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Processes and Techniques in Digital Marketing Analytics

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Abstract— With the growing technologies and the dominance of digital media, the way companies market has changed and businesses are doing all they can to surpass their competitors. With the advancements in technology, as of 2019, 82% of businesses engage in digital marketing. With ever increasing data analysis tools and growth of statistical machine learning as a field, digital marketing channels have seen tremendous growth, and are now considered as an essential part of every company. Though each "company" carries out its analysis in their own way, there are five basic steps involved in digital marketing analysis. This paper presents the steps involved in the process of digital marketing analytics, along with their importance and the most prominent method in each step by exploring popular machine learning tools and proposes a general framework for digital marketing analytics.

Keywords— digital marketing analytics, digital marketing, machine learning, analytics

I. Introduction

We live in a technology abundant world where we depend on the Internet for any of our needs, including shopping. Whether purchasing groceries, clothes, shoes, books or even medicines, customers are spoilt for choice. The only way to stand out as an exclusive option to the customers is to properly utilize digital media platforms such as social media, e-mail, display ads and more [1]. Companies are investing 30-35% of their budget in digital marketing, as it has a large return on investments [2].

The customers reached are very large in number and this makes it near impossible to perform any analytics manually. For this reason, data analytics is a very important part of digital marketing [3, 4]. These tools have been developed over the years and machine learning concepts have been integrated into. The introduction of machine learning in these tools has many advantages [5, 6, 7] –

- It helps in easily identifying trends and patterns in the data collected.
- It is dynamic – which is very useful in digital marketing as live data is being captured. Codes do not need to be written for each new data set. We can simply refresh the code.
- Many processes can be automated – redundant processes such as transferring the live data into a structured format can be automated through the help of machine learning tools.
- Increased accuracy – due to the learning capabilities of these tools they constantly show improvement in the results.

Digital marketing is constantly improving and drawing in more and more customers. The tools being utilized must be able to adapt to a large amount of data that is to be processed. In this paper, the processes involved in digital marketing analytics and some of the most popular tools and techniques that are in play in the industry today are being discussed.

II. Methodology

1. Information extraction:

Information Extraction (IE) refers to the task of automatic extraction of structured information from an unstructured or a semi-structured source from various digital sources. These sources in the world of marketing generally include social media platforms such as – Facebook, LinkedIn, Twitter, Instagram and more. Social media provides up to date information regarding the performance of a product rather than conventional sources such as survey forms [8]. IE systems help analyze the different human text to retrieve information such as product likability, product purchasability and general product sentiment. This will help predict:

- If any changes need to be made to the product
- If more units need to be manufactured
- If the demographics of the customer needs to be changed

Hidden Markov Model:

Hidden Markov Model (HMM) is a powerful statistical data analytics technique that has been successfully tested on various language-related tasks such as text segmentation, text extraction, sentiment analysis and other Natural Language Processing (NLP) tasks. HMM is used to, extracted the data and it is stored in Knowledge

Bases (KBs) which collects all the unstructured data from various sources into a format that can easily be used for training [9, 10].

Hidden Markov Model for Information Extraction:
The goal is HMM in digital marketing is to extract information regarding the product from the various social media channels available [11]. The comments contain information regarding the liked product features, disliked product features, which demographic is more likely to buy, which demographic is least likely to buy, features that need to be changed to increase sales and more. Extracting such fields is extremely valuable to increase product sales and revenue [12].

Hidden Markov Modeling provides a framework for the extraction of comments from social media platforms. Using this we can label different words of the comments as belonging to a class such as –positive, negative, neutral and more. To begin with we group words together based on certain criteria. These groups are called SIGs (Similar Syntactic and Sentimental Information Groups). In the initialization, these groups or SIGs are used as the hidden or unobservable states for the Hidden Markov Model. Because of the sentiment and syntactic information contained by these SIGs it helps the Model identify and extract transition patterns found in the comments [13].

There are two basic steps in HMM:

a. Text Extraction: using the hidden states, information needs to be extracted from the various social media platforms.
b. Output Labeling: the data extracted and stored in the KBs need to be labelled.

2. Customer Behavior Prediction:
The increased use of digital marketing has resulted in more access to customers. This helps in not only gathering information regarding their sentiments towards a product but also helps in predicting their behaviour. Here behaviour refers to their click history and product purchase history [14]. These two main factors help in determining whether a customer is likely to buy a similar product or brand as what they have already purchased before.

