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The use of Artificial Intelligence in marketing and sales

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Introduction

In the dynamic and rapidly evolving technological landscape of the 21st century, Artificial Intelligence (AI) and Data Science (DS) have emerged as monumental pillars, driving transformative changes across multiple industries and redefining traditional paradigms. These technological advancements are not just reshaping how businesses operate but are also reconstructing the foundations of modern commerce. One domain that has been particularly influenced by these advancements is the realm of marketing and sales. Historically, these areas were anchored in human intuition, experience, and a traditional interpretation of historical data. Today, however, the industry is evolving, and decisions can be taken with the help of AI models that focus on the meaningful patterns of the data.

According to a report by Forbes [1], marketing and sales teams are increasingly pivoting towards Artificial Intelligence, leading this transformation. This underscores the profound and transformative impact AI has on shaping consumer experiences, tailoring marketing campaigns, and driving forward-thinking business strategies. This shift toward AI-based approaches is not merely a passing trend, but a proof of the capabilities of modern algorithms in understanding intricate user behaviour, predicting market dynamics with precision, and offering content aligned to individual preferences.

This white paper reviews the application of AI techniques in the field of marketing and sales. The main part of the report is dedicated to show some practical applications, along with three use cases, through which possible tangible impacts of the application of these techniques can be exemplified. The document includes a technical review, where some of the core technologies and algorithms that underpin these advancements are reviewed.

Applications of AI in Marketing and Sales

The integration of Artificial Intelligence and Data Science in marketing and sales has yielded numerous practical applications, enhancing efficiency and effectiveness in these domains. This section offers a brief overview of the applications of different AI techniques within the context of marketing and sales. Following this overview, selected use cases are further examined to illustrate some practical applications. This analysis aims to furnish a better understanding of how AI and DS technologies are being employed to support data-driven decision-making and promote business growth.

One of the AI tools that is revolutionizing the landscape of marketing and sales is chatbots. These AI-driven interfaces, powered by advancements in Artificial Intelligence and natural language processing, offer businesses the ability to provide 24/7 support, automating significant portions of customer service operations. For instance, according to Juniper Research [2], the banking industry saw an estimated cost savings of $209M in 2019 from using chatbots, a figure projected to reach $7.3B globally by 2023.

Chatbots can also have an impact in sales. A study [3] discovered through a combination of field and laboratory studies, that chatbots have the potential to influence consumer preferences and purchase decisions. One of the standout findings was the consumers' appreciation for engaging in natural dialogue and connecting with the chatbot's "personality." In practical applications, such as car rentals, consumers were almost twice as likely to opt for more expensive options when presented by a humanized chatbot. Similarly, in the financial advisory domain, users displayed a higher level of trust in recommendations provided by a chatbot that simulates a human-like character even when the advice was objectively incorrect. However, the new AI Act regulation in the EU may pose restrictions on the use of these technologies in case they are used to produce a cognitive behavioural manipulation of people (which would be classified as prohibited practices).

Chatbots offer additional advantages. They are scalable, managing multiple inquiries simultaneously. They provide consistent responses and can operate in various languages. With the development of Large Language Models, the capabilities of chatbots are expected to improve. By leveraging the sophisticated linguistic understanding and contextual awareness inherent in LLM, a chatbot becomes more adept at comprehending user inputs, leading to sharper and more contextually relevant responses. This integration enables the chatbot to engage in conversations maintaining coherence over extended interactions and contributing to a more natural and dynamic user experience [4].

Another tool with a large impact is image recognition, that can be used for different purposes. For example, one of the possible uses is brand logo detection. Modern search engines, equipped with object detection algorithms (like YOLO, You Only Look Once [5]), can swiftly scan the vast digital landscape to identify images containing specific brand logos. This capability is invaluable for companies aiming to monitor their brand's online presence, assess the effectiveness of marketing campaigns, or even detect unauthorized use of their brand imagery. There are many tools, such as Visua [6] or UnamoX [7], that assist in this task. In the mentioned two examples, the former is used for brand protection, whereas the latter specialises in social media monitoring. According to UnamoX creators, its 60% accuracy is the currently the state-of-the-art, so currently there is still some room for improvement.

Recommender systems are another technique commonly used in various applications, such as e-commerce, streaming services, social media, etc. In the second use case these systems are applied to an audiovisual content platform.

