit	Yes	Unit testing is a way by which individual units of source code with associated control data, usage, procedures, and operating procedures, are tested to determine if they are fit for use.	Check to see if the source data can be read by the module and produce the required result.
Integration	Yes	This testing is done after all the groups have been completed to test their relation. This is particularly necessary and important as these modules have been made solely for the purpose of integration with the existing organization.	Check if all the variables data work together in cohesion.
Performance	Yes	Needed to assess various factors which will eventually lead to customer satisfaction.	Full table is being checked with proper input output entries.
Stress	No	The stress of the system is measured as the large number of data crawled is managed.	Several numerical datas should be checked simultaneously on net.

5.2 Testing Types

Table 5.2 Testing Types

Type of Test	Will Test be Performed	Comment/Explanation	Software Component
Compliance	Yes	Complacency was checked right as the data crawled were all under proper specifications.	Demo Data/Kaggle
Security	No	Security of our predictions have been kept proper i.e. pure live data pure algorithms based results.	Check to see if the source data can be read by the module and produce the required result.

Type of Test	Will Test be Performed	Comment/Explanation	Software Component
Load	No	Though all the data crawled are quite large in number inspite of that load on a system was neutral.	Large data crawled were simultaneously stored also to depressurize the load on the system.
Volume	Yes	-	Full table is being checked with proper input output entries.
Stress	No	The stress of the system is measured as the large number of data crawled is managed.	Several numerical datas should be checked simultaneously on net.

5.3 Component decomposition and type of testing required

Table 5.3 Component Decomposition and type of testing required

S.No.	List of Various Components (modules) that require testing	Type of Testing Required	Technique for writing test cases
1	Data (Content Generation, Sales Forecasting/ Product Demand Forecasting)	Requirement	Black Box(Boundary Values)
2	Algorithms	Unit	White Box
3	Neural Network & TS (output)	Unit	White Box
4	Graphs and Table	Volumes	White Box

CHAPTER 6
Experiment and Results

6.1 Experiment and Results

- **Sales Forecasting**

month	sales	forecast
2016-08-01	63120.89	76283.294353
2016-09-01	87866.65	54468.138204
2016-10-01	77776.92	57060.341683
2016-11-01	118447.83	70144.552684
2016-12-01	83829.32	61795.383738

Figure 6.1: Sales Forecasting Result

Above snapshot depicts the forecasting of sales for first five months and it can understood forecast is nearly equal to the actual sales which gives a positive position of the business.