Customer behaviour prediction will help us understand our factors demographic, product purchase type and most importantly the customer value [15]. Customer value is a quantitative value that is assigned to a customer based – the likelihood of their purchase and product purchase history. Customer behaviour prediction is extremely helpful in cost-cutting and budget allocation for marketing [16].

Naïve Bayes Algorithm:
Bayesian classification is a generic term for a wide range of classification algorithms as they are all based on the classical Bayesian Probability Theorem. In machine learning, Naive Bayes is defined as simple probabilistic classifier based on the application of Bayes Theorem with naïve independence assumptions among the features [17].

Naïve Bayes is a popular algorithm widely utilized thanks to its predictive capabilities and ability to achieve higher accuracy levels. It also can process large amounts of data with the attributes having little to nothing in common with each other, i.e., they are partially or fully independent of each other.

Naïve Bayes Algorithm in Customer Behavior Prediction:
Bayesian theory classifies by judging the probability of the occurrence of an event based on some criterion. It uses prior knowledge or in this case, purchase history to calculate the probability that an event might occur, in this case, a purchase of the product.

$$P(c \mid x) = \frac{P(c)P(x \mid c)}{P(x)} = \frac{P(x, c)}{P(x)} \quad (1)$$

Here P(c|x) refers to the possibility that the customer will purchase the product given their purchase history. P(c) refers to the probability that the customer will buy the product. P(x|c) refers to the likelihood and P(x) refers to the probability of the purchase history, i.e., have they bought that product or a similar product in the past [18].

3. Customer Segmentation:

Customer segmentation or customer categorization refers to the process of dividing customers based on the different hyperparameters [19] –

- Demographics
- Psychographic
- Behavioural
- Geographic
- Others – generational, cultural and online customer segmentation

Demographic segmentation: refers to categorizing customers based on criterion such as – age, gender, occupation, socio-economic background, marital status, family size, etc.
This type of segmentation helps in identifying which type of customers to target, for example – children, married people, teachers, large families etc.

Psychographic segmentation: sometimes also known as lifestyle segmentation is the process of dividing customers based on how they spend their leisure time, where they go for vacations, the types of brands they usually purchase, etc.
This type of segmentation helps in identifying customers to target during marketing, such as – those who frequently travel abroad, those who buy luxury products, those who engage in exclusive hobbies, etc.

Behavioural segmentation refers to the categorizing customers based on their shopping/purchasing behaviour

– both online and offline. Here we divide customers based on – purchase frequency, purchase occasion, loyalty status, user status, etc.
This helps in not only identifying our target audience but also in providing monetary compensations such as discounts to those who are loyalty cardholders, first-time buyers (to encourage next purchase), etc.

Geographic segmentation: refers to the process of dividing customers based on their location, i.e., the city, state, region, country, population density, etc.
This helps in marketing specific products, for example – products targeting those who live in snowy regions, those who live in crowded cities, those who live in the countryside, etc.

Decision Tree Learning:
Decision tree learning is a predictive modelling approach extensively used in data analytics and digital marketing analytics. This method uses a decision tree as a predictive model to go through the different assumptions about a node and draw conclusions by travelling through the different branches of the decision tree [20].

Decision trees are used to divide the customers into the different segments mentioned above. Using the data available about each customer we travel down the tree and try to place the customers in the current segments. However, we will not stop after the customer has been placed in one segment. This is because a customer can belong to one segment, for example, a single woman (demographic segmentation) can live in a sunny region (geographic segmentation) [21].

Decision Tree Learning in Customer Segmentation:
There are many decision tree learning algorithms in the data science world. Some of the algorithms include – ID3, C4.5, CHAID, MARS and CART. ID3 is, however, a widely popular one most commonly used in the world of digital marketing and analytics. ID3 is an algorithm invented by Ross Quinlan and is used for generating a decision tree from a given dataset [22].

Some terms need to be understood before going ahead with the ID3 algorithm [23]:

- Information gain: refers to the amount of information gained about a random variable using observation of another random variable in the dataset
- Entropy: refers to the amount of surprise associated with the results of a random variable.

