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Deep Learning and Optimization Approaches in E-commerce Systems for Sale Prediction Using Triple Pseudo-Siamese Network with Giant Trevally Optimizer: A Review

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Abstract

The rapid growth of e-commerce platforms has resulted in the generation of vast amounts of transactional and behavioral data, enabling the use of predictive analytics for sales forecasting and recommendation systems. Accurate sales prediction is essential for effective inventory management, demand planning, and strategic decision-making in online retail. However, traditional statistical models often fail to capture the nonlinear relationships and complex patterns present in high-dimensional datasets. To overcome these limitations, deep learning approaches have been widely adopted, with Siamese and pseudo-Siamese neural networks gaining prominence due to their ability to learn similarity relationships across diverse feature spaces. The Triple Pseudo-Siamese Network further enhances this capability by integrating multiple feature streams, including customer behavior, product attributes, and temporal sales patterns, to improve prediction accuracy. Efficient training of such deep models requires robust optimization techniques, and metaheuristic algorithms like the Giant Trevally Optimizer (GTO) have shown strong potential by effectively exploring complex search spaces. By combining advanced neural architectures with optimization strategies, modern approaches significantly enhance forecasting performance. This review highlights recent developments, identifies research gaps, and outlines future directions for scalable e-commerce prediction systems.

Introduction

The global growth of digital commerce has dramatically transformed the retail industry. E-commerce platforms such as Amazon, Alibaba, and eBay generate enormous volumes of data related to customer behavior, product transactions, inventory levels, and marketing activities. This data provides valuable insights into purchasing trends and customer preferences, enabling businesses to improve operational efficiency and customer satisfaction. One of the most critical applications of data analytics in e-commerce is **sales prediction**, which involves forecasting future demand for products based on historical data and external factors.

Accurate sales prediction is essential for several operational processes, including inventory planning, supply chain management, dynamic pricing, and marketing strategy development. Overestimating product demand can result in excessive inventory and increased storage costs, while underestimating demand can lead to stockouts and lost sales opportunities. Therefore, developing accurate and reliable sales forecasting models has become a key research area in both academia and industry.

Traditional sales prediction methods rely on statistical approaches such as autoregressive integrated moving average (ARIMA), exponential smoothing, and regression analysis. Although these methods are effective for simple time-series forecasting tasks, they often struggle to capture complex nonlinear relationships present in large e-commerce datasets. Modern e-commerce systems involve interactions among multiple variables, including customer demographics, product attributes, seasonal trends, promotional campaigns, and external market conditions.

With the rapid advancement of artificial intelligence, deep learning models have been widely adopted for sales prediction and recommendation tasks. Deep neural networks can automatically learn hierarchical representations of complex data, enabling them to capture nonlinear patterns and interactions among features. Convolutional neural networks (CNNs), recurrent neural networks (RNNs), and long short-term memory (LSTM) networks have been extensively applied to sales forecasting problems.

Despite their success, traditional deep learning architectures face challenges when dealing with heterogeneous data sources and similarity learning tasks. In many e-commerce applications, different types of information such as product descriptions, customer browsing history, and transaction sequences must be analyzed simultaneously. Siamese neural networks provide an effective solution to this problem by learning similarity relationships between pairs of inputs.

A Siamese network consists of two identical neural networks that share the same parameters and are trained to learn feature representations for comparison tasks. The architecture is widely used in applications such as face recognition, signature verification, and recommendation systems. In e-commerce systems, Siamese networks can learn relationships between different products or customers by comparing their feature representations.

Pseudo-Siamese networks extend this architecture by allowing each branch of the network to learn different feature representations while maintaining a shared objective function. This flexibility enables the model to capture relationships between heterogeneous data sources that may have different feature distributions. A **triple pseudo-Siamese network** further extends this concept by incorporating three feature streams, enabling the model to simultaneously analyze multiple aspects of e-commerce data such as product features, customer interactions, and temporal trends.

While deep learning architectures can provide powerful predictive capabilities, their performance heavily depends on the optimization techniques used during training. Conventional gradient-based optimization methods such as stochastic gradient descent (SGD) and Adam are commonly used for training neural networks. However, these methods may become trapped in local minima or suffer from slow convergence when dealing with complex optimization landscapes.

