

PHASE 2

PRODUCT DEMAND PREDICTION

INNOVATION:

Innovations in product demand prediction are crucial for businesses to optimize their operations, reduce waste, and meet customer needs effectively. Here are some innovative approaches and technologies that have emerged in recent years for product demand prediction:

- 1. Machine Learning and AI:** Machine learning algorithms, including deep learning, have revolutionized demand forecasting. These algorithms can analyze vast amounts of historical data, identify patterns, and make accurate predictions. They adapt to changing market conditions and can handle complex relationships between variables.
- 2. Predictive Analytics:** Predictive analytics combines historical data, statistical algorithms, and machine learning techniques to forecast future demand. It's being used in various industries, from retail to manufacturing, to optimize inventory management and supply chain operations.
- 3. Big Data:** The proliferation of data sources, including social media, IoT sensors, and online customer behavior, has provided businesses with a wealth of information for demand prediction. Big data analytics can identify emerging trends and consumer preferences.
- 4. Advanced Forecasting Models:** Beyond traditional statistical methods like time series analysis, businesses are adopting advanced forecasting models like Prophet, ARIMA, and Exponential Smoothing. These models can capture seasonality, trends, and irregularities in data.

5. Demand Sensing: Demand sensing is a real-time approach to demand forecasting that uses data from various sources like point-of-sale data, weather forecasts, and social media to adjust forecasts dynamically. This helps companies respond quickly to changing market conditions.

6. Supply Chain Visibility: Innovations in supply chain technology, such as the Internet of Things (IoT), blockchain, and RFID, provide greater visibility into supply chain operations. This visibility can enhance demand prediction accuracy by tracking inventory movements and identifying potential bottlenecks.

7. Collaborative Forecasting: Businesses are involving various stakeholders, including suppliers and customers, in collaborative forecasting efforts. This approach can lead to more accurate predictions by incorporating real-time data and insights from all parts of the supply chain.

8. Demand Forecasting Software: Many software solutions offer advanced demand forecasting capabilities, often integrating AI and machine learning. These tools make it easier for businesses to implement sophisticated forecasting methods.

9. Demand Forecasting as a Service (DFaaS): Cloud-based DFaaS platforms provide businesses with on-demand access to powerful demand forecasting tools without the need for extensive infrastructure investments. These platforms often come with pre-built models and data integration options.

10. Behavioral Economics: Understanding consumer behavior and psychology is becoming increasingly important in demand prediction. Businesses are incorporating principles from behavioral economics to account for irrational consumer decision-making in their forecasts.

11. Simulations and Scenario Planning: Businesses are using simulation models and scenario planning to assess the impact of various external factors on demand, such as economic downturns, natural disasters, or geopolitical events.

12. Edge Computing: In industries where real-time data is critical, edge computing can be used to process data locally at the source, allowing for faster demand predictions and responses.

Innovation in product demand prediction continues to evolve rapidly as technology advances and as businesses seek to improve their competitive edge. Adopting these innovations can help companies make more accurate forecasts, reduce costs, and better meet customer expectations.

TRAINING AND TESTING:

Data Collection: Gather historical data related to your product's demand. This data should include information about the product, such as price, promotions, seasonality, and any other relevant factors that might influence demand.

Data Preprocessing: Clean and prepare your data. This may involve handling missing values, encoding categorical variables, and normalizing or scaling numerical features.

Feature Engineering: Create relevant features that can help your model better understand the patterns in the data. For example, you might create lag features to capture past demand trends.

Split Data: Split your data into a training set and a testing set. Typically, you might use 70-80% of the data for training and the remaining 20-30% for testing.

Choose a Model: Select a machine learning or time series forecasting model that is suitable for your problem. Common choices include linear regression, decision trees, random forests, or more advanced techniques like ARIMA or LSTM for time series forecasting.

Train the Model: Fit your chosen model to the training data. Make sure to use appropriate evaluation metrics, such as Mean Absolute Error (MAE) or Root Mean Squared Error (RMSE), to assess its performance during training.

Hyperparameter Tuning: Fine-tune your model's hyperparameters to optimize its performance. This might involve techniques like grid search or random search.

Evaluate the Model: Once your model is trained, evaluate its performance on the testing set to ensure it generalizes well to unseen data.

Iterate and Improve: Depending on the results, you may need to iterate on your model, data preprocessing, or feature engineering to improve its accuracy.

Deployment: When you are satisfied with the model's performance, you can deploy it in a production environment to make real-time predictions.

Monitoring and Maintenance: Continuously monitor the model's performance in the production environment and retrain it periodically with new data to ensure it remains accurate.