In the ID3 algorithm, each customer is converted to a decision tree and their different attributes decide the branch to be taken. The algorithm will first calculate the information gain and the entropy of the chosen attribute. It will then choose the branch which has the highest information gain or lowest entropy and takes that path and this procedure recurs [24].

4. **Analytics**:

Analytics refers to the process of discovering, interpreting and communicating meaningful processed information and patterns in data. It greatly helps in increasing the efficiency and accuracy of the decision-making process [25, 26]. It helps in understanding the connection between raw data and high-level decision making. It helps in improving business performance and revenue drawn [27].

Data Analytics and Machine Learning:
When the world of machine learning and data analytics collide, they can be categorized into 4 broad types [28, 29]:

- Descriptive analysis
- Diagnostic analysis
- Predictive analysis
- Prescriptive analysis

Descriptive analysis: a type of analysis that can easily summarize raw data in a way that can be understood by the majority of the general public [30]. It explains in detail the past occurrences and this can help determine if there are any recurring patterns in the data to help frame better strategies for the future.
The typical questions that are answered in this step would include:

- Who were my customers?
- What products did they buy?
- What products have they purchased before?

Some of the characteristic techniques include - average, summaries, cumulative frequency, relative frequency, etc.

A diagnostic analysis is the next step to descriptive analysis. In this type of analysis, the problem is further broken down and a deep dive is done to thoroughly understand the problem at hand. To make informed and efficient business decisions both these types of analysis are very important.
In this type of analysis, we observe correlations in products by looking into the different results we have arrived at and the different patterns. For example, a customer who bought a Nintendo Switch also bought the game Animal Crossing.
Some of the characteristic techniques include – drill-down, data discovery, data mining and correlations.

Predictive analysis: any good business must have an accurate insight into the future to better their business and revenue generation. This type of analysis helps in building a forecast chart based on current trends [31]. This will help in increasing product sales and revenue from that product.

In this type of analysis, we use the different results available to us and draw conclusions based on them. For example, those customers who like posts about luxury fashion are more likely to buy a designer bag.
Some of the characteristic techniques include – regression techniques, logistic regression model, discrete choice models, multinomial logistic regression, classification and regression trees, multi-layer perception, etc.

Prescriptive analysis: this is the type of analytics that has the biggest impact on business decisions. It predicts what event will take place, when and even why this event will occur. It also suggests the best decision options available then. It is also capable of taking new data and performing the predictions and prescriptions again, helping improve the accuracy of the model which will result in better decision options generated [32].

This analysis helps in the improvement of the business on a broader scale. For example, if product A is not selling well, a prescriptive analysis will suggest selling product A for a discounted price over the next two weeks to help improve product sales. The algorithm can also be equipped to automatically adjust the prices for such products.

Some of the characteristic techniques include – heuristics, complex event processing, recommendation engines, simulation, etc.

5. Data Visualization:

Data visualization is a graphical representation of data. The data we have collected and processed cannot be used as it is. Reading the results will become difficult for those inexperienced in data analytics [33]. For this reason, visualization is a very important step.

To communicate information, results and ideas more coherently we take the help of statistical graph plots, scatter plots, bar charts, column charts, information graphics, etc. [34]. Effective charts and graphs help the user analyze and better understand the raw data and the results. They help in making comparisons and drawing conclusions which result in more informed business decision making.

Some of the tools used for the process of data visualization are:

- Matplotlib
- Seaborn
- Excel
- Tableau

Matplotlib: is the most widely used Python plotting library in data analytics. It is a low-level library with an interface similar to Matlab which offers a lot of freedom to the developers to write their codes to visualize their data in the form of 2D and 3D graphs. It is capable of constructing many different types of charts and graphs including – line plot, histogram, 3D plot, contour plot, image plot, polar plot, etc.

Seaborn: is also a Python data visualization library that is based on the Matplotlib library. It is a high-level interface that allows us to create graphs. Since it is of a higher-level API compared to Matplotlib it requires lesser code. It allows representation of data in many ways including – bar charts, box plots, heatmaps, pair-plots, etc.