Metaheuristic optimization algorithms provide an alternative approach to optimizing neural network parameters. These algorithms are inspired by natural phenomena such as evolutionary processes, swarm intelligence, and animal behaviors. Examples include genetic algorithms, particle swarm optimization, ant colony optimization, and grey wolf optimization.

Among these approaches, the **Giant Trevally Optimizer (GTO)** has recently gained attention as a powerful population-based optimization algorithm. The algorithm models the hunting behavior of giant trevally fish, which attack seabirds by jumping out of the water. The optimization process consists of three main phases: exploration of the search space, selection of promising regions, and exploitation of optimal solutions. This strategy allows the algorithm to balance exploration and exploitation effectively while searching for global optima.

Researchers have demonstrated that the Giant Trevally Optimizer can outperform several existing metaheuristic algorithms in solving complex optimization problems across engineering and computational domains. By integrating this optimization strategy with deep learning models, it is possible to improve training efficiency and enhance prediction performance.

In e-commerce systems, hybrid models that combine deep neural networks with metaheuristic optimization algorithms have shown promising results. These hybrid approaches leverage the representation learning capability of deep learning models while utilizing metaheuristic algorithms to optimize network parameters and hyperparameters. As a result, such models can achieve higher prediction accuracy and improved generalization performance compared with conventional deep learning methods.

The triple pseudo-Siamese network combined with the Giant Trevally Optimizer represents an emerging research direction for e-commerce sales prediction. By integrating multiple data streams and advanced optimization techniques, this framework aims to capture complex relationships among customers, products, and sales patterns.

This review paper examines existing research on deep learning architectures and metaheuristic optimization algorithms used for e-commerce sales forecasting. The study focuses on methods that integrate Siamese-based neural networks with advanced optimization strategies. The objectives of this review include:

1. Analyzing deep learning architectures used for e-commerce sales prediction.
2. Examining Siamese and pseudo-Siamese network models for similarity learning in recommendation systems.
3. Investigating metaheuristic optimization algorithms such as the Giant Trevally Optimizer for neural network training.
4. Comparing existing approaches in terms of prediction accuracy and computational efficiency.
5. Identifying research challenges and future directions for intelligent e-commerce forecasting systems.

By exploring the integration of deep learning and optimization algorithms, this review aims to provide insights into the development of next-generation sales prediction systems capable of supporting intelligent decision-making in modern e-commerce environments.

Literature Review

The rapid growth of e-commerce platforms has generated large volumes of data related to customer behavior, product transactions, and market trends. This data has created opportunities for developing intelligent predictive systems that support demand forecasting and strategic decision-making. Sales prediction is a critical component of e-commerce analytics because accurate demand forecasts enable businesses to optimize inventory management, reduce operational costs, and improve customer satisfaction. In recent years, researchers have increasingly adopted machine learning and deep learning techniques to improve forecasting accuracy in complex retail environments.

Traditional forecasting models such as autoregressive integrated moving average (ARIMA), regression analysis, and exponential smoothing have been widely used in demand prediction tasks. However, these models are limited in their ability to capture nonlinear relationships and high-dimensional interactions present in large-scale e-commerce datasets. As a result, deep learning architectures have become popular alternatives for sales prediction due to their ability to automatically learn complex feature representations from large datasets. Zhang et al. (2020) demonstrated that deep neural networks significantly outperform conventional statistical models when applied to large transaction datasets. Their research showed that neural networks can effectively identify nonlinear patterns in historical sales data, leading to improved forecasting accuracy.

Convolutional neural networks (CNNs) have been widely used in e-commerce analytics to extract spatial relationships among product attributes and customer behavior patterns. CNN-based architectures are particularly effective when analyzing high-dimensional datasets that contain multiple feature categories. Li et al. (2022) proposed a hybrid deep learning model that integrates convolutional neural networks with long short-term memory networks for sales forecasting tasks. In this approach, CNN layers extract spatial features from product and customer data, while LSTM layers capture temporal dependencies in historical transaction records. Experimental results indicated that the hybrid CNN-LSTM architecture achieved significantly higher prediction accuracy compared with traditional machine learning models.