- **Product Demand Forecasting**

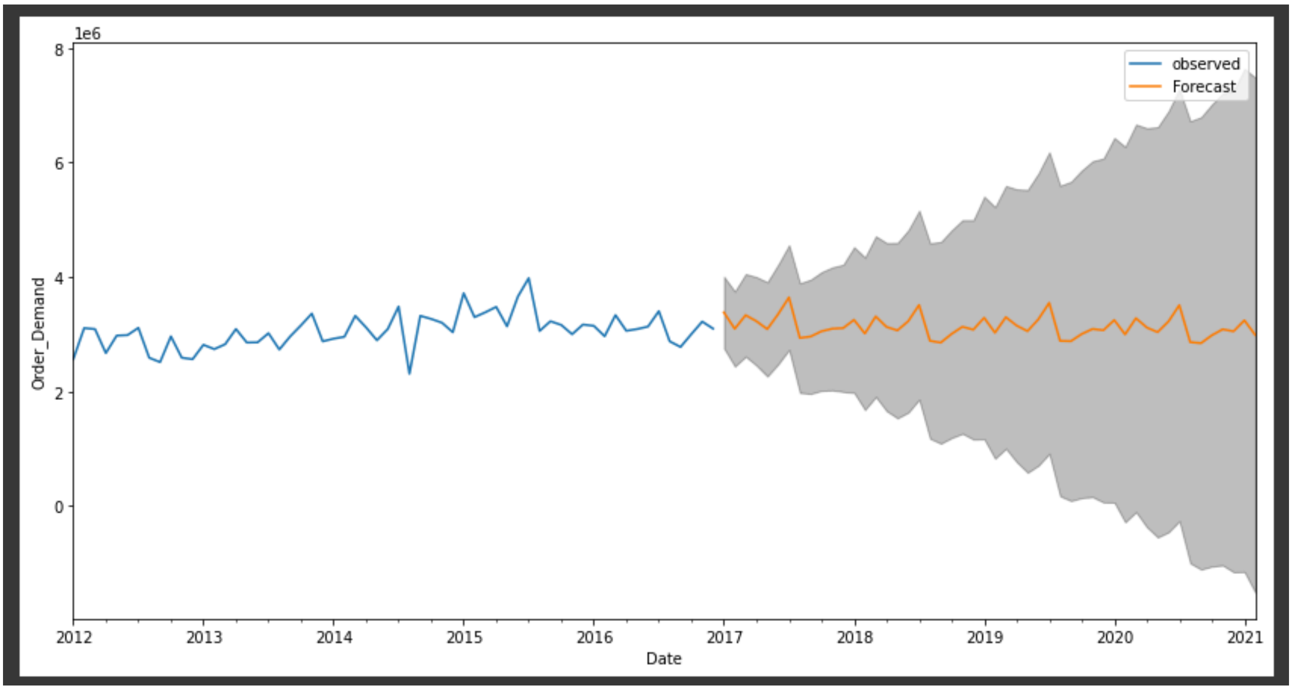


Figure 6.2: Product Demand Forecasting Result

Above result of product demand forecasting depicts the how much demand of a specific product can be occurred from the year 2017 to 2021. Blue line graph tells the observed pattern and orange with shaded regions predicts the demand. Thus it solves the ‘OUT OF STOCK’ e-commerce problem.

