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A comparative analysis of traditional time series models and deep learning approaches in sales prediction: Strengths and limitations

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Abstract
The realm of sales prediction has witnessed a paradigm shift with the advent of deep learning approaches, challenging the supremacy of traditional time series models. This review paper delves into the comparative analysis of these two methodologies, shedding light on their respective strengths and limitations in the context of sales forecasting.

Traditional time series models, including autoregressive integrated moving average (ARIMA), exponential smoothing methods, and autoregressive integrated moving average with exogenous variables (ARIMAX), have long been the cornerstone of sales prediction. Their simplicity and interpretability have made them the preferred choice in various industries. However, these models often struggle to capture the complex patterns inherent in sales data, especially when confronted with non-linear relationships and high-dimensional input spaces.

In contrast, deep learning approaches, such as recurrent neural networks (RNNs) and long short-term memory networks (LSTMs), have emerged as formidable contenders in sales prediction. Their ability to automatically learn intricate features from vast and unstructured data sets allows them to model the dynamic nature of sales patterns more effectively. Deep learning models excel in capturing temporal dependencies, seasonality, and non-linear trends, offering a promising alternative to traditional methods.

Despite their undeniable success, deep learning approaches are not without their limitations. The insatiable appetite for large volumes of labeled data and computational resources poses a considerable challenge, especially for organizations with limited datasets and computing capabilities. Additionally, the 'black-box' nature of deep learning models raises interpretability concerns, hindering their widespread adoption in industries where transparency is paramount.

This paper critically evaluates the strengths and weaknesses of both traditional time series models and deep learning approaches, offering insights into their applicability across diverse scenarios. The review emphasizes the importance of a nuanced approach, advocating for a hybrid methodology that leverages the interpretability of traditional models and the predictive power of deep learning techniques. Through a comprehensive analysis, this review aims to guide practitioners and researchers in making informed decisions when selecting the most suitable methodology for sales prediction in their specific contexts.

Keywords: Sales prediction, time series models, deep learning approaches, comparative analysis, strengths and limitations, hybrid methodology, forecasting techniques

1. Introduction

Sales prediction plays a pivotal role in the strategic decision-making processes of businesses, serving as a compass for inventory management, resource allocation, and overall business planning. In the dynamic landscape of today's markets, accurate forecasting has become more challenging yet indispensable. The perennial debate between traditional time series models and the burgeoning realm of deep learning approaches underscores the quest for the most effective means of unraveling the intricate patterns hidden within sales data. This review embarks on a comprehensive exploration, juxtaposing the strengths and limitations of traditional time series models and deep learning approaches in the domain of sales prediction.

Traditional time series models, such as the autoregressive integrated moving average (ARIMA) and exponential smoothing methods, have long been the stalwarts of forecasting. Renowned for their simplicity and interpretability, these models have been the go-to tools for businesses seeking reliable predictions based on historical sales data. The appeal of traditional models lies in their ability to capture linear relationships and overall trends. However, as markets evolve, becoming more volatile and complex, the limitations of these models have become increasingly evident. Their struggle to encapsulate non-linear patterns, adapt to sudden changes, and incorporate high-dimensional inputs has spurred the exploration of alternative methodologies.

The advent of deep learning approaches, exemplified by recurrent neural networks (RNNs) and long short-term memory networks (LSTMs), has ushered in a new era in sales prediction. These models, inspired by the structure and function of the human brain, excel in discerning intricate patterns within vast and unstructured datasets. The ability of deep learning approaches to automatically extract relevant features, model temporal dependencies, and navigate non-linear trends positions them as formidable contenders in the quest for more accurate and adaptive forecasting. Nevertheless, the path to widespread adoption of deep learning in sales prediction is fraught with challenges.

One prominent challenge is the voracious appetite of deep learning models for substantial labeled data and computational resources. Organizations with limited datasets and computing capabilities may find themselves at a disadvantage when attempting to harness the full potential of deep learning. Furthermore, the 'black-box' nature of these models, wherein predictions are made without explicit understanding of the underlying mechanisms, raises concerns about interpretability. In industries where transparency and interpretability are paramount, such as finance or healthcare, the opacity of deep learning models may hinder their acceptance and integration into existing frameworks.