Another promising approach in deep learning research involves the use of Siamese neural networks. Siamese networks consist of two identical neural network branches that share the same weights and are trained to learn similarity relationships between input pairs. These architectures are widely used in tasks such as image recognition, recommendation systems, and similarity learning. Chicco (2021) provided a comprehensive overview of Siamese neural networks and their applications in machine learning tasks. The study emphasized that Siamese networks can effectively learn relationships between different data inputs by comparing feature representations. In e-commerce systems, this capability enables models to analyze similarities between products, customer preferences, and purchasing patterns.

Despite their advantages, traditional Siamese neural networks are limited in their ability to process heterogeneous data sources. In many real-world e-commerce systems, different types of information such as product descriptions, customer browsing behavior, and transaction histories must be analyzed simultaneously. Pseudo-Siamese networks were introduced to address this limitation by allowing each branch of the network to learn independent feature representations rather than sharing identical parameters. Chen et al. (2021) proposed a pseudo-Siamese neural network architecture for multimodal data processing tasks. Their model demonstrated improved performance in tasks involving heterogeneous datasets because each branch of the network could learn specialized features for different data modalities.

The concept of a **triple pseudo-Siamese network** extends the pseudo-Siamese architecture by incorporating three independent network branches that process multiple feature streams simultaneously. In e-commerce sales prediction systems, such architectures enable models to analyze product features, customer interaction data, and temporal sales patterns in parallel. By integrating multiple feature streams, triple pseudo-Siamese networks can capture complex relationships among different aspects of e-commerce datasets. This architecture has shown potential in improving prediction accuracy for tasks that require the integration of heterogeneous information sources.

While deep learning models provide powerful predictive capabilities, their performance is strongly influenced by the optimization techniques used during training. Conventional gradient-based optimization methods such as stochastic gradient descent (SGD), Adam, and RMSProp are commonly used to train neural networks. However, these methods may suffer from slow convergence or become trapped in local minima when optimizing highly complex neural network architectures. To overcome these limitations, researchers have explored the use of metaheuristic optimization algorithms for neural network training.

Metaheuristic algorithms are population-based optimization techniques inspired by natural phenomena such as evolutionary processes, swarm intelligence, and predator-prey interactions. These algorithms provide efficient mechanisms for exploring complex search spaces and identifying optimal solutions. Mirjalili and Lewis (2016) introduced the whale optimization algorithm, which simulates the hunting behavior of humpback whales to search for optimal solutions in complex optimization problems. Similarly, Mirjalili et al. (2017) proposed the salp swarm algorithm inspired by the collective behavior of salp chains in oceans. These algorithms have been successfully applied to various engineering and computational optimization tasks.

Among recent optimization techniques, the **Giant Trevally Optimizer (GTO)** has attracted significant attention in the research community. Abdollahzadeh et al. (2022) proposed the GTO algorithm based on the hunting strategy of giant trevally fish that attack seabirds by jumping out of the water. The algorithm models three main stages of hunting behavior: searching for prey, selecting promising hunting areas, and executing the final attack. These stages are mathematically formulated to guide the optimization process toward global optimal solutions while maintaining a balance between exploration and exploitation. Experimental studies demonstrated that the GTO algorithm outperforms several well-known optimization algorithms in solving complex optimization problems.

The integration of metaheuristic optimization algorithms with deep learning architectures has emerged as an important research direction in recent years. Hybrid models that combine neural networks with optimization algorithms can improve training efficiency and enhance prediction performance. Wang et al. (2023) proposed an optimization-driven neural network framework that integrates evolutionary algorithms with deep learning models for demand forecasting. Their results showed that optimization-based training strategies significantly improve model convergence and prediction accuracy.

Similarly, Huang et al. (2023) developed an attention-based deep learning model for analyzing customer purchase behavior in e-commerce platforms. The model incorporates attention mechanisms to identify the most relevant features in large transaction datasets. Their experimental results demonstrated that attention-based architectures can improve forecasting performance by focusing on key features that influence purchasing decisions.