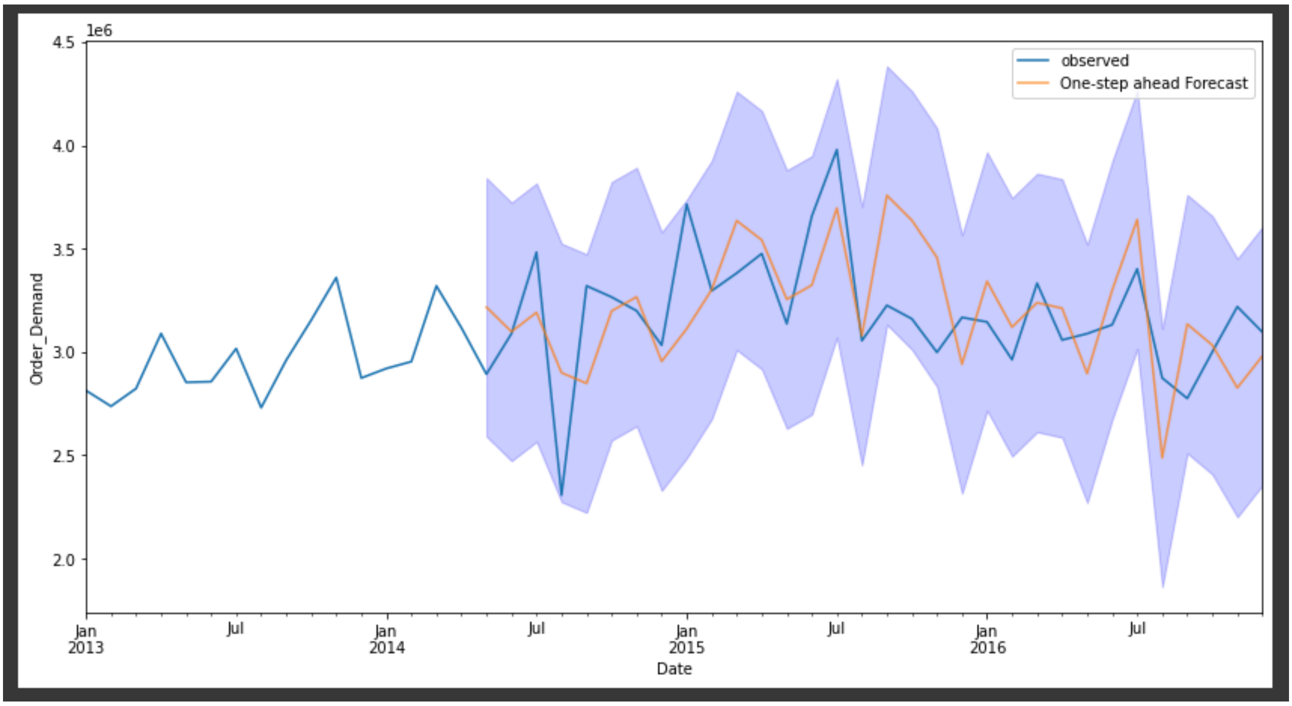


Figure 6.3: Product Demand Forecasting One-step ahead

Figure 6.3 shows demand forecasting using historical data applying predictive analysis to find the future demand of a product for next few months.

• Content Generation

```
hessons
the nature the greatesty defication and man foh
interpics one freews, make religion! and which facr of his could that in their
people despehing
----- diversity: 1.2
----- Generating with seed: "apable of absolutely unegoistic conduct "
apable of absolutely unegoistic conduct re's
in they act human immorition, in simplificord2--in imquites and indders, fattentiveble sands great, that say, besto opiced and nomen-who w
science to he bleus itselfvempessy comes ouf he.ceetly, the gantertus, but operid. necausate canromarity their new "greates,--the geastys
percause; andold unething plictly in the recrest"
and extence intellected any astr
1565/1565 [==============================] - 238s 152ms/step - loss: 1.6201
Epoch 3/60
1565/1565 [==============================] - ETA: 0s - loss: 1.5308
----- Generating text after Epoch: 2
----- diversity: 0.2
----- Generating with seed: "ither originated in a ruling caste, plea"
ither originated in a ruling caste, pleasure the strength of the conscious of the end of the called the higher and the strength the strong
----- diversity: 0.5
----- Generating with seed: "ither originated in a ruling caste, plea"
ither originated in a ruling caste, pleasure of the work and the morals of the soul of the essentially the superior which so the means of
really the read morals of the interrordy "the comes the ender in the higher of the historical lange of the pression are what is no an inst
the are the conceitus, manger into the free of the
----- diversity: 1.0
----- Generating with seed: "ither originated in a ruling caste, plea"
ither originated in a ruling caste, pleash, iniquest in tempt the
stryngth oporuous philosophers it is not fnent-sestooblief of pleasupuning
intaid
about hengaliof something of-recolutionly, a say be"wererible the greats, shim the good "same by the
```

Figure 6.4: Content Generation Result

Content generation results totally depends on the number of epochs and model training. With that due above figure predicts content from more than 2000 words article, which is plagiarism free and can be used for any marketing agency and content writing influencers.