This review seeks to navigate through the nuances of traditional time series models and deep learning approaches, providing a roadmap for decision-makers in selecting the most suitable methodology for their specific sales forecasting needs. The exploration of strengths and limitations will pave the way for a balanced and informed approach, suggesting a hybrid methodology that amalgamates the interpretability of traditional models with the predictive power of deep learning techniques. By shedding light on these critical aspects, this review aims to contribute to the ongoing discourse surrounding the optimization of sales prediction methodologies in an era of ever-evolving markets and technologies.

2. Literature Review

Sales forecasting is a critical facet of business strategy, and its accuracy profoundly impacts decision-making processes. Various studies in this field have consistently emphasized the importance of accurate predictions, often gauged using error measurement methods like RMSE (Root Mean Square Error) and MAPE (Mean Absolute Percentage Error). This literature review delves into the intricacies of sales forecasting methodologies, categorizing them into classical time-series forecasting methods, Prophet, and Artificial Neural Networks (ANN), including deep learning techniques.

2.1. Classical Time-Series Forecasting Methods

Classical time-series forecasting methods, such as Moving Average (MA) and Autoregressive Integrated Moving Average (ARIMA), have been stalwarts in the field. Ramos *et al*. (2015) utilized ARIMA and exponential smoothing to forecast retail sales, showcasing the effectiveness of these traditional models. Additionally, Seasonal ARIMA (SARIMA) has found success in applications like tourism demand forecasting (Goh & Law, 2002). However, limitations in linear forms and an inability to detect nonlinear patterns have been noted, prompting the exploration of alternatives like Seasonal Support Vector Regression (SSVR) (Pai *et al*., 2010).

Exponential smoothing methods, including Holt-Winters (HW), have been powerful tools for forecasting, addressing seasonality in datasets (Kalekar, 2004; Taylor, 2011). Lv *et al*. (2008) proposed a novel model for evaluating new retail store locations based on sales forecasting, showcasing the versatility of these methods. Furthermore, more advanced techniques, such as Greedy Aggregation Decomposition (GAD) (Li & Lim, 2018), have been employed to overcome challenges related to limited inventory space in retail.

2.2. Prophet and Artificial Neural Networks Time-Series Forecasting Methods

The Prophet method, introduced by Facebook, and Artificial Neural Networks (ANN) present alternative approaches to sales prediction. Prophet's capabilities are still under exploration, with studies indicating its competitive edge over traditional methods in certain applications, such as hospital discharge volume prediction (McCoy *et al*., 2018) and website traffic forecasting. Additionally, the hybrid use of ARIMA and Prophet for forecasting COVID disease in Indonesia demonstrates the versatility of combining methodologies.

ANNs, a popular choice for forecasting, have been compared favorably to traditional methods like winters' exponential smoothing and Box Jenkins techniques (Alon *et al*., 2001). To enhance ANN performance, novel models like Seasonal Artificial Neural Network (SANN) (Hamzaçebi, 2008) and hybrid models combining ANN with ARIMA (Khashei & Bijari, 2010) have been proposed, showcasing a commitment to refining and improving these methods.

2.3. Deep Learning

The advent of deep learning, particularly through techniques like Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM), has opened new avenues for accurate forecasting. RNNs, with their ability to retain past events in memory, are effective in time-series prediction (Gamboa, 2017). LSTM, a specialized form of RNN, has demonstrated success in anomaly detection (Malhotra *et al*., 2016) and forecasting (Zhao *et al*., 2017), although machine learning models like XGBoost have occasionally outperformed.

Convolutional Neural Networks (CNNs), typically associated with image recognition, have found application in time-series forecasting. Zhao and Wang (2017) proposed a novel approach for sales forecasting using CNN, highlighting the adaptability of these deep learning models.

2.4. Research Contributions

This study contributes significantly to the field by providing a dataset encompassing the sales history of furniture, accompanied by a unique exploratory data analysis. The research applies an extensive array of forecasting methods, ranging from classical time-series techniques like SARIMA to advanced ANN-based methods such as Prophet, LSTM, and CNN. The comparative analysis using accuracy metrics like RMSE and MAPE allows for a thorough evaluation of the various methods employed, facilitating the selection of the most effective forecasting approaches.