With regards to the use of specific techniques employed in marketing, although a traditional one, it is worth mentioning A/B testing, which can be applied in numerous ways. For example, it can be used to design a new landing page for an e-commerce platform. Initially, the objective is defined, such as increasing sales on a product. Variations of the page element to be tested are created, for instance, different colours or text for the call-to-action button. Traffic is then split between these variations and data on user interactions is collected. This data is analysed to ascertain which variation performs better in achieving the defined objective. The winning variation is implemented on the website, and the insights gained are used for future optimization efforts. This process facilitates data-driven decisions to enhance conversion rates and improve the overall user experience on the e-commerce platform. As an example, Xerox employed this data-driven approach to optimize page design for returning customers to make a purchase, a succeeded after obtaining an 86.7% growth in conversion rate with the new design [8].

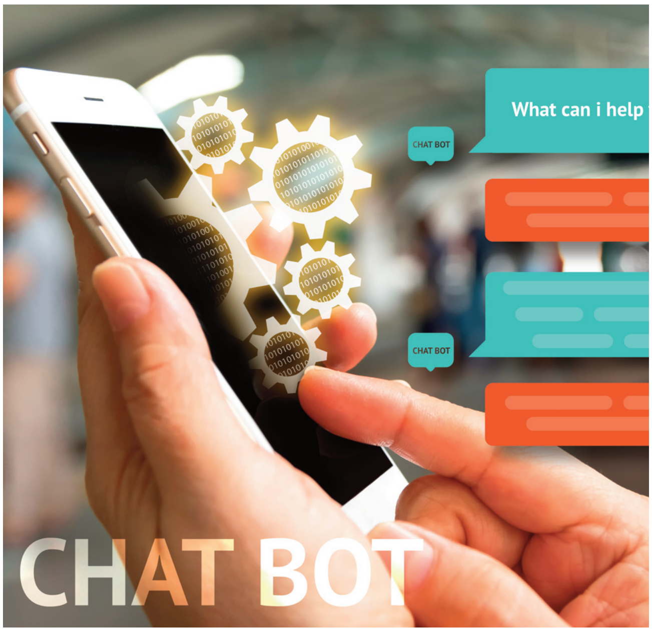
Client segmentation is another pivotal strategy in marketing and sales, allowing businesses to categorize their customer base into distinct groups based on shared characteristics, behaviours, or needs. Clustering techniques, a subset of unsupervised learning, are particularly suited for client segmentation, as these methods automatically group data points (in this case, clients) based on their similarities without any prior labelling. A study [9] provided a dataset sourced from e-commerce transactions, analysing the purchase behaviours of numerous customers. Using this dataset, the k-means clustering algorithm was employed to categorize customers based on their buying patterns. The results revealed three distinct customer segments, each with its unique set of preferences and behaviours, one of which was found to be the most profitable. With this type of information, businesses can guide their marketing strategies to further increase profits by appealing to the appropriate customer base.

Many other techniques can be used to support the need for predictions by the marketing departments. For example, one of the concerns of marketing departments is the churn prediction, that is the identification of customers likely to leave a business. Building and maintaining strong relationships with customers is essential for business success. According to R. Kumar, S. Velu and V. Ravi [10], even a modest 5% increase in customer retention can result in a substantial 25%-95% growth in a business's net present value. Similarly, decreasing the customer churn rate by a mere 5% can enhance the average profit margin by 25%-85%.

The study by Customer Churn Prediction Using AdaBoost Classifier and BP Neural Network Techniques in the E-Commerce Industry [11] provided a dataset sourced from e-commerce transactions, encompassing 95,388 data entries from 8,156 customers. Of these, 92.8% were classified as churned, with the remaining 7.2% as non-churned. Using this dataset as a foundation, the AdaBoost algorithm was employed, achieving a 96% accuracy. This high accuracy demonstrates the algorithm's potential in predicting the likelihood of future customers churning based on similar data patterns. Outside of the academic scope, professional tools (e.g. Churnly [12]) are being used to predict churn in B2B software-as-a-service companies.

Finally, time series analysis is a technique applied across various sectors to analyze and interpret data collected over time. Some key sectors where time series analysis is often employed include finance, meteorology, manufacturing, transport, and logistics.