Recent studies have also explored hybrid artificial intelligence models that combine deep learning techniques with swarm intelligence algorithms for predictive analytics. Patel et al. (2023) investigated the use of hybrid deep learning frameworks integrated with optimization algorithms for demand forecasting tasks. Their research demonstrated that hybrid AI models provide improved prediction accuracy and enhanced robustness compared with standalone deep learning approaches.

Overall, the literature indicates that deep learning architectures combined with metaheuristic optimization algorithms represent a promising approach for improving sales prediction systems in e-commerce environments. Triple pseudo-Siamese networks provide an effective framework for processing heterogeneous data sources, while optimization algorithms such as the Giant Trevally Optimizer enhance neural network training by improving parameter selection and convergence behavior. These hybrid models have the potential to significantly improve forecasting accuracy and support intelligent decision-making in modern e-commerce systems.

However, several research challenges remain in this field. One major challenge involves the computational complexity associated with training deep learning models combined with metaheuristic optimization algorithms. Large-scale e-commerce datasets require efficient training strategies and high-performance computing resources. Additionally, data quality and availability can significantly affect the performance of predictive models. Many e-commerce datasets contain missing values, noisy data, or incomplete customer information, which may reduce model accuracy.

Future research should therefore focus on developing scalable hybrid AI frameworks capable of processing large datasets while maintaining computational efficiency. Integrating explainable artificial intelligence techniques may also improve the transparency and interpretability of deep learning models used in business decision-making systems. By addressing these challenges, researchers can develop more robust and reliable sales prediction systems that support the evolving needs of digital commerce platforms.

Comparative Table and Analysis

Study	Year	Model	Application	Key Contribution	Limitations
Zhang et al.	2020	Deep Neural Network	Demand forecasting	Captures nonlinear sales patterns	Requires large datasets
Chicco	2021	Siamese Network	Recommendation systems	Learns similarity between inputs	Limited handling of heterogeneous data
Chen et al.	2021	Pseudo-Siamese Network	Multimodal learning	Handles heterogeneous datasets	Higher training complexity
Li et al.	2022	CNN-LSTM Hybrid Model	Sales prediction	Combines spatial and temporal features	Computationally expensive
Mirjalili & Lewis	2022	Metaheuristic Optimization	Neural network training	Avoids local minima in training	Slower convergence
Abdollahzadeh et al.	2022	Giant Trevally Optimizer	Global optimization	Efficient search strategy	Relatively new algorithm
Huang et al.	2023	Attention-based Deep Learning	Sales forecasting	Improves feature weighting	Sensitive to hyperparameters
Wang et al.	2023	Optimization-driven NN	Forecasting systems	Optimizes neural network parameters	Complexity in tuning
Zhou et al.	2023	Deep Recommendation System	E-commerce platforms	Captures customer preferences	Data sparsity issues
Patel et al.	2023	Hybrid AI Model	Demand forecasting	Combines deep learning and optimization	Increased training cost

Comparative Analysis

The reviewed literature indicates that deep learning approaches have become dominant in e-commerce sales prediction due to their ability to capture nonlinear relationships in large datasets. Traditional forecasting models such as regression and ARIMA are limited in their ability to analyze complex interactions between customer behavior, product attributes, and seasonal demand patterns.

Siamese and pseudo-Siamese neural networks offer advantages in similarity learning tasks, allowing models to compare different feature spaces effectively. These architectures are particularly useful in recommendation systems where relationships between products and customer preferences must be learned. However, conventional Siamese networks are limited when dealing with multiple heterogeneous inputs.

Triple pseudo-Siamese architectures address this limitation by incorporating multiple input streams that capture different aspects of e-commerce data. This architecture enables the model to simultaneously analyze product attributes, customer behavior, and historical sales patterns.

Another important trend in the literature is the integration of metaheuristic optimization algorithms with deep learning models. Algorithms such as the Giant Trevally Optimizer provide efficient mechanisms for optimizing neural network parameters and improving model convergence. By combining deep learning architectures with optimization algorithms, researchers can develop hybrid systems that achieve higher prediction accuracy and improved computational efficiency.

Overall, the literature suggests that hybrid deep learning frameworks that integrate Siamese architectures and metaheuristic optimization techniques represent a promising direction for improving sales prediction in e-commerce systems.

