INVENTORY MANAGEMENT: AN ARTIFICIAL INTELLIGENCE MODEL WITH TRANSFERT LEARNING

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SUMMARY

INTRODUCTION

In today's dynamic business world, effective inventory management is crucial to a company's profitability and competitiveness. Yet many organizations continue to struggle with inventory management challenges such as costly overages, disastrous stock-outs, and high operational costs. That's where Artificial Intelligence (AI) and Deep Learning come in.

This white paper explores how the judicious application of AI, highlighting transfer learning, can transform inventory management and optimize your company's operations.

The AI Model for Optimal Inventory Management

In an ever-changing business environment, effective inventory management is crucial to a company's profitability and competitiveness. That's why we've developed a powerful artificial intelligence (AI) model focused on predicting optimal stock levels. The main aim of this model is to enable companies to accurately determine how many products need to be stocked to meet demand, while avoiding the unnecessary costs associated with overstocking.

This revolutionary model combines AI expertise with historical sales data, purchase price data, inventory levels and other relevant variables to create a proactive, intelligent inventory management solution. By adopting this approach, companies can enjoy several significant benefits in managing their inventory:

1. Optimized supply: Optimal stock levels avoid costly overstocking, while maintaining sufficient quantities to meet customer demand.

2. Cost reduction: More accurate inventory management reduces the costs associated with maintaining stock and frequent replenishment.

3. Improved customer service: By avoiding stock-outs, companies can better respond to customer demand, improving customer satisfaction and avoiding lost sales opportunities.

4. Strategic planning: Forecasting stock levels helps companies to plan production, supplies and resources more strategically.

5. Market trend anticipation: Enables companies to anticipate fluctuations in demand and adapt sales strategies more effectively.

This innovative approach to inventory management is based on an AI model, which is developed in two main phases: the creation of a robust base model, and its adaptation to the specific needs of each company through transfer learning. In this first part of our white paper, we'll explore in detail how this basic model is built and trained, and the benefits it can bring to a company's inventory management. In the second part, we'll detail how this model can be adapted to the specific needs of each company, paving the way for smarter, more profitable inventory management.

BASE MODEL TRAINING: A METICULOUS APPROACH

The central objective of our initiative is to use the knowledge acquired during the training of the basic model to carry out transfer learning and adapt it to the specific needs of companies, a process we'll detail in greater detail in the second part of this white paper. To better understand this approach, we'll begin by exploring in detail the first stage of our project, which consists of training a basic model for inventory management.

Fundamental data collection and preparation

We used a massive dataset including over 70 stores and a significant amount of transactions, over a million transactions for 6890 products. This historical sales data, combined with information on purchase prices, inventory levels and other relevant variables, forms the essential backdrop to our model. The data collection and preparation process was essential to ensure its quality and usefulness in training our model. The diversity of stores and products, as well as the impressive volume of transactions, required careful management to ensure an accurate representation of reality in our case study. The data cleaning, processing and structuring steps were crucial to ensure that our inventory management model could take full advantage of this rich source of information.

Creating Reference Models

Before diving into the design of our AI-based inventory management model, we took care to create reference models. These reference models encompass classic machine learning methods, such as linear regression and ensemble methods. The main purpose of these reference models is to serve as a point of comparison, enabling us to evaluate the performance of our basic model in a rigorous and thorough way.

Designing the Basic Inventory Management Model: Multilayer Perceptron (MLP), the Ideal Choice

In our exploration of intelligent inventory management, we focus on the selection of the initial model, a crucial step for the future of our project. This model will serve as a solid foundation for our transfer learning approach, which we'll describe in greater detail later in this document.

After a careful analysis of the various options, we opted for the Multilayer Perceptron (MLP) as the basic model. The MLP stands out for its ability to efficiently and accurately extract key features from data. This feature makes it the ideal choice for our initial model.

By using MLP as a starting point, we ensure that our inventory management model is robust and flexible, ready to be adapted to the specific needs of each company. This reinforces our confidence in our ability to offer tailor-made solutions that exceed business expectations.

Optimization of Base Model Hyperparameters

Hyperparameter optimization plays a crucial role in the formation of our base model. This step involves adjusting the internal parameters of our model so that it can best extract the important information from our data.