In conclusion, the integration of Artificial Intelligence and Data Science into marketing and sales has demonstrated significant potential for enhancing both efficiency and effectiveness in these sectors. Techniques ranging from traditional A/B testing to advanced methodologies like chatbots and image recognition have been explored. These advancements not only optimize operational processes but also yield insights into consumer behaviour and preferences.



Practical use cases

Use case 1: life cycle of a commercial action

Nowadays, commercial actions play a key role in determining the success and profitability of companies. In the constantly evolving landscape of the banking industry, commercial actions are paramount to meet the diverse financial needs of customers. Some of these actions include building sound pension plans that secure the future of account holders, offering flexible credit solutions or facilitating home ownership through mortgages. The multifaceted nature of banking services requires a strategic and adaptable approach.

In this context, the integration of AI is emerging with great force, redesigning the way financial institutions execute their commercial action plans. AI technologies bring a new dimension to the banking industry by offering capabilities that improve decision-making processes, personalize customer interactions, and optimize operational efficiency.

The introduction of a new product necessitates strategic marketing campaigns aimed at capturing the attention of potential clients. Crafting effective advertising initiatives is crucial not only for improving product visibility but also for optimizing promotional costs. To achieve this, targeting the right audience becomes paramount.

The process of launching a new banking product involves a series of strategic stages that commence with the application of customer segmentation techniques. Once these segments are identified, scoring techniques are employed to assess the affinity of each segment with the new product. Following the segmentation and scoring phases, techniques are applied to determine the product pricing based on factors such as customer type, cost, and the prices of similar products in the market. Finally, a personalized communication campaign is executed, defining the type of message, design, layout, colours, etc., tailored to each specific customer segment. Following, the application of Artificial Intelligence techniques in each of these steps is explained.

Customer segmentation

Identifying the ideal demographic for a new banking product involves a strategic approach. Leveraging the power of Artificial Intelligence becomes instrumental in dealing with the complexities of customer segmentation. The task of determining which subset of clients should receive offers for the new product demands a detailed understanding of consumer behaviour and preferences.

AI, with its advanced analytics and machine learning capabilities, plays a pivotal role in this complex process. Through sophisticated algorithms, such as clustering [13], AI can analyse vast datasets to discern patterns and categorizes customer based on unique characteristics and behaviours. This not only streamlines the marketing strategy but also enhances cost-effectiveness by ensuring that promotional efforts are directed towards individuals who are more inclined to engage with the product.

Customer Scoring and classification

The classification of the clients can be done by assigning a score, constructed through models that evaluate each customer within a segment based on a multitude of factors. These factors may include historical transaction data, banking behaviour, credit history, and even external data sources. Through machine learning algorithms, such as decision trees [14], the system assigns a score to each customer, indicating the probability of their interest in the new product. This enables banks to prioritize and target high-scoring individuals for their marketing efforts, maximizing the chances that the customer will purchase the product offered. In case of having several scores obtained from different models, recommendation models are usually applied to select the best score.

While identifying promising segments is crucial, so is filtering out individuals who may not be suitable candidates for the new product. The exclusion filters are designed to screen out customers who do not meet specific criteria, ensuring that promotional efforts are directed towards individuals with a higher likelihood of conversion. Example scenarios could include excluding customers with insufficient purchasing power, individuals who do not align with the target age group for the new product, or retired individuals if the product is tailored to the working population.

Pricing strategies

Through predictive analytics and customer-centric optimisation, a pricing strategy for new customers can be defined. Leveraging historical data, market trends, and customer behaviour, machine learning models forecast future demand, allowing banks to set prices in alignment with anticipated market needs. This foresight ensures competitiveness and responsiveness to customer expectations. Additionally, AI tailors pricing strategies based on customer segmentation insights, optimizing for varying preferences within different segments. By identifying price thresholds that adapt to specific customer groups, AI enhances the chances of successful market penetration, maximizing appeal and engagement.

Furthermore, the monitoring and analysis of competitors' pricing strategies provides banks with continuous information on the market landscape. By monitoring competitors' prices in real time, banks can make informed decisions, strategically positioning prices not only to attract customers, but also to compete effectively. Machine learning algorithms play a key role in this process, continuously optimising pricing strategies [15]. This iterative approach ensures that pricing adapts to evolving market dynamics and customer behaviour, ultimately contributing to sustained commercial success.