Discussion

The rapid growth of e-commerce platforms has created an increasing demand for intelligent sales prediction systems capable of analyzing large-scale transaction datasets and identifying complex patterns in customer behavior. Traditional forecasting models such as regression analysis, ARIMA, and exponential smoothing have been widely used in retail demand prediction; however, these models often fail to capture nonlinear relationships and high-dimensional interactions present in modern e-commerce environments. As a result, deep learning architectures have emerged as powerful alternatives for developing advanced predictive analytics systems.

The literature reviewed in this study highlights the significant potential of deep learning models for improving sales prediction accuracy in e-commerce systems. Neural network architectures such as convolutional neural networks (CNNs), recurrent neural networks (RNNs), and long short-term memory networks (LSTMs) have demonstrated strong capabilities in extracting meaningful features from complex datasets. CNN models are effective for learning spatial relationships in product attributes and customer interaction data, while recurrent architectures such as LSTM networks are capable of capturing temporal dependencies in historical sales data. Hybrid models that combine CNN and LSTM layers have shown improved performance by simultaneously analyzing spatial and temporal patterns.

Despite these advantages, traditional deep learning models still face several challenges when applied to e-commerce sales forecasting. One major limitation is the difficulty in integrating heterogeneous data sources such as customer profiles, product attributes, user browsing history, and transaction records. In many cases, these data sources have different feature distributions and require specialized architectures to effectively extract relevant information. Siamese and pseudo-Siamese neural network architectures have been proposed as solutions to this problem.

Siamese networks are designed to learn similarity relationships between pairs of inputs by sharing weights across network branches. This architecture is particularly useful for tasks such as product recommendation, fraud detection, and user similarity analysis. However, traditional Siamese networks are limited to processing two input streams and assume that both streams share similar feature representations. In complex e-commerce environments, this assumption may not hold because different data sources may contain diverse information.

Pseudo-Siamese networks address this limitation by allowing each branch of the network to learn independent feature representations while maintaining a shared objective function. This flexibility enables the network to capture relationships between heterogeneous datasets more effectively. The concept of a **triple pseudo-Siamese network** further extends this architecture by incorporating three input streams that analyze different aspects of e-commerce data simultaneously. For example, one branch may process product features, another branch may analyze customer behavior, and the third branch may examine temporal sales patterns. By integrating these inputs, the model can generate more accurate predictions regarding future product demand.

Another critical factor influencing the performance of deep learning models is the optimization algorithm used during training. Conventional gradient-based optimization techniques such as stochastic gradient descent (SGD), RMSProp, and Adam are widely used for training neural networks. Although these methods are effective for many machine learning tasks, they may struggle to find global optimal solutions in highly complex search spaces. In particular, deep neural networks often contain millions of parameters, making the optimization process computationally challenging.

Metaheuristic optimization algorithms provide an alternative approach to neural network training. These algorithms are inspired by natural phenomena such as evolutionary processes, swarm behavior, and predator-prey interactions. By exploring the search space using population-based strategies, metaheuristic algorithms can avoid local minima and improve convergence toward global solutions.

Among recent optimization techniques, the **Giant Trevally Optimizer (GTO)** has gained attention as a promising metaheuristic algorithm. Inspired by the hunting behavior of giant trevally fish attacking seabirds, the algorithm models three main phases: exploration of the search space, selection of promising hunting areas, and exploitation of optimal solutions. This behavior allows the algorithm to maintain a balance between exploration and exploitation during optimization. When applied to neural network training, GTO can optimize parameters such as weights, biases, and hyperparameters to improve model performance.

Integrating a triple pseudo-Siamese network with the Giant Trevally Optimizer represents a novel approach for developing intelligent sales prediction systems in e-commerce platforms. The deep learning architecture provides the ability to learn complex feature representations from heterogeneous datasets, while the optimization algorithm enhances the training process by improving parameter selection and avoiding local minima.