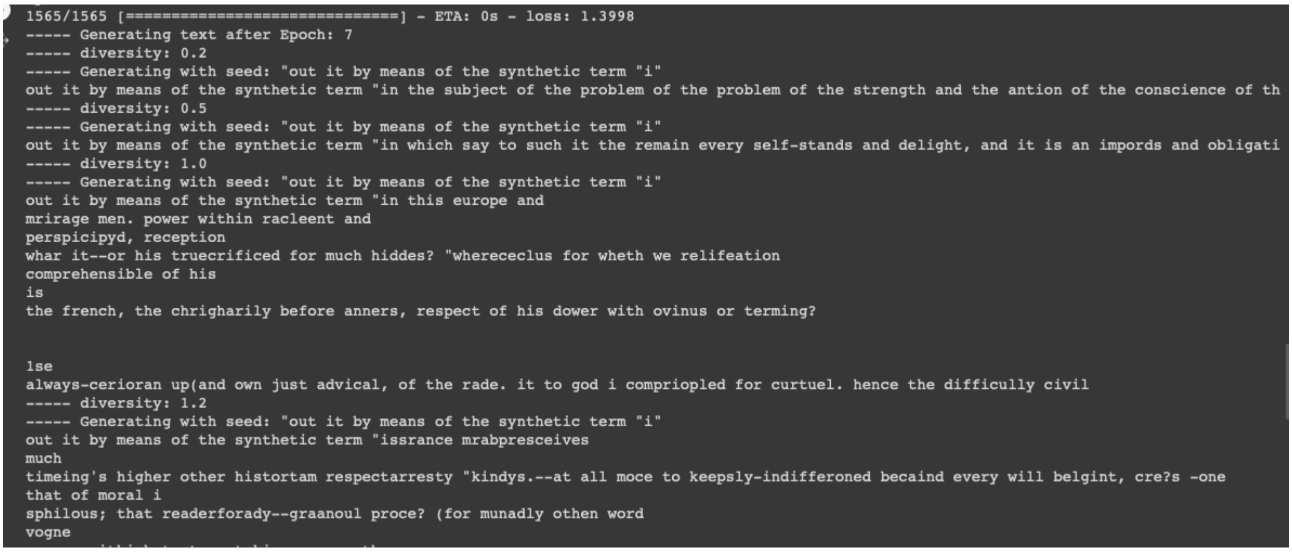


Figure 6.5: Generated Content

Figure 6.5 shows the generated content with training of 8 epochs.. Sample shown below:

Generating with seed: "out it by means of the synthetic term "i"

out it by means of the synthetic term "in the subject of the problem of the problem of the strength and the antion of the conscience of the conscience of the present the stronger and subject of the cause of the most relation of the subject of the most respect of the subject of every sense in the subject of the sense of the subject is an action to the conscious of the subject, in the self-call the subject of the enjoyment of the subject

CHAPTER 7

Limitations of the Solutions

7.1 Limitations of the Solutions

The solution has a few limitations which are relevant to the proper functioning of our application:

- Time-Intensive Completion: While there are various methods of sales forecasting, the two broad approaches include manual and data-driven processes. In either case, significant time is required to develop forecasts.
- Expensive Technology Tools: Manual processes are not as technology-oriented, but computer tools such as spreadsheets are commonly used. Typical sales organizations will also use database software to monitor ongoing relationships with customers.
- Internal Bias: Forecasting is not always intended to be a realistic projection of anticipated sales and not a depiction of desired sales. The challenge for company marketing and sales reps in preparing forecasts is that internal bias is hard to avoid.
- Lack of trained forecaster, many companies do not have efficient, trained experienced forecaster.
- The benefits aren't immediate: content marketing can be a long process. There is normally a period of trial and error to discover what works best before you see results.
- Evaluation: it's relatively easy to measure the effect your content marketing has on web traffic and online conversions. It can be harder to determine the impact of your content on brand reputation, awareness and loyalty.
- When working on a large project, small bugs can creep in and easily go unnoticed for some time (e.g. array indices of by one). Particularly when running simulations, the results may be greatly affected and the error may be hard to track down.

CHAPTER 8

Future Work

Future Work

- More work on refining key phrases extraction will definitely produce better results. Enhancements in the preprocessor unit of this system will help in improving more accurate predictability in sales and demand forecasting.
- Embedding more data which are internal factors of the company likes Sales, Assets etc.
- Experiment with different types of forecasting will enhance the chances of trying different algorithm with different dependent features.
- Continuously qualify sales opportunities which will ultimately help the sales forecasting and also product demand.
- CRM data entry process is manual, then chances are inaccuracies are going to creep in--considering accurate forecast results mainly rely on clean data thus automating will be future case.
- Moreover, a tool with built-in dashboards, reports, and analytics can inform CROs of how their quarterly forecasts look like, measure and compare sales growth over time, and even manage sales territory assignments.

CHAPTER 9

Conclusion

Conclusion

Evaluating the different module prediction has at all times been tough work for developer. Thus, I attempt to make use of vast written data to forecast the product demand also sales forecast and generate content. Artificial neural network is qualified to forecast next content and Time series analysis to predict the sales and demand. E-commerce shop owner, marketing agency can use this prediction model to take decision. Extrapolations of sales are inexpensive and often adequate for the decisions that need to be made. In situations where large changes are expected or where one would like to examine alternative strategies, causal approaches are recommended. Demand this model can be useful for increasing the accuracy of other prediction systems as part of committee. Practical value of the obtained results for the international community in avia-industry is ability to use the proposed method to increase efficiency of logistics in onboard trade and catering.

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