We have used two techniques for this optimization, each with its own advantages:

- Grid Search: This technique is a systematic method that explores a predefined set of hyperparameter combinations. This allows us to test different configurations for our model, such as learning speed and neural network structure. It ensures that we don't overlook any potential options.
- Bayesian optimization: This more advanced approach relies on probabilistic models to estimate the expected performance of different hyperparameter configurations. It takes into account previous results to decide which configurations deserve further attention. This is particularly useful when the hyperparameter space is complex.

By combining these two techniques, we were able to find the best settings for our base model, resulting in an improvement in the accuracy of our predictions. This reinforces the overall robustness of our inventory management model, preparing it to be adapted to your company's specific needs, as we'll see in the rest of this white paper.

Rigorous evaluation of the basic model

Before moving on to the next stage of our project, we carefully evaluated the performance of our basic model. We used a set of relevant metrics such as Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and Coefficient of Determination (R^2) to measure the accuracy of our predictions and make a comparison with the reference model.

To visualize the performance of our base model in relation to the reference models, we created comparison curves. These graphs clearly illustrate the differences in accuracy and reliability between the models.

Model	RMSE	Correlation	MAE	RAE	RRSE	R2
Random Forest	23.3435	0.812994	8.96228	0.504168	0.58709	0.655325
Linear Regression	23.8307	0.802579	11.2327	0.631891	0.599343	0.640788
Lasso	33.9357	0.547551	15.9419	0.896799	0.853486	0.271562
Ridge	23.8388	0.801596	11.1452	0.626969	0.599547	0.640543
ElasticNet	38.4939	0.251833	17.1119	0.962617	0.968125	0.0627341
KNN	26.1298	0.765809	10.7885	0.606903	0.657167	0.568132
Base Model	17.1057	0.923358	7.52769	0.406239	0.3849	0.85185

In summary, evaluation of the basic model revealed remarkable performance. Its low RMSE (Root Mean Squared Error) of 17.01 attests to its ability to produce predictions close to actual values on average. A high correlation of 0.92 indicates a robust linear relationship between predictions and actual observations, highlighting the model's accuracy in capturing trends. The MAE (Mean Absolute Error) of 7.53 reveals moderate individual errors, while the RAE (Relative Absolute Error) of 0.40 demonstrates a clear improvement over a naive prediction. A RRSE (Relative Root Squared Error) of 0.38 and an R2 (Coefficient of Determination) of 0.85 confirm that the model explains a significant proportion of the variance. These results unequivocally confirm the unquestionable effectiveness of the basic model in extracting relevant knowledge.

Conclusion of Part One

In this first part of our white paper, we delved into the world of Artificial Intelligence-assisted inventory management. We explored why AI has become an essential tool in modern inventory management, highlighting its abilities to make informed decisions and optimize operations.

We established the key objectives of our project, including the development of a basic model that will serve as the foundation for transfer learning, utilizing Deep Learning principles, and the use of diverse data to train this model.

In a methodical way, we described the complete process of training our basic model, focusing on data collection and preparation, the creation of reference models, the design of our basic model, the optimization of hyperparameters, and finally, the rigorous evaluation of this model.

We examined the results of our model, illustrated its performance with comparative curves, and provided information on the time required to train it. All this forms the solid foundation on which we will build the rest of our AI-based inventory management initiative.