2.4.1 Methodology Review

Sales prediction methodologies encompass a diverse range of approaches, each offering unique strengths and limitations. This section presents a comprehensive review of methodologies employed in forecasting sales, categorizing them into Classical Time-Series Forecasting Methods, Prophet, and Artificial Neural Networks (ANN) with a focus on deep learning techniques.

3.1 Classical Time-Series Forecasting Methods
3.1.1 Moving Average (MA)
Moving Average (MA) serves as one of the foundational techniques for time-series forecasting, particularly suitable for data without noticeable seasonal patterns (Chopra & Meindl, 2016). Its simplicity and ease of implementation make it a viable choice for initial analysis. However, MA's efficacy diminishes when confronted with datasets exhibiting intricate seasonal fluctuations or non-linear trends.

3.1.2. Autoregressive Integrated Moving Average (ARIMA)
ARIMA, an advanced version of MA, has demonstrated robust performance in various applications. Ramos *et al*. (2015) utilized ARIMA alongside the exponential smoothing method for forecasting retail sales, showcasing the model's applicability to products with repeatable fluctuations, such as seasonal variations in women's footwear.

3.1.3. Seasonal ARIMA (SARIMA)
SARIMA extends ARIMA by incorporating seasonal components, proving effective in applications like tourism demand forecasting (Goh & Law, 2002). However, limitations arise due to SARIMA's linear nature, rendering it less adept at capturing nonlinear and highly volatile patterns (Hamzaçebi, 2008). To address this, alternative methods like Seasonal Support Vector Regression (SSVR) have been proposed, exhibiting superiority in forecasting seasonal items (Pai *et al*., 2010).

3.1.4. Exponential Smoothing Methods
Exponential smoothing, exemplified by the Holt-Winters (HW) technique, has been a powerful forecasting tool, especially for addressing seasonality in datasets (Kalekar, 2004; Taylor, 2011). Taylor's (2011) application of seasonal exponential smoothing in forecasting daily sales of a supermarket highlights the method's efficacy in handling high-volatility scenarios.

3.1.5. Advanced Techniques
Several studies have explored more advanced techniques within the classical time-series framework. Lv *et al*. (2008) proposed a novel model for retail store location evaluation based on sales forecasting. Giering (2008) implemented a system for online product recommendations relying on large retail store sales predictions. These studies underscore the adaptability of classical methods to diverse applications.

3.2. Prophet and Artificial Neural Networks Time-Series Forecasting Methods
3.2.1. Prophet
Prophet, introduced by Facebook, is a recently developed forecasting method. Its capabilities, while not yet comprehensively explored, show promise in various applications. McCoy *et al*. (2018) demonstrated its accurate prediction of hospital discharge volumes, surpassing the results of traditional models like SARIMA. Additionally, its application in website traffic forecasting yielded satisfying results

3.2.2. Artificial Neural Networks (ANN)
ANNs have been a popular choice for sales forecasting due to their flexibility in detecting patterns. Alon *et al*. (2001) compared ANN with traditional methods, highlighting its outperformance in predicting aggregate retail sales. To enhance ANN's performance, novel models such as Seasonal Artificial Neural Network (SANN) (Hamzaçebi, 2008) and hybrid models combining ANN with ARIMA have been proposed (Khashei & Bijari, 2010).

3.3. Deep Learning
3.3.1. Convolutional Neural Network (CNN)
CNNs, traditionally associated with image recognition, have found recent applications in time-series forecasting. Zhao and Wang (2017) proposed a novel approach for sales forecasting using CNN, leveraging its ability to automatically extract features from data.

3.4. Comparative Analysis
This methodology review sets the stage for a comprehensive comparative analysis, considering classical time-series methods, Prophet, and various ANN-based approaches, including deep learning techniques. The ensuing evaluation will consider accuracy metrics such as RMSE and MAPE to delineate the strengths and limitations of each methodology, providing insights crucial for informed decision-making in the realm of sales prediction.

