IST 707 – Applied Machine Learning

Project Proposal

Title: Inventory Demand Forecasting

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Introduction

Our project aims to develop an AI system to revolutionize inventory forecasting for retailers. We will simplify the process of predicting demand and segmenting customers to optimize stock levels and marketing strategies. The goal is to enhance inventory management and customer engagement without the need for complex technical language. If our system works well, it will help stores and customers a lot. Stores can save money by stocking the right amount of stuff and not wasting anything. Customers will enjoy shopping more because they'll always find what they want in stock. Overall, our system helps stores make more money and keeps customers happy. This is important for stores to do well in the competitive retail world.

Literature Review

The use of machine learning (ML) and artificial intelligence (AI) is changing how we manage inventory and predict demand, moving away from old-school stats to smarter, data-driven methods. Articles like "Inventory Management and Demand Forecasting Improvement of a Forecasting Model Based on Artificial Neural Networks" show us how neural networks and a mix of stats and AI can make guessing future demand more accurate, especially for seasonal items and in real shops. This shift is exciting because ML and AI can understand and learn from complex patterns in the data we give them, leading to better guesses about what people will buy. But, getting these systems right depends a lot on choosing the right ML tools and tweaking them to work well together, especially when it comes to using new tricks to make predictions more accurate.

However, it's not all smooth sailing with ML and AI in this field. A big hurdle is making sure we have good, complete data to feed into these systems. If the data is missing bits or out of date, the predictions won't be as good. Also, it's tough to make one system that works for all kinds of inventory or market situations without a lot of custom work. And, for smaller teams or businesses, the techy side of setting up and keeping these ML systems running can be too much to handle.

To really get the most out of ML and AI for keeping stock and figuring out what will be in demand, we need to get better at collecting and handling our data, make these systems more flexible for different situations, and find ways to make them less of a hassle to use. If we can tackle these issues, ML and AI could make a huge difference in making sure businesses have what customers want, when they want it, without overspending or wasting resources, all while keeping customers happy.

Data and Methods

The Walmart Sales and Demand Dataset contains information from 45 Walmart stores across the US, with 421.5k rows and 10 columns. It includes data on weekly sales, holiday events, markdown events, and economic indicators like CPI and Unemployment Index. The dataset has been widely used and vetted by data scientists and machine learning practitioners, making it reliable for predictive modeling tasks in retail. We'll preprocess the data by handling missing values and encoding categorical variables. We'll use different kinds of models to make predictions, like fancy math models (Gradient Boosting, Random Forest) and smart computer models (RNNs, LSTM networks). We'll also mix these models together to get even better predictions. Before we do any math, we'll clean up the data, make new features from it, and make sure all the numbers are in the same scale. Then, we'll check how good our predictions are by comparing them with what happened, making sure they work well for both guessing how much stuff we need and understanding what customers like to buy.

Impact

The adoption of LSTM and CNN models in inventory management and demand forecasting impacts several key stakeholders, highlighting the project's widespread significance.

Businesses, particularly in retail and manufacturing, will directly benefit from improved forecasting accuracy. This leads to optimized inventory levels, reduced costs, and enhanced profitability. For them, better demand predictions mean more informed production and distribution decisions, directly impacting their bottom line and market responsiveness.

Supply chain professionals and logistics managers also have a vested interest in this project's success. Enhanced forecasting models can make supply chains more adaptable and efficient, improving service levels and reducing waste. This not only supports operational goals but also aligns with sustainability efforts.

The academic and research community will find value in the advancements this project promises. It enriches the academic discourse on AI's role in supply chain management, potentially guiding future research and influencing educational content. This synergy between practical application and theoretical exploration fosters a richer understanding and innovation in the field.

In summary, the successful implementation of advanced forecasting models stands to benefit a broad spectrum of stakeholders by setting new benchmarks in supply chain efficiency and knowledge expansion.

Risks

Integrating LSTM and CNN models for inventory management and demand forecasting brings about its share of risks, including the challenge of securing high-quality, comprehensive data for model training. Without adequate data, the precision of these advanced models could be compromised. Additionally, the complexity of LSTM and CNN models requires a deep understanding of machine learning to fine-tune and manage effectively, presenting a risk of overfitting where models excel on training data but falter on new data.

Addressing these risks demands a proactive strategy, emphasizing data management, technical expertise, and effective stakeholder engagement to ensure the project's success.

Project Plan

Period	Activity	Milestone
3/4 - 3/11	Stakeholder analysis EDA Initial model exploration	Stakeholder needs clarified, EDA completed
3/11 - 3/18	Data preprocessing Initial LSTM and clustering models	Preprocessed data, baseline models established
3/18 - 3/25	Model refinement and evaluation	Refined models with improved accuracy
3/25 - 4/1	Integration testing with inventory system	Successful model integration
4/1 - 4/8	Final evaluation and project report preparation	Project report finalized and ready for submission

References

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