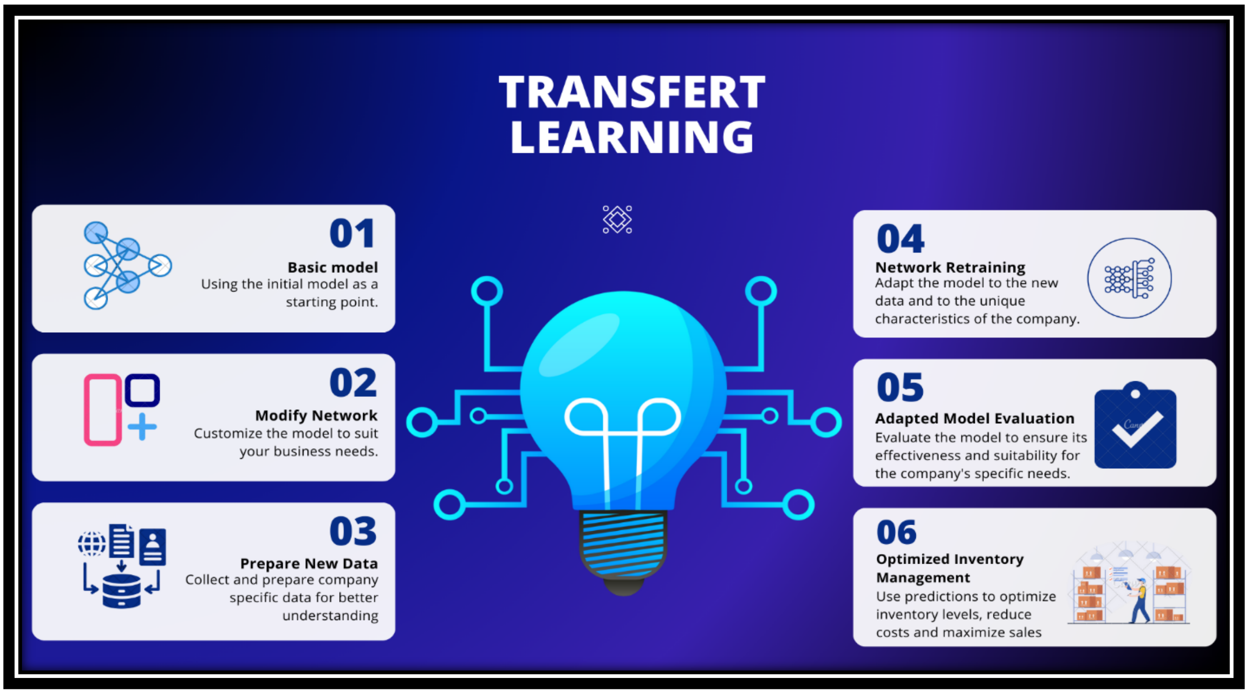
In the second part of this white paper, we will dive even deeper by exploring how we're using our basic model as a starting point for transfer learning. We will also detail how we adapt the model to specific company data, with a particular focus on the tangible benefits that businesses can derive from this approach.

PART 2: TRANSFER LEARNING FOR CUSTOMIZED ADAPTATION

In the first part of this project, we established a Deep Learning-based inventory management model, ready to be refined to meet your company's specific needs. Now, in this crucial second phase, we explore how to use this initial model as a starting point for personalized adaptation using transfer learning.

Why Transfer Learning?

Transfer learning is a powerful machine learning strategy that transfers the knowledge acquired by a model when learning on one dataset to another model intended for a different dataset. In our case, this means that we can leverage the initial model we developed in the first part of the project, and adjust it to align with the specifics of your business.



Transfert Learning Steps

1. Data Customization: Collect and prepare your specific company data, including historical sales data, purchase price information, inventory levels and other variables unique to your business.

2. Knowledge Transfer: Integrate your company's data into the initial model to create a version tailored to your needs.

3. Fine-Tuning: Adjust the model's parameters so that it learns from your company's specific data, while preserving previously acquired knowledge.

4. Validation and Evaluation: Test the adapted model with your validation data and evaluate its performance.

5. Put into production: Once the model is optimized and validated, deploy it for production use in your company.

Benefits of Transfer Learning

Using Transfer Learning to adapt the initial model to your company offers a number of advantages:

- Save time and effort: Avoid starting from scratch by using a pre-existing base model.
- Improved accuracy: The model will be better aligned with your specific data, improving its accuracy.
- Cost savings: By avoiding the need to build a model from scratch, you save time and money.
- Leverage pre-existing expertise: Capitalize on the knowledge already acquired by the initial model.

