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Deep Learning Drives Consumer Insight - The Revolution of Natural Language Processing in Marketing

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Abstract. In recent years, with the rapid development of artificial intelligence technology, we have gradually entered the era of big data. As traditional marketing paradigms exhibit numerous limitations, there is an urgent need for their transformation and upgrading. This paper employs a research methodology combining literature review and case analysis to explore how natural language processing (NLP) technologies can replace conventional marketing approaches in reconstructing consumer behavior analysis, while investigating the technical pathways and commercial value of deep learning in marketing text mining. Through NLP, deep learning achieves efficient processing of unstructured consumer data such as social media comments and customer service conversations, overcoming the limitations of traditional research methods that rely on structured data. A tripartite analytical framework integrating "technology-scenario-value" is established, adapting transfer learning theories from other fields to marketing scenarios and expanding the application boundaries of interdisciplinary methodologies. The study reveals the comprehensive optimization value of multimodal data analysis (e.g., joint mining of live broadcast bullet comments and voice texts) in optimizing consumers' decision-making journeys (cognition-purchase-loyalty), addressing gaps in traditional single-dimensional research. By leveraging NLP, deep learning enables intelligent marketing for small and medium-sized enterprises (SMEs), reduces costs, promotes fair competition in industries, and enhances consumer equity through anti-corruption algorithm design, thereby improving consumer loyalty.

Keywords: Deep learning, Natural language processing, Marketing, Consumer behavior

1. Introduction

In the digital economy era, consumer behavior data is experiencing explosive growth. Unstructured text data such as social media comments, online customer service conversations, and product reviews now accounts for over 70% of corporate data assets. Traditional marketing approaches relying on questionnaires and structured data analysis face two core challenges: First, manually annotated sentiment lexicons struggle to capture semantic complexity (e.g., "apple" meaning both fruit and brand in different contexts), resulting in up to 40% error rates in sentiment analysis; Second, rule-based engines fail to identify emerging consumption trends in real-time, leading to delayed market responses. Breakthroughs in natural language processing (NLP) technology—particularly deep learning-based pre-trained models like DeepSeek and GPT-4—are fundamentally

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transforming consumer insight methodologies. Through domain-adaptive model fine-tuning, companies can achieve precise semantic analysis of vertical scenario texts (e.g., beauty product reviews), boosting purchase intent recognition accuracy to 89%. This technological revolution not only shifts marketing decision-making from "experience-driven" to "data-driven," but also spawns innovative application scenarios like automated ad generation and real-time public opinion alerts, increasing marketing ROI by 3-5 times on average.

This article systematically examines the technological evolution of deep learning in marketing NLP, revealing its mechanism of reconstructing consumer decision journeys (cognition-concept-purchase-loyalty). For the purpose of this paper, the research method of combining literature method and case analysis method is used, different literature sources related to deep Learning, NLP, marketing are analyzed: articles; papers; publications in various media; Internet platforms; data from different marketing agencies. Artificial intelligence driven personalized marketing through the in-depth analysis of user data by AI, we can achieve personalized service adaptation for "thousands of people". mitigates customer uncertainty, one of the key challenges in tech marketing [1].When communications are tailored, customers more quickly grasp how a product fits their specific needs, increasing their likelihood of trial.It is beneficial for enterprises to optimize business indicators, improve user engagement, increase conversion and repurchase rates, accumulate user value and reduce operating costs. For the service itself, it can realize dynamic evolution and expand the boundary of scenarios.This ultimately establishes a three-dimensional assessment framework encompassing "technology compatibility, business value, and compliance risks", providing theoretical support and practical guidance for enterprises to achieve balance between data intelligence and commercial objectives under regulatory constraints like GDPR.

2. Literature review

2.1. The need for transformation of marketing paradigm

In today's information age,the internet, evolving technologies, and social media have led to the evolution of consumer behavior [2].The irreversible trend of consumer behavior becoming "digital, emotional, and social" means businesses clinging to traditional marketing models will face three major crises: customer attrition, operational inefficiency, and brand obsolescence. Only by reimagining marketing strategies and organizational capabilities in response to these behavioral shifts can companies break through the dual challenges of the "experience economy" and "data compliance", ultimately achieving sustainable growth.

The size of the databases used in today's enterprises has been growing at exponential rates day by day. Hence, industries requirement to quickly process and analyze the big data volumes for business decision making and customer insights has also grown exponentially [3]. Companies need to better understand consumer behavior and needs to develop accurate marketing strategies.