It's important to note that the choice of model and approach can vary greatly depending on the specifics of your product and dataset. Additionally, machine learning models for demand prediction can be complex, and it's often helpful to consult with data scientists or machine learning experts if you're new to this field or dealing with a particularly

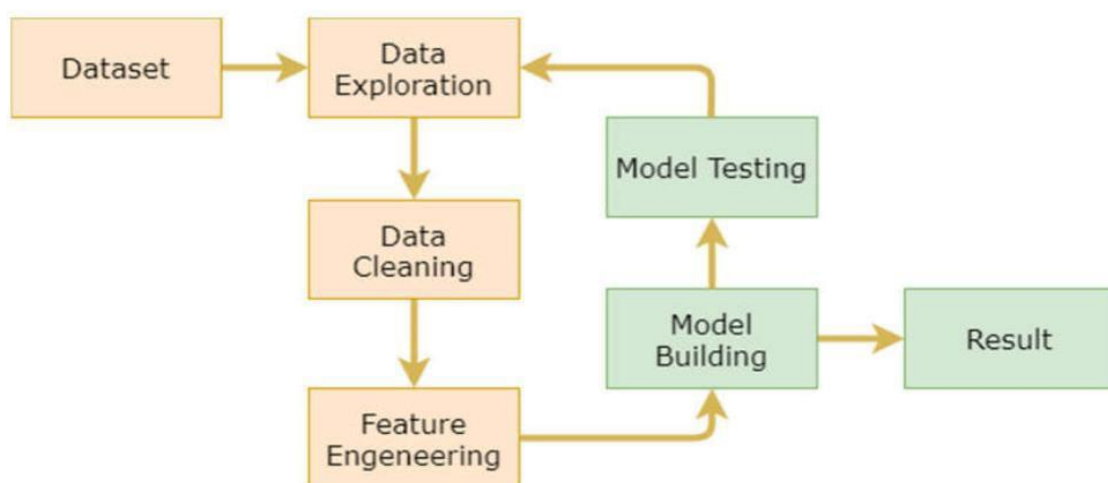


Table 1. Features types description.

Category	Features	Description
Date	8	Features based on date: day of week, weekend etc.
Price and promotions	3	Information about price and sales
Identity	1	Category
Aggregates	2	Averages over all available data on different aggregation levels

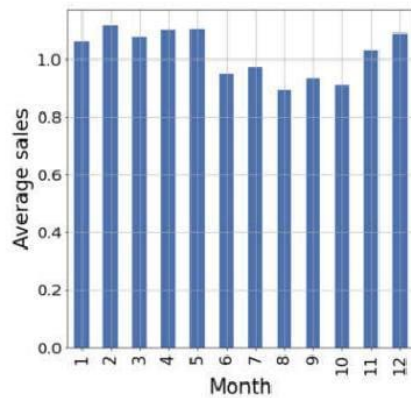


Figure 3. Sales distributions by month.

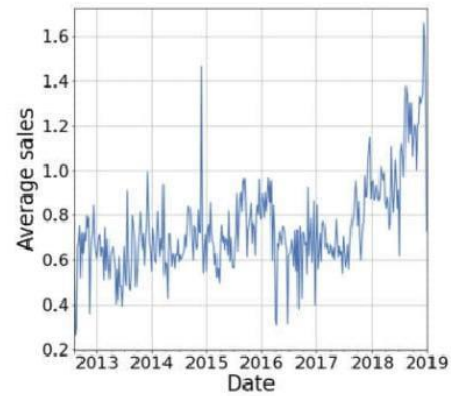


Figure 4. Sales by date.

For the correctness of training, validation and testing procedures, data were divided according to the rules of time series cross-validation as presented in figure 5. This avoided both types of data leaks from future and between items.

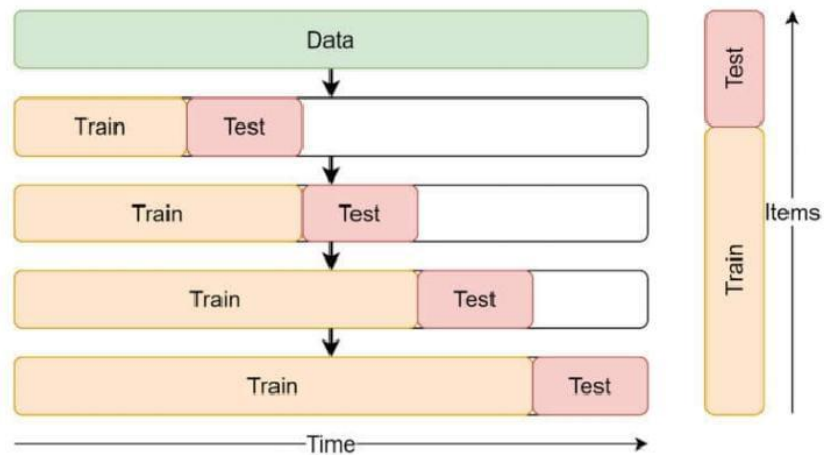


Figure 5. Time series and items cross validation.

Rest of Explanation: After splitting the data, you'll preprocess it, selecting features, handling missing data, and scaling numerical features as necessary. Then, you'll choose a machine learning algorithm (e.g., linear regression, decision trees, or neural networks) and train the model on the training data. Once trained, you'll evaluate its performance on the testing data.

Accuracy Metrics: Common metrics for accuracy evaluation in product demand prediction include Mean Absolute Error (MAE), Mean Squared Error (MSE), and Root Mean Squared Error (RMSE). These metrics help you quantify how well your model predicts demand by measuring the difference between predicted and actual values.