Personalized communication campaign

By leveraging LLM capabilities [16] [17], banks can craft highly personalized messages that cater to the unique needs and preferences of individual customers. Analysing datasets encompassing transaction histories, financial behaviours, and stated goals, generative models enable the generation of content that adapt more effectively to preferences and needs of customers. This personalized approach not only enhances customer engagement but also strengthens the overall relationship between the bank and its customers, fostering a sense of understanding and attentiveness.

Moreover, AI ensures a seamless and personalized experience for customers across diverse communication channels. From websites and mobile apps to social media and email, AI helps banks maintain consistency in their messaging from a linguistic point of view, creating a unified and personalised language and interaction. Furthermore, automating the process of creating and executing marketing campaigns may reduce marketing costs and significantly enhance the efficiency of customer engagement strategies.

Use case 2: recommendation systems

In the digital age, the surge of online content and products inundates consumers and businesses with choices. Recommender systems, also known as recommendation engines, emerge as crucial tools, guiding users through a plethora of options by offering personalized suggestions tailored to their preferences. Integral to daily online experiences, these systems revolutionize user interaction, enhancing platform user-friendliness and increasing engagement and profitability for businesses by acting as invisible hands in navigating the vast online landscape. An example that can be explored is Netflix, a digital streaming content platform. Having a global subscriber base that exceeds 238 million [18], counts with a large database to apply recommendation systems.

Consumer research suggests that a typical Netflix member loses interest after perhaps 60 to 90 seconds of choosing, during which they may review approximately 10 to 20 titles (perhaps 3 in detail) on one or two screens [19]. The challenge of recommendation systems lies in ensuring that, within those brief moments and on those two screens, every member from a diverse audience discovers something captivating to watch.

Netflix utilizes a varied approach to gather user data, encompassing both explicit and implicit feedback mechanisms. Explicit feedback is solicited through user actions like thumbs-up or thumbs-down ratings on titles [20]. In contrast, implicit data is continuously collected in real-time as users interact with the platform, including their viewing history, time, genre and device preferences, and the titles they watch [21].

Netflix employs a diverse array of recommender systems to shape the user experience. These systems collectively define the content recommendations visible on the platform's homepage across different devices. The homepage features a matrix-like layout, with each entry representing a recommended title grouped under specific themes like "Award-Winning Documentaries". This design enhances transparency and intuitiveness [19].

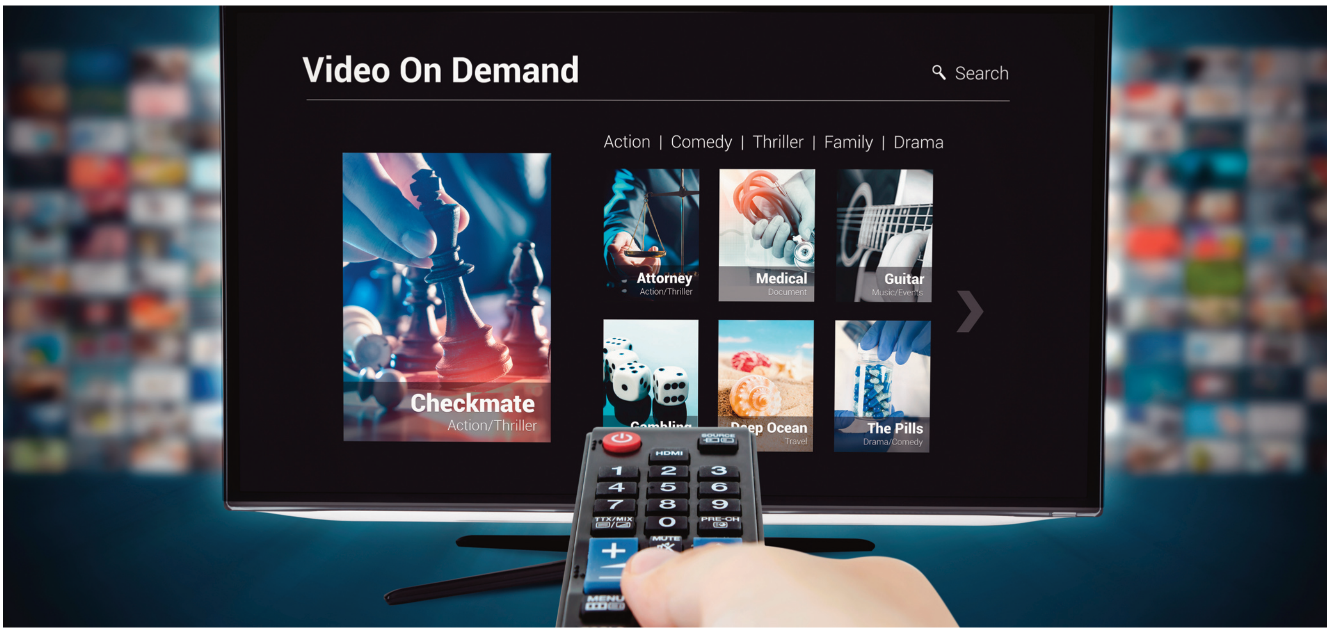
The Netflix homepage serves as a convergence point for various recommendation algorithms, as detailed by Gomez and Hunt [19]. Following, the more relevant algorithms are presented:

Personalized Video Ranker (PVR)

This algorithm orders subsets of movies, TV series, and documentaries, ensuring a highly personalized experience based on user preferences. Because of the PVR, the homepage experience is highly personalized to each user, same genre will have different items depending on the user.

Top-N Video Ranker

Netflix employs the Top N Video-Ranker algorithm to generate recommendations for the "Top Picks" row, offering personalized suggestions from the entire catalogue based on highly ranked titles. This hybrid filtering combines collaborative and content-based approaches.



Video-Video Similarity

The similarity algorithm, shaping the Because You Watched (BYW) row, utilizes a user's viewing history to recommend titles with similar themes. This unpersonalized content-based filtering method ranks and displays related titles.

Use case 3: sales prediction

In the constantly evolving market landscape, the ability to accurately predict sales is indispensable for sustaining a competitive edge. Accurate sales forecasts empower organizations to make informed decisions regarding inventory levels, resource allocation, and strategic planning. Furthermore, they provide crucial insights into market trends and consumer behaviour, enabling a more targeted approach to marketing and sales initiatives. However, traditional sales forecasting methods often have limitations in capturing the complexities and volatilities inherent in today's market dynamics. They rely heavily on historical data and may fail to adapt to changing conditions promptly, thereby leading to suboptimal predictions and missed opportunities [22].

The advent of Artificial Intelligence (AI) in sales forecasting emerges as a robust solution to these challenges. AI-driven sales forecasting systems are capable of continuously learning from new data, thereby enhancing their predictive accuracy over time. For instance, AI models can increase the prediction rate by between 20%-50%, translating into a reduction in lost sales and product unavailability of up to 65% [23].

AI significantly elevates the forecasting accuracy by interpreting a vast array of data points, reducing uncertainty, and providing clarity in forecasts. This enables a more strategic and data-driven decision-making process in a competitive market, paving the way for increased efficiency and profitability. The automation facilitated by AI not only enhances data analysis and predictive analytics but also reduces the burden of manual tasks, saving substantial time and resources. By leveraging AI's capability to handle an immense amount of information and its continuous learning from the evolving market trends, businesses are better positioned to make informed decisions promptly, thereby gaining a competitive edge [24].

To apply AI techniques for sales forecasting of a product, the first step is to gather data. The most basic type of information is usually related to past trends in the sales of the product. In a dataset, this might be represented in a table by three columns: date, number of units sold of the product, and cost of the product at the time of the sale. When the demand on the market is stable, this is often enough data and can be used with time series models with good performance [25].

However, demand of a product cannot always be best predicted by past demand alone, sometimes exogenous factors must be considered. For example, a customer may be more likely to demand a ride service such as UBER if it is a rainy day to avoid getting wet on the trip back home, or demand may increase on the morning due to people requiring the service to travel to the airport [26]. Additionally, data such as market trends, social media reviews, website traffic, competitor sales, etc. may be useful for a more precise forecast.

Once the data is gathered, a process of feature engineering begins. This process entails the creation of meaningful attributes or "features" from the raw data, which significantly contribute to the AI model's predictive power. For instance, the date column in the dataset could be engineered into separate features like day of the week, month, or even time of day, each potentially offering unique insights into sales trends. Similarly, textual data from social media reviews might be processed through sentiment analysis to numerically represent customer satisfaction towards a product, which could serve as an additional feature [27] [28].