2.2. Comparison with traditional marketing paradigm

Traditional marketing relies on the paradigm of questionnaire survey and structured data analysis, which is inefficient and has a small coverage. It often has disadvantages such as insufficient sample size and unconvincing survey results.On the other hand, using of E-marketing will exceed the boundaries and introduce goods and services to the demographic of internet users. Also using the internet would be chipper, faster and convenient for marketing [4].AI-driven marketing relies on data and algorithms (user behavior data, model prediction), with the core goal of "precise

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transformation and user lifetime value" (precise capture) and real-time decision-making (algorithmic analysis of data and dynamic adjustment of strategies), which greatly improves decision-making efficiency.

Traditional marketing's reliance on "experience and emotion" remains irreplaceable by AI (such as the need for manual planning in conveying brand values), yet AI-driven marketing effectively addresses conventional approaches' shortcomings of "low precision, inefficiency, and scalability limitations." In practice, these two methods are often combined— For instance, using traditional marketing to build brand awareness while leveraging AI-driven strategies to acquire traffic and achieve precise conversions, creating a closed-loop transformation from "being widely recognized" to "being actively utilized."

2.3. Challenges in marketing data analysis

2.3.1. Semantic bias in dictionary matching and mechanical defects of rule engines

In social media, daily conversation and other scenarios, semantic deviation of dictionary matching is very common. The rapid spread and wide use of social media lead to the change of word meaning, and the update of dictionary often can not keep up with the speed of word meaning change.Challenging semantics coupled with different ways for using natural language in social media make it difficult for retrieving the most relevant set of data from any social media outlet [5].Existing natural language processing algorithms and models may have inaccurate semantic understanding when processing social media texts, such as errors in word segmentation, part-of-speech tagging and other processes, resulting in deviations in dictionary matching.The inability to identify metaphors and irony (such as "the phone's heat dissipation is a hand warmer") resulted in a leakage rate of 35 percent for negative word-of-mouth. It can only cover known consumption patterns and has poor adaptability to emergency situations (for example, after the popularity of New Oriental live broadcast, the traditional model cannot identify the "knowledge delivery" label in time).

2.3.2. Exploding unstructured data

The explosion of unstructured data stems from the popularity of mobile Internet (users generate massive graphics, text and video) and the surge of Internet of Things devices (sensors, monitoring and other real-time data generation). At the same time, business data (such as customer service recordings, documents) in enterprise digital transformation is no longer limited to traditional structured forms. The data generated no longer have a standard format or structure like the conventional ones and cannot be processed using relational models,makes searching and analysis complex [6]. Social media comments (e.g., Weibo and Xiaohongshu) contain emojis and internet slang like "yyds" and "shuan Q", where traditional regular expressions have a 62% false positive rate, requiring NLP for contextual disambiguation. Customer service interactions involve nested colloquial expressions and industry-specific jargon (e.g., "burn screen" in mobile repair contexts needing technical reference to "OLED screen ghosting"). The cost of manual annotation for such content is three times higher than structured data processing.

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3. Infrastructure of deep learning in marketing NLP

3.1. Deep learning architecture and technical basis

Deep learning is a branch of machine learning. Its core is to simulate the structure of human brain by constructing multi-layer neural networks (such as CNN and RNN), so that computers can automatically learn features from massive data without manual extraction, and finally realize intelligent processing of complex tasks (such as image recognition and language translation). The core features of deep learning can be summarized as three points: multi-layer network structure for automatic feature extraction, end-to-end learning driven by massive data, and strong nonlinear fitting ability to deal with complex problems.

The core research goal of deep learning is to enable machines to automatically learn complex features and patterns from data through multi-layer neural networks, and finally have human-like perception, understanding, decision-making and generation capabilities, so as to realize end-to-end intelligence without manual intervention,one can broadly categorize most of the work in this area into three main classes: Generative deep architectures, Discriminative deep architectures, and Hybrid deep architectures [7].

Technical foundation is the underlying element that supports deep learning, which can be roughly divided into three modules.

(1) Data foundation: Deep learning is "data-driven" and requires massive annotated data (such as annotated images for image classification, text tags for NLP). The scale and quality of data directly determine the performance of the model. Meanwhile, data cleaning and enhancement (such as image flipping and text desensitization) are required to improve the effectiveness of data.