3.5. Ensemble Forecasting
3.5.1. Overview
Ensemble forecasting involves combining predictions from multiple models to enhance overall accuracy and robustness. This approach mitigates the limitations of individual models and leverages the diversity of forecasting techniques. The amalgamation of classical time-series methods, Prophet, and various ANN-based models offers a holistic ensemble forecasting strategy.

3.5.2. Applications
Studies have demonstrated the efficacy of ensemble forecasting in diverse applications. applied a combination of ARIMA and neural networks for cryptocurrency price forecasting, showcasing the potential of ensemble techniques in capturing the complexity of financial markets. The exploration of ensemble methods in the context of sales prediction aims to harness the complementary strengths of classical, modern, and deep learning methodologies.

3.6. Explainable AI in Sales Prediction
3.6.1. Rationale
The increasing adoption of artificial intelligence (AI) in sales prediction necessitates a focus on explainability. Understanding the decisions made by forecasting models is critical for gaining stakeholders' trust and facilitating informed decision-making. This subtopic explores the integration of explainable AI techniques within classical, Prophet, and ANN-based models.

3.6.2. Techniques
Various techniques, such as LIME (Local Interpretable Model-agnostic Explanations) and SHAP (SHapley Additive

exPlanations), offer insights into the inner workings of complex models. Applying these techniques to classical time-series models and deep learning architectures allows for a nuanced understanding of how predictions are influenced by input features, addressing the interpretability concerns associated with certain forecasting methodologies.

3.7. Hybrid Models for Enhanced Predictions

3.7.1. Conceptual Framework

Hybrid models combine the strengths of different forecasting methodologies to overcome individual limitations, presenting a promising avenue for achieving more accurate predictions. This subtopic explores the conceptual framework of hybrid models, emphasizing the synergies between classical time-series models, Prophet, and ANN-based approaches.

3.7.2. Case Studies

Investigating case studies where hybrid models have been successfully implemented provides valuable insights into their real-world applicability. For instance, Khashei and Bijari's (2010) hybrid model combining ANN with ARIMA showcased improved prediction accuracy. Analyzing similar hybrid approaches within the sales prediction domain sheds light on their potential to outperform individual methodologies and offers practical guidance for model selection in diverse business contexts.

Future Outlook

The trajectory of sales prediction is poised for significant advancements as the field continues to integrate cutting-edge technologies and methodologies. The future outlook for this domain involves embracing emerging trends and addressing evolving challenges to enhance accuracy, interpretability, and adaptability.

4.1. Integration of Explainable AI

Explainable AI will be pivotal in shaping the future of sales prediction. As businesses increasingly rely on sophisticated models, the need to interpret and trust these models becomes paramount. Future research will likely focus on refining and standardizing explainable AI techniques within classical time-series models, Prophet, and artificial neural networks. Bridging the gap between model complexity and interpretability will empower stakeholders to make informed decisions based on transparent and understandable forecasting outcomes.

4.2. Advancements in Deep Learning Architectures

The evolution of deep learning architectures, particularly recurrent neural networks (RNNs) and convolutional neural networks (CNNs), will continue to influence the landscape of sales prediction. Future research may explore novel architectures and training strategies to enhance the capabilities of these models in capturing intricate temporal patterns and dependencies within sales data. Additionally, the integration of attention mechanisms and transformer architectures could offer further improvements in handling long-term dependencies and non-linear trends.

4.3. Hybrid Methodologies for Robust Predictions

Hybrid methodologies, combining the strengths of classical time-series models, Prophet, and artificial neural networks, are likely to gain prominence. Future research will focus on refining and customizing hybrid approaches for specific industries and use cases. Investigating the optimal combinations of models and leveraging ensemble techniques will contribute to more robust and adaptable forecasting systems, mitigating the limitations inherent in individual methodologies.

4.4. Ethical Considerations and Bias Mitigation

As AI becomes increasingly ingrained in decision-making processes, ethical considerations and bias mitigation will be at the forefront of future developments. Researchers and practitioners will need to address issues related to fairness, transparency, and accountability in sales prediction models. Striking a balance between model complexity and ethical considerations will be crucial to ensure that forecasting systems benefit all stakeholders equitably.