Handling outliers and missing data is also crucial to ensure the robustness and accuracy of the model [29]. Outliers, being extreme values that deviate significantly from other observations, may skew the model's understanding and predictions [30]. They can be addressed through methods such as clipping, transformation, or even removal after thorough analysis. On the other hand, missing data is inevitable but can introduce bias or misrepresentation. Various imputation techniques from more traditional, like mean imputation, to more sophisticated approaches, like spatial interpolation [31], can be employed to fill in the gaps. Furthermore, scaling and normalization of the data, especially when features have different units or magnitudes, are essential steps to ensure that the model can learn effectively from the data.

Once the data is ready to be fed to a forecasting model, the appropriate one must be chosen. This can depend on how much data is available, as well as requirements on the model explainability. For instance, in the study by Sajawal et al. [32], it was found that models such as Random Forests [33] and XGBoost [34] perform significantly better than classical models like ARIMA and Linear Regression [35]. However, the output of these ensemble models is harder to explain, which may cause mistrust in said models' output. There are however some techniques such as SHAP which can mitigate the issue by computing the impact of each variable in the prediction [36].

The real-world application of AI in sales forecasting can be seen in the operations of giant online retailer, Amazon. When toilet paper sales soared by 213% at the height of the Covid-19 pandemic, Amazon utilized AI-driven predictive forecasting to rapidly respond to unforeseen demand signals, ensuring adequate inventory levels to meet the surge in demand [37]. Similarly, a chemical distributor applied machine learning techniques and advanced analytics for sales forecasting, which led to a 6% increase in sales due to more accurate and efficient demand planning [38]. These examples demonstrate the transformative potential of AI in sales forecasting.

By harnessing the analytical prowess of AI, companies are not only able to substantially improve their forecasting accuracy but also to better adapt to market volatilities, thereby achieving a competitive edge in today's fast-paced market environment. Through the implementation of AI, the issues posed by traditional forecasting methods can be mitigated, paving the way for more informed decision-making and ultimately, enhanced business profitability.

REVIEW OF MODELS AND TECHNIQUES

There are many models and techniques usually applied in marketing and sales applications. These are briefly reviewed.

Models for NLP tasks: LLM

LLarge Language Models (LLM) are advanced machine learning models, primarily based on deep learning techniques (more precisely, on the so-called transformers, a complex structure of neural networks). These models are trained on vast amounts of text data to understand and generate human-like natural language. Through the configuration and training of an extensive number of parameters, LLM are empowered to excel in various generative language-related tasks, including answering questions, summarizing content, paraphrasing, translation, or spell and grammar checking, among many others.

Models for NLP tasks: Chatbots

A chatbot is a computer program that simulates human conversation with an end user. It employs natural language processing and Artificial Intelligence techniques to understand and respond to user queries or commands. Chatbots are used for various purposes, such as customer support, information retrieval or task automation, providing a more interactive and user-friendly experience in applications like websites, messaging platforms, and mobile apps.

Models for image recognition

Image recognition, also known as image classification or image analysis, is a discipline under the computer vision that focuses on enabling machines to interpret and understand visual information from the environment, particularly images and videos. Machine learning algorithms, especially deep learning models like Convolutional Neural Networks (CNNs), are widely utilized in image recognition to automatically extract relevant features from images, such as objects, people, and entities, allowing for precise classifications.

Recommendation systems

Recommendation systems are information filtering tools that provide users with personalized suggestions or recommendations based on their past behaviour, preferences, or the behaviour of similar users [39] [40]. They are widely used in various online platforms to help users discover products, content, or services that are most relevant to their interests.

There are a lot of different methods and algorithms to enhance recommendation systems, enabling the creation of highly personalized recommendations. These recommendation techniques are commonly categorized into three well-known categories

Content-based filterings

The content-based filtering technique is an algorithm that places a strong emphasis on analysing item attributes to generate predictions. In content-based filtering, recommendations are based on user profiles, utilizing features extracted from the content of items the user has evaluated in the past. Various models, including probabilistic ones like Naïve Bayes Classifier [41], Decision Trees [42], or Neural Networks [43], can be employed to establish connections between different documents within a corpus. These techniques make recommendations by learning the underlying model with either statistical analysis or machine learning techniques. An advantage of content-based filtering is that it doesn't rely on the profiles of other users, as they do not influence recommendations.