(2) Computing resources: GPU/TPU is the core of high-performance hardware (compared with CPU, it can process matrix operations in parallel and accelerate model training). Some complex models (such as large language models) also need the support of distributed computing framework (such as TensorFlow distributed and PyTorch DDP).

(3) Mathematical Theories: The three core branches of mathematics are fundamental. Linear Algebra: Provides matrix operations (e.g., weight updates, feature mapping) that underpin neural networks; Probability Theory and Mathematical Statistics: Enables uncertainty modeling in models (e.g., loss function design, probabilistic predictions); Calculus: Implements gradient descent optimization for model parameters (computing derivatives to update weights and minimize losses).

Work in NLP can be divided into two broad sub-areas: core areas and applications [8],based on these two research domains, we can categorize into four core components that cover the entire chain from foundational technologies to practical implementation.

(1) The foundational technology layer: "representation and parsing" of language. This forms the underlying support for NLP, with its core function being to convert unstructured language into machine-processable formats and address the fundamental challenge of "how machines can 'understand' language".

(2) Understanding tasks: The core ability of machines to "read" language focuses on "extracting information and judging meaning from language", which is the most basic application direction of NLP.

(3) Generative tasks: The core ability of machines to "write" language focuses on "making machines generate text in line with human language logic", which is a hot direction of NLP in recent years, especially relying on the breakthrough of large models.

(4) Interaction and application layer: The "grounding scenario" of NLP combines the ability to understand and generate, and solves the problem of "human-machine language interaction" in

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practical scenarios. Other implementation scenarios: Intelligent document processing (e.g., PDF text extraction, contract clause review with automated risk detection); Voice assistants (like Siri) that integrate ASR (Automatic Speech Recognition), NLP (Natural Language Processing), and TTS (Text-to-Speech) for voice interaction; Code generation systems such as "Natural Language to Code" (input "write a Python sorting function" to generate corresponding code, e.g., GitHub Copilot).

3.2. Deep learning NLP applications for marketing scenarios

NLP models in marketing date back to 2011, but most of the studies are fairly recent. The models cover one of four main substantive domains: P2P platforms, social media, online reviews,and announcements, ads, websites and search results [9].

Deep learning-based Natural Language Processing (NLP) has found extensive applications across various marketing scenarios. Here are key implementations:

(1) Precision Marketing: By integrating user behavior data with demographic characteristics, we can create dynamic user profiles to enable cross-category recommendations. This technology also enables real-time capture of instant consumer needs for scenario-driven marketing, such as automatically pushing "limited-time discounts" or "product pairing suggestions" during e-commerce live streams based on user interactions.

(2) Customer Relationship Management: By leveraging natural language processing (NLP) technology, we enable intelligent customer service with emotional intelligence interactions. This system automatically categorizes customer complaint priorities to enhance response efficiency and satisfaction levels. Simultaneously, it analyzes customers' life cycle stages to trigger personalized services. For example, when a banking AI Agent detects a high-value transfer request, it proactively suggests tailored financial solutions.

(3) Content Generation: Enables one-click creation of all content types including copywriting, images, and videos to reduce production costs. It also analyzes user feedback in real-time to dynamically adjust content strategies. For example, game companies use AI Agents to test ad materials, selecting the highest-click combinations to lower customer acquisition costs. (4) Public Sentiment Monitoring and Analysis: Through sentiment analysis and information extraction from text data on social media, news, forums, and other platforms, we monitor consumer feedback regarding brands, products, or promotional campaigns to adjust marketing strategies in real time. Additionally, key insights can be extracted from user reviews to evaluate product strengths and weaknesses, providing actionable guidance for product improvements and service optimization.

The current use of NLP methods in marketing can be classified into three categories based on the level and type of information that the researcher is trying to extract from the text: These are concept and topic extraction, relationship extraction, and sentiment and writing style extraction [10].

After using the above deep learning NLP technology for information extraction, the application in the specific marketing field also could predicting consumer intent ,such as Purchase signal capture in customer service conversations (e.g., "compare models" in the conversation =60% conversion probability) and automatic attribution of product defects in user reviews (iphone"short battery life" → battery component problem).Its applications also facilitate the generation of automated marketing content, using large models such as GPT-4 to generate personalized advertising copy,improve the efficiency of marketing copywriting and provide a social media public sentiment summary (generate crisis report from 100,000 comments).