CASE STUDY WITH TRANSFER LEARNING

COMPANY DATA

In this case study, we focus on demand prediction for thousands of product families sold in Favorita stores, located in Ecuador. The training data is rich in detail, including information such as dates, store characteristics, product attributes, the presence of promotions for each item, as well as numerical sales data. Additional files provide additional information that can be valuable in the process of creating predictive models.

id	date	store_nb	family	sales	onpromotion
0	2013-01-01	1	AUTOMOTIVE	0	0
1	2013-01-01	1	BABY CARE	0	0
2	2013-01-01	1	BEAUTY	0	0
3	2013-01-01	1	BEVERAGES	0	0
4	2013-01-01	1	BOOKS	0	0
:	:	:	:	:	:
3000883	2017-08-15	9	POULTRY	438.133	1
3000884	2017-08-15	9	PREPARED FOODS	154.553	148
3000885	2017-08-15	9	PRODUCE	2419.729	8
3000886	2017-08-15	9	SCHOOL AND OFFICE SUPPLIES	121.000	0

DATA PRE-PROCESSING

To ensure the quality and relevance of the data in our analysis, data pre-processing is essential. There are several key aspects to this step:

→ **ATTRIBUTE SELECTION GUIDE**

The decision to retain or delete certain columns depends on the context of your sales prediction model and the nature of the data. Here are some recommendations to guide you:

- COLUMNS TO KEEP

  1. Target variables: Keep the columns representing your target variable, i.e. the quantity of sales to be predicted.

2. Relevant variables : Keep columns likely to influence sales, such as information on prices, promotion, product availability, etc.

3. Temporal variables: Keep columns linked to date or season, to enable sales to be aggregated by time interval.

4. Relevant categorical variables : If certain product categories have an impact on sales, keep these columns to segment the data and create specific models if necessary.

- COLUMNS TO DELETE

1. Redundant columns: Eliminate columns containing essentially the same information.

2. Unnecessary or irrelevant data: Remove columns that have no direct link to sales or do not provide significant predictive value.

3. Columns with missing values: If a column has a large number of missing values and cannot be meaningfully imputed, consider deleting it.

4. Columns with data leakage: Be aware of columns containing information on future sales or not available at the time of prediction.

In our case study, we retain all columns, including date, store_nbr (store identifier), product family, quantitative sales and the Boolean variable onpromotion. All this information is relevant to our sales prediction model.

→ **DATA AGGREGATION**

Data aggregation plays an essential role in inventory management. It consists in grouping raw data into forecast-relevant time intervals, thus simplifying analysis and decision-making. Aggregated information and forecasts help optimize procurement, replenishment and stock level management decisions. There are two main aspects to this step:

- Interval selection

  the time intervals best suited to your business, whether daily, weekly, monthly, or according to other relevant criteria. In our case study, we chose monthly aggregation for efficient inventory management.

- For each interval, you'll calculate aggregates such as sum of sales, average price, or other relevant measures. This provides a consolidated view of performance and trends for each period.

  In our study, we opted to aggregate data by month, grouping data by month, product family and store to obtain monthly sales by product category at store level.

→ **DATA NORMALIZATION AND STANDARDIZATION GUIDE**

Data normalization and standardization are essential, especially when working with machine learning, deep learning or transfer learning models. These techniques aim to put data into a consistent, scalable format for reliable results and easier model convergence. The main reasons for data normalization are to ensure that numerical variables are at the same scale. This prevents weight updates in the neural network from being dominated by variables with higher values. In our case, as our data contains no continuous numerical variables, normalization is not necessary. Months, years and the target variable "sales" do not require normalization.

→ DATA ENCODING

Machine learning algorithms require data in digital format. Encoding is essential to convert textual, categorical and other data formats into numbers that the algorithms can handle efficiently. In many applications, certain attributes are categorical or textual, such as product types, store identifiers or categories. Encoding transforms these attributes into numerical form, enabling learning models to use them efficiently. In our case, we use one-hot encoding for categorical variables such as 'store_nbr' and 'family'. One-hot encoding consists in creating a binary vector for each category, which facilitates use by machine learning models.