However, several research challenges remain in the development of such hybrid models. One major challenge is the computational complexity associated with training deep neural networks combined with metaheuristic optimization algorithms. These models may require substantial computational resources, particularly when processing large-scale e-commerce datasets. Another challenge involves data quality and availability. Accurate sales prediction models require high-quality datasets that include detailed information about customer behavior, product characteristics, and market conditions.

Additionally, interpretability and transparency remain important considerations for AI-driven decision-making systems in business environments. While deep learning models can achieve high prediction accuracy, they often function as “black boxes,” making it difficult for managers to understand how predictions are generated. Future research should therefore focus on developing explainable AI techniques that improve the interpretability of deep learning models used in e-commerce analytics.

Overall, the integration of deep learning architectures with advanced optimization algorithms offers a promising direction for improving the performance of sales prediction systems in e-commerce environments. By leveraging the strengths of triple pseudo-Siamese networks and metaheuristic optimization techniques such as the Giant Trevally Optimizer, researchers can develop intelligent forecasting models capable of supporting data-driven decision making in modern digital commerce systems.

Conclusion

The rapid expansion of digital commerce has significantly increased the importance of predictive analytics in e-commerce platforms. Sales prediction plays a critical role in inventory management, supply chain planning, marketing strategies, and customer satisfaction. Traditional forecasting techniques based on statistical models are often limited in their ability to analyze complex relationships in large-scale transaction datasets. Consequently, researchers have increasingly adopted deep learning techniques to address these limitations.

This review examined recent developments in deep learning and optimization approaches used for sales prediction in e-commerce systems. The literature analysis demonstrated that deep neural network architectures such as convolutional neural networks, recurrent neural networks, and hybrid CNN-LSTM models provide significant improvements in predictive accuracy compared with traditional forecasting methods. These models are capable of capturing nonlinear relationships and extracting meaningful patterns from high-dimensional datasets.

The review also highlighted the importance of Siamese and pseudo-Siamese neural network architectures for similarity learning and multimodal data analysis. These architectures enable models to analyze relationships between different data sources, such as customer profiles, product attributes, and transaction histories. The concept of a triple pseudo-Siamese network further extends this capability by incorporating multiple input streams that capture various aspects of e-commerce datasets. This architecture allows the model to simultaneously analyze product characteristics, customer behavior, and temporal demand patterns, leading to improved prediction accuracy.

Another key focus of this review was the role of optimization algorithms in improving deep learning model performance. Traditional gradient-based optimization methods may struggle to find global optimal solutions in complex neural network architectures. Metaheuristic optimization algorithms inspired by natural phenomena offer alternative approaches for exploring the search space and optimizing neural network parameters.

The Giant Trevally Optimizer represents a promising metaheuristic algorithm that has demonstrated strong performance in solving complex optimization problems. By simulating the hunting strategies of giant trevally fish, the algorithm balances exploration and exploitation during the optimization process. Integrating this optimization strategy with deep learning architectures such as triple pseudo-Siamese networks can enhance the training process and improve model convergence.

Despite the promising results reported in recent studies, several challenges remain in the development of intelligent e-commerce forecasting systems. One major challenge involves the integration of heterogeneous data sources that include structured transaction data, unstructured product descriptions, and behavioral data from customer interactions. Developing models capable of effectively processing these diverse datasets remains an active area of research.

Another important challenge relates to computational complexity and scalability. Deep learning models combined with metaheuristic optimization algorithms may require substantial computational resources, particularly when applied to large-scale e-commerce datasets. Future research should therefore focus on developing efficient training algorithms and distributed computing frameworks that support large-scale deployment.

In addition, improving the interpretability and transparency of deep learning models remains an important research direction. Business decision makers require clear explanations of how predictive models generate recommendations or forecasts. Integrating explainable AI techniques into deep learning models may help address this issue and increase trust in AI-driven decision systems.

In conclusion, the integration of deep learning architectures with metaheuristic optimization algorithms offers a promising framework for developing intelligent sales prediction systems in e-commerce platforms. The combination of triple pseudo-Siamese networks and the Giant Trevally Optimizer provides a powerful approach for analyzing heterogeneous datasets and improving forecasting performance. As research in this area continues to evolve, such hybrid AI models are expected to play a key role in supporting data-driven decision-making and improving operational efficiency in modern e-commerce environments.

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