Excel: is a spreadsheet that was developed by Microsoft. Its features include – calculation, pivot tables, macro-programming in Visual Basic for Applications, graphing tools, etc. Excel supports the generation of graphs from groups of cells inside the spreadsheet. It can be generated in the same sheet or a separate sheet as well. It allows the visualization of data through 2D and 3D means such as – pie charts, bar graphs, column graphs, time series charts, combination charts etc.

Tableau: is an interactive data visualization tool widely used in the digital marketing analytics industry. It is one of the most popular visualization tools in the market today. It helps in representing data interactively and colourfully. The biggest advantage of tools like Excel and Tableau is that they do not require any programming knowledge, giving non-programmers the freedom to visualize their data. Another added feature in Tableau is that it considers latitude and longitude which gives rise to a map graph that is a unique feature of this tool. Some of the other graphs available include – treemaps, Pareto charts, bubble charts, motion charts, area charts, scatter plots, box plots, bar and column charts, heatmaps and many more.

III. RESULTS AND DISCUSSION

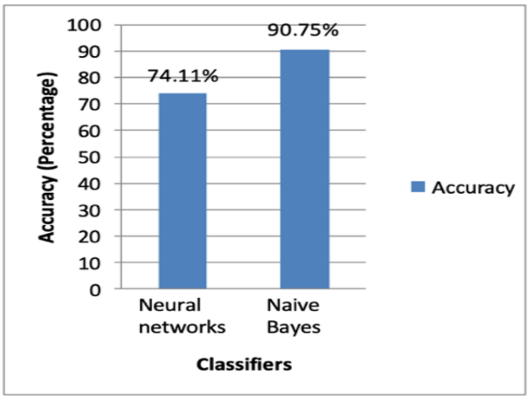
1. Performance of the Hidden Markov Model in Information Extraction:

Attribute	Precision/Accuracy
Username	0.9216
Name	0.8632
Email	0.9892
Comment	1.0000
Comment ID	0.9802
Account ID	0.9022
Time	0.9173
Product ID	0.9009
Product name	0.8410

The dataset used was a set of comments on Instagram left by customers about a certain product. When performing digital marketing analytics, there are a few fields that of importance. Hidden Markov Model has high precision, i.e., when extracting information from social media and other digital platforms, it can extract information accurately most of the times.

2. Customer Behavior Prediction using Naïve Bayes Classifier:

Naïve Bayes is the most widely used classifier in digital marketing analytics for a few reasons, the most important being – it can work efficiently in the presence of missing data and it is highly scalable, making it an appealing choice for the developers.



Even compared to complex algorithms such as Neural Networks, Naïve Bayes in machine learning has proven to be more accurate.

3. Customer Segmentation using Decision Trees:

Algorithm	Total entries	Entries whose classification was accurate	Accuracy %	Execution time (in seconds)
ID3	1500	1130	75.33%	32.61
C4.5	1500	1027	68.48%	29.59

ID3 and C4.5 are the most popular decision tree algorithms for datasets involving customer data.

Both the algorithms have been run of the same dataset of 1500 entries. Although the ID3 algorithm takes more time to execute than C4.5, in case of digital marketing analytics precision and accuracy of the results is of utmost importance.

4. Analytics:
The most important type of analytics performed is predictive analysis. This helps the companies get a glimpse into the future. Based on that they make a business decision regarding products. While traditional predictive analysis is helpful, its lack of learning capabilities holds it back. Each dataset run is considered new and therefore there is no scope to improve the accuracy. However, with the introduction of machine learning in predictive analysis, the accuracy has increased.

IV. Conclusion

Algorithm	Number of customers predicted to buy the product	Number of customers who bought the product	% difference between predicted and actual values
Traditional Predictive Analysis	3028	2173	32.92
PA with ML	2245	2173	17.62

In this paper, the different processes involved in digital marketing analytics are discussed. Millions of customers are exposed to digital marketing through various channels every day and multitudes of data are being collected. With the help of various machine learning tools and techniques patterns and trends and other insights are gained from the results of the digital marketing analysis. Using these results intelligent and informed business decisions are being taken to increase overall revenue generated.

The world of digital marketing will only continue to develop at a rapid pace, the analytics tools and techniques being used must adapt to it and grow accordingly. New tools and techniques must be introduced and tested with live data to check its durability and scale of use. Although we have discussed the import and widely used techniques in this paper, the world of digital marketing analytics is extremely large and ever-growing, and we have much to discover.

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