MODEL ADAPTATION

Model adaptation to your business data is based on the central principle of transfer learning. The aim is to transfer the knowledge and skills acquired by the initial model to the new task, while allowing customization to meet your company's specific needs. This step is as follows:

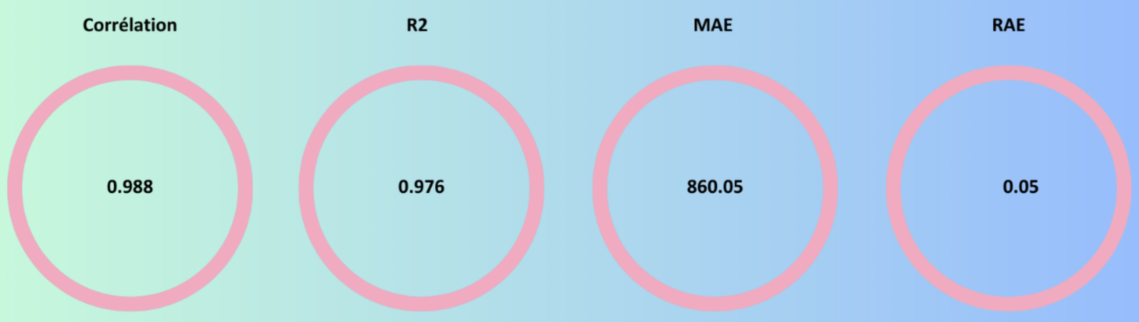
1. First, the base model is loaded using the weights obtained during its initial training.

2. Creating the Adapted Model: Next, a model is created with inputs adapted to your specific data, and the various layers of the basic model are incorporated into this adapted model.

This ensures that the knowledge previously gained from the initial model is put to good use, while allowing customization to meet the unique needs and characteristics of your business.

CASE STUDY RESULTS

After adapting the inventory management model to your company's specific business data using transfer learning, it is essential to closely examine the results of this adaptation. This assessment allows us to measure the model's ability to produce accurate predictions and optimize your inventory levels based on the unique characteristics of your business. Here is an overview of the key findings from our case study:



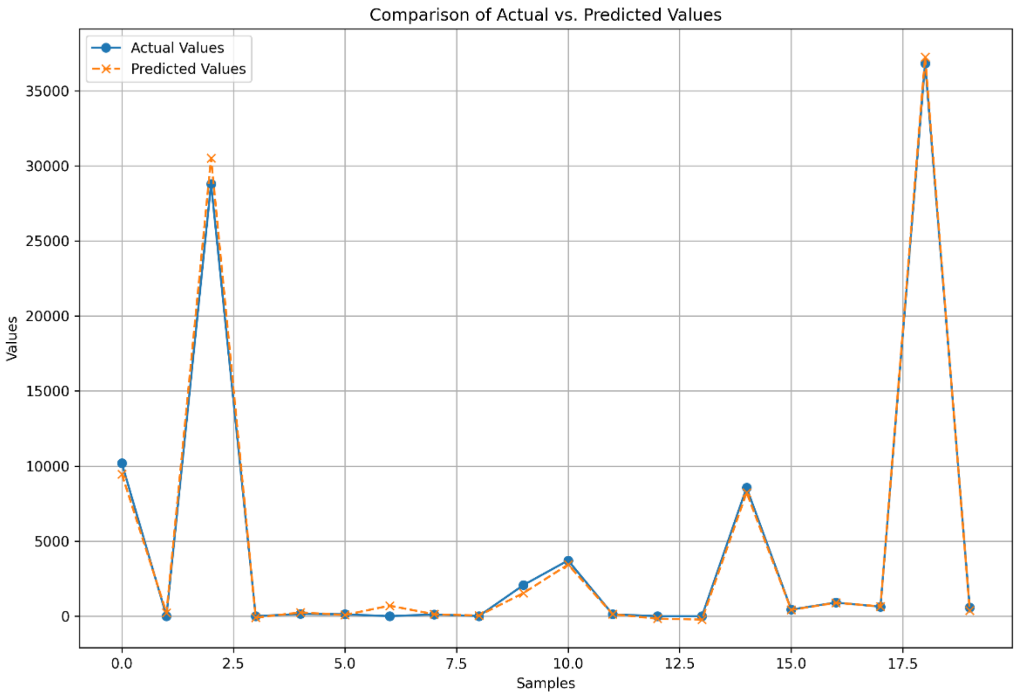
1. Correlation:
- Correlation measures the linear relationship between the model's predictions and the actual values.
- The model achieved a correlation of 0.9883, indicating a strong correspondence between predictions and actual data.

5. Coefficient of Determination (R2):
- The coefficient of determination R2 measures the proportion of total variance in the data explained by the model.
- The model achieved an R2 of 0.9768, indicating that it explains nearly 97.68% of the variance in the data, demonstrating its strong predictive capability.