Collaborative filtering

Collaborative Filtering systems suggested and recommended objects and information to a user according to the history valuation of all users communally. This technique works by building a database (user-item matrix) of preferences for items by users. It then matches users with relevant interest and preferences by calculating similarities between their profiles to make recommendations [44]. Users in this system collectively form a group referred to as a neighbourhood. Each user then receives recommendations for items they haven't rated previously but have been positively rated by other users within their neighbourhood.

Hybrid filtering

Hybrid filtering technique combines Content-based and Collaborative Filtering to gain better system optimization to avoid some limitations and problems of pure recommendation systems [45]. The concept behind hybrid techniques is that a combination of algorithms can offer more precise and efficient recommendations compared to a single algorithm, as the drawbacks of one algorithm can be mitigated by another. The integration of these approaches can be achieved through separate algorithm implementations and result combination, the inclusion of content-based filtering within collaborative approaches, the incorporation of collaborative filtering within content-based strategies, or the creation of a unified recommendation system that brings together both approaches [46]..

A/B testing

This is a method of comparing two versions of a webpage or app against each other to determine which one performs better in terms of a specific metric, usually conversion rate. It begins with a hypothesis about a potential improvement, followed by creating a control version (A) and a variant version (B) with the proposed changes. Users are then randomly assigned to either version, and their interactions are tracked and analysed. After collecting sufficient data, the results are analysed to see which version achieved better outcomes, such as higher conversion rates. This data-driven approach aids in making informed decisions about design or content changes, optimizing for desired results.

Clustering

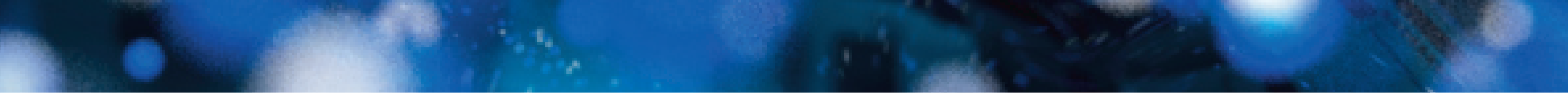
This technique involves grouping a set of objects in such a way that objects in the same group (or cluster) are more like each other than to those in other groups (clusters). It's a form of unsupervised learning, which means that it's used when you have unlabelled data (i.e., data without defined categories or groups). The goal of clustering is to find inherent groupings in the data. Some of the most common algorithms for clustering are hierarchical clustering, k-means, or DBSCAN (Density-Based Spatial Clustering of Applications with Noise).

Time series

Time series forecasting is a technique used to predict future values based on previously observed values in a time-ordered sequence. Time series data points are typically measured at consistent time intervals (e.g., daily stock prices, monthly sales data, yearly temperature readings). The primary objective of time series forecasting is to develop a model that captures the underlying patterns and structures in the data to predict future points. Some of the most common algorithms for modelling time series are: ARIMA (Autoregressive Integrated Moving Average), Recurrent Neural Networks (RNN) or Long Short-Term Memory (LSTM) Networks.

Tree based methods for supervised learning

Tree-based methods for supervised learning are a class of algorithms based on decision trees to make predictions or classifications. These methods, such as Decision Trees, Random Forests, Gradient Boosted Trees, or AdaBoost recursively partition the input space into regions based on feature values, creating a hierarchical tree structure. Tree-based methods are widely used in various domains, providing robust and versatile solutions for tasks such as classification and regression in supervised learning scenarios.



Conclusions

The integration of Artificial Intelligence (AI) and Data Science (DS) is reshaping the landscape of marketing and sales, ushering in an era of data-driven decision-making and innovative business strategies. These technologies are no longer mere supplements but have become integral pillars of modern commerce, revolutionizing consumer experiences, personalizing marketing campaigns, and enhancing sales forecasting accuracy. The real-world applications presented, from advanced recommendation systems to AI-driven sales predictions, provide compelling evidence of the potential for AI and DS to drive business growth and operational efficiency.

It is expected that the collaboration between AI and DS will continue to redefine how businesses engage with their customers, optimize operations, and stay competitive in rapidly evolving markets. By harnessing the power of these technologies, organizations have the tools necessary to navigate the complexities of the digital age, make data-informed decisions, and ultimately, succeed in the ever-evolving world of marketing and sales. This shift towards data-driven strategies underscores the indispensability of AI and DS in shaping the future of commerce, making it a pivotal area of focus for businesses and researchers alike.

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