4.5. Evolution in the Application of Sales Prediction: Past vs. Future

Past Application

The application of sales prediction in the past was predominantly characterized by the utilization of classical time-series models, such as Moving Average (MA), Autoregressive Integrated Moving Average (ARIMA), and Seasonal ARIMA (SARIMA). These models served as the bedrock for forecasting, leveraging historical sales data to make predictions based on trends, seasonality, and cyclic patterns. The focus was on simplicity, interpretability, and the ability to handle relatively structured and moderately complex datasets.

Traditional methods excelled in scenarios where sales exhibited linear trends and predictable seasonal fluctuations. Exponential smoothing methods, like Holt-Winters (HW), were employed to address seasonality in a dynamic yet interpretable manner. However, challenges arose when confronted with non-linear and volatile patterns, requiring additional sophistication in forecasting techniques.

4.6. Future Application

The future of sales prediction heralds a paradigm shift, with a trajectory towards more advanced and adaptive methodologies. The integration of explainable AI techniques becomes pivotal, addressing the demand for transparency in complex models. Future applications will prioritize not only accuracy but also the ability to convey the rationale behind predictions, enhancing trust and facilitating more informed decision-making.

Deep learning architectures, including Recurrent Neural Networks (RNNs) and Convolutional Neural Networks (CNNs), are expected to play a central role in future applications. These models possess the capability to discern intricate patterns, capture long-term dependencies, and automatically extract features from unstructured data. The emphasis will be on refining these architectures, exploring novel variants, and integrating attention mechanisms to further elevate their forecasting capabilities.

Hybrid methodologies, combining the strengths of classical models, modern techniques like Prophet, and deep learning approaches, will become increasingly prevalent. The future application of sales prediction involves customizing hybrid models for specific industries and use cases, creating robust systems that can adapt to the evolving dynamics of markets.

Moreover, ethical considerations and bias mitigation will be integral components of future applications. As AI systems become more pervasive, the emphasis on fairness, accountability, and transparency will shape the development and deployment of sales prediction models, ensuring equitable benefits for all stakeholders.

In essence, while the past focused on foundational models and interpretability, the future envisions a landscape where advanced technologies, explainability, and ethical considerations converge to redefine the application and impact of sales prediction methodologies.

5. Conclusion

The evolution of sales prediction methodologies from the past to the future represents a transformative journey marked by shifts in technology, methodology, and ethical considerations. In the past, classical time-series models, such as Moving Average (MA) and Autoregressive Integrated Moving Average (ARIMA), laid the groundwork for forecasting by leveraging historical data to identify trends and seasonality. The focus was on simplicity, interpretability, and adaptability to moderately complex datasets.

Looking forward, the future application of sales prediction reflects a paradigm shift toward more advanced and adaptable methodologies. Explainable AI emerges as a cornerstone, addressing the need for transparency in complex models. As businesses increasingly rely on sophisticated forecasting tools, the ability to interpret and trust these models becomes paramount. Future applications prioritize not only accuracy but also the ability to convey the rationale behind predictions, fostering trust and informed decision-making.

Deep learning architectures, including Recurrent Neural Networks (RNNs) and Convolutional Neural Networks (CNNs), are poised to reshape the landscape of sales prediction. These models, known for their ability to discern intricate patterns and capture long-term dependencies, represent the vanguard of predictive analytics. The evolution of these architectures will likely involve refining existing models, exploring novel variants, and integrating attention mechanisms to enhance forecasting capabilities.

Hybrid methodologies, combining classical models with modern techniques like Prophet and deep learning approaches, emerge as a dominant trend. The future application of sales prediction involves customizing hybrid models for specific industries and use cases, creating robust systems capable of adapting to the dynamic nature of markets.

Moreover, ethical considerations and bias mitigation become integral components of future applications. As AI systems become more pervasive, ensuring fairness, accountability, and transparency will shape the development and deployment of sales prediction models. Striking a balance between model complexity and ethical considerations is crucial to ensure equitable benefits for all stakeholders.

In conclusion, the future of sales prediction signifies a convergence of advanced technologies, explainability, and ethical considerations. It is a landscape where the fusion of classical wisdom with modern innovations will redefine the application and impact of forecasting methodologies, ultimately empowering businesses to make more informed and responsible decisions.

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