2. Mean Absolute Error (MAE):
- MAE measures, on average, the absolute difference between the model's predictions and the actual values.
- The model achieved an MAE of 860.05, meaning that predictions have an average absolute error of 860 units compared to the true values.

3. Relative Absolute Error (RAE):
- RAE is a normalized metric expressing MAE as a percentage of actual values.
- The model obtained an RAE of 0.0566, indicating that predictions have an average absolute error of only 5.66% relative to the true values.

Additionally, to provide a more concrete visualization of the quality of the predictions, the following figure compares the actual values to the values predicted by the model. This allows you to visually see the agreement between the model predictions and the actual data.



These results highlight the effectiveness of the model, highlighting that it can be successfully applied in various companies to meet their specific needs. The model convincingly demonstrates its ability to generate accurate predictions, thereby optimizing inventory levels and facilitating informed management of operations in varied industrial contexts. This is strong evidence of its relevance and adaptability, demonstrating its potential to significantly contribute to improving inventory management and operational efficiency within your industry.

MODEL DEPLOYMENT

Once the inventory management model has been adapted to your company's specific data, deployment enables you to use it for making informed stock management decisions. Here's how to use the deployed model:

1. Integration into Inventory Management System: Integrate the model into your company's inventory management system. You can create an API or a custom interface to facilitate easy interaction with the model.

2. Input Data: Provide the model with the required input data to make predictions. This data can include information about current stock levels, purchase prices, recent sales data, and other relevant variables.

3. Model Invocation: Use the API or interface to call the model with the input data. The model will process this data and generate predictions for optimal stock levels.

4. Stock Level Predictions: The model will return predictions for stock levels for each product or product category. These predictions will indicate recommended order quantities or quantities to maintain in stock.

5. Decision Making: Use the model's predictions as a guide for making stock management decisions. You can adjust stock levels accordingly by placing additional orders or adjusting forecasts based on the model's predictions.

6. Monitoring and Reassessment: Regularly monitor the model's performance in a real production environment. Periodically reassess the model's parameters and input data to ensure that predictions remain accurate.

7. User Integration: Train users within your company to use the model's predictions effectively. Ensure they understand how to interpret the results and make informed stock management decisions.

8. Automation: For more efficient management, consider automating order or replenishment processes based on the model's predictions. This can result in time and resource savings.

9. Continuous Improvement: Continue to collect data and update the model over time. Market trends and customer behaviors change, and the model needs to adapt to remain accurate.

By using the deployed model in this manner, your company can optimize its stock levels, reduce inventory management costs, and improve customer satisfaction. It also allows you to better anticipate demand fluctuations and adjust sales strategies accordingly.

CONCLUSION

This white paper has provided an in-depth exploration of AI-assisted inventory management and the role of Deep Learning in this domain. It has underscored the crucial importance of effective inventory management in today's dynamic business landscape and has shed light on the advantages of AI in making informed decisions and optimizing operations.

We have developed a groundbreaking artificial intelligence (AI) model focused on predicting optimal stock levels, offering businesses the ability to accurately determine the quantity of products to stock to meet demand while avoiding unnecessary costs associated with overstocking. This model combines AI expertise with historical sales data, purchase price data, inventory levels, and other relevant variables to create a proactive and intelligent inventory management solution.

Using this model as a starting point, we meticulously detailed the training of the basic model, emphasizing data collection and preparation, the creation of reference models, the design of the basic management model, hyperparameter optimization, and the rigorous evaluation of this model. The results unequivocally confirm the undeniable effectiveness of this basic model in extracting relevant knowledge. In the second part of this white paper, we explored how we leverage this basic model as a foundation for transfer learning, adapting it to the specific data of each company. Transfer learning is a powerful strategy that enables us to transfer the knowledge gained from the initial model to a model intended for a different dataset, allowing for customization to meet unique business needs.

In conclusion, the judicious application of AI, with a focus on transfer learning, has the potential to revolutionize inventory management and optimize your company's operations. This approach can save time, reduce costs, improve accuracy, and leverage pre-existing expertise for smarter and more profitable inventory management.