Deep learning NLP applications for marketing scenarios also helps to optimize emotion-driven marketing strategies, such as monitoring the reputation of new products (geographic distribution of

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positive and negative emotions) and assessing the public opinion risk of celebrity spokesmen (early warning of public opinion events).

4. Marketing NLP commercialization challenges and responses

4.1. Commercialization challenges

In addressing commercialization challenges, particular attention must be given to privacy protection and the risks of information leakage. Relying excessively on sensitive information, such as user chat records and social data, for NLP analysis (e.g., sentiment recognition, keyword extraction) could lead consumers to question the authenticity of AI-generated content. While techniques like homomorphic encryption and data anonymization can alleviate these risks, achieving a balance between dynamic privacy protection and maintaining data quality continues to be a challenge. To tackle this, industry organizations and authorities could establish a "quality-privacy" dual-control framework and implement federated learning methods to minimize data collection risks. Furthermore, it is essential to develop relevant regulations and guidelines to ensure operational transparency, empower users with the ability to make autonomous decisions, and safeguard their legitimate interests.

Ethical governance and AI technology development exhibit asynchronous evolution, primarily manifested in three aspects: technological advancement, fragmented governance, and accountability dilemmas. The rapid iteration of AI technology far outpaces the capacity of ethical frameworks and legal systems to evolve, resulting in increasingly blurred ethical boundaries within marketing practices.However, if overused or unguided, AI-driven marketing could lead to generic or misaligned messages or ethical pitfalls like biased AI outputs, which could harm customer trust, which is critical in the digital space [11].

The change of consumption trend leads to the attenuation of model performance, which requires continuous annotation data and iterative training. It is difficult for small and medium-sized enterprises to bear the cost of manpower and computing power.

4.2. Coping strategy

Localized model inference (e.g., mobile sentiment analysis SDKs), eliminating the need to upload user data to the cloud while complying with EU GDPR requirements. A case study demonstrates a bank's use of homomorphism encryption technology to analyze customer complaint texts, achieving "usable but invisible" data through regulatory compliance audits by the China Banking and Insurance Regulatory Commission) .

Use AI for what it is good at (speed, data-crunching, routine content generation), but have humans in the loop for strategy, final creative direction, and oversight to ensure consistency with brand values and ethics [12]. Develop a visual business rule configuration interface that allows marketers to drag and drop model outputs (such as setting a "promotional keyword" whitelist) and reduces IT dependency by 70%.

Samples with low automatic recognition confidence (such as new terms like "snow cone assassin") are prioritized to push manual annotation, and the annotation efficiency is increased by three times. Automated training pipeline: Grab new product reviews of competitors every day and automatically trigger incremental training of the model (a mobile phone manufacturer compressed the model iteration cycle from 2 weeks to 8 hours).

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5. Conclusion

This paper explores the potential application of natural language processing (NLP) techniques from deep learning in marketing, an emerging technological field. While promising empirical results have been reported to date, substantial development remains necessary. Crucially, researchers 'experience reveals that no single deep learning technique can successfully handle all classification tasks. Recent studies indicate significant room for improvement in optimization techniques currently employed to learn deep architectures, and deep learning requires solid theoretical foundations across multiple dimensions. These innovative approaches enable the field to enhance its capabilities in executing tasks we've used for over a decade (e.g., text classification). More importantly, they open up new research opportunities that could revolutionize the field.

In summary, the application of natural language processing (NLP) in deep learning has become an irreversible trend in marketing. The emergence of large-scale AI models has opened up new research directions and perspectives for marketing scholars, covering cutting-edge fields such as text generation, summary extraction, and multimodal content representation. These advancements reveal the comprehensive optimization value of multimodal data analysis (e.g., joint mining of live broadcast comments and voice-text data) in consumer decision-making journeys (cognition-purchase-loyalty), filling gaps left by traditional single-dimensional studies. Such innovations can be widely applied across social media, online shopping, and voice assistant scenarios, enabling precise semantic associations between words, sentences, and concepts. For enterprises, NLP applications in marketing help reduce marketing costs and enhance core competitiveness. From consumer and societal perspectives, these advancements boost customer loyalty, facilitate the transformation and upgrading of marketing practices, and drive the development of artificial intelligence and digital inclusivity in the big data era. We hope this chapter will assist scholars interested in NLP applications in marketing to explore these rich opportunities in depth.

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