Welcome to:

Applications of Machine learning in Retail Industry and Supply Chain

Unit objectives

After completing this unit, you should be able to:

- Understand inventory management
- Gain knowledge on the machine learning use cases in inventory management
- Understand the benefits of predictive analytics to retailers in terms of intelligent inventory management
- Learn about the applications of inventory management with machine learning
- Understand the machine learning techniques for analyzing buying patterns
- Gain knowledge on make use of machine learning algorithms for retail analytics
- Understand the demand forecasting methods

Introduction

- The retail industry's use of data for competitive advantage is not new it has taken on a leading role in fostering digital and in-store consumer analytics.
- Deep learning approaches are currently in the process of transforming the retail industry.
- As artificial neural networks are becoming increasingly efficient, and as Graphics Processing Units (GPUs) are becoming more and more powerful, so is their retail influence.
- For retailers, data is clearly efficient, but it's all about putting it to function in the right areas and incorporating predictive capabilities.

Inventory management

- Inventory refers to the goods stored for use in the future.

- The distributor keeps track of the stored items and ensures that there is an inventory shortage to prevent "out of stock“.

- A system is called the management of inventory.

Few use case examples

- Use autonomous front-end sales robots to help customers find products, as well as back-end stock audits.

- Use of Internet-of-Things (IoT) to provide linked supply chain sensors and equipment capable of sending warnings regarding possible issues before they become complicated that would interfere with the action of goods.

- Use predictive analytics technology to help assess the availability of supply chain and weather-based demand.

Benefits of predictive analytics to retailers

- Filling customer needs faster by running comprehensive simulations that allow for evaluating the consequences of lateness or missed deadlines before they become a problem.

- Shrinkage reduction and stock maximization.

- Classification methods can be used to estimate the probability of a late order and how many days it will take.

Applications of inventory management with machine learning

- Robots: Seeing to customer satisfaction.
- IOT: Prevention first.
- Predictive analytics: Weathering demand.
- Analysing buying patterns.
- Analysing traffic patterns.

Robots-seeing to customer satisfaction

- The advanced commercial machines not only support buyers.
- Generate actual-time data through the use of device vision and machine learning to search stock and seek for brand and cost differences trends.
- The 5 multilingual commercial robot functions help buyers locate the items they are searching for by a viewable device interface, enhanced speech recognition and laser-based sensors that help them navigate the shop.

IOT: Prevention first

- Connectivity refers to their state beyond the position of items.

- Connected distribution equipment monitors will pass warnings regarding possible problems before the problem arise which would interrupt product motion.

- An Industrial IoT Accenture 2016 study concluded that strategic resources can preserve up to 12% on planned corrections and 30% on servicing, thus decreasing interruption from up to 70%.

- In 2014, Intel's the first full-united IoT production pilot ensured in saving of $9 million in only one plant.

Predictive analytics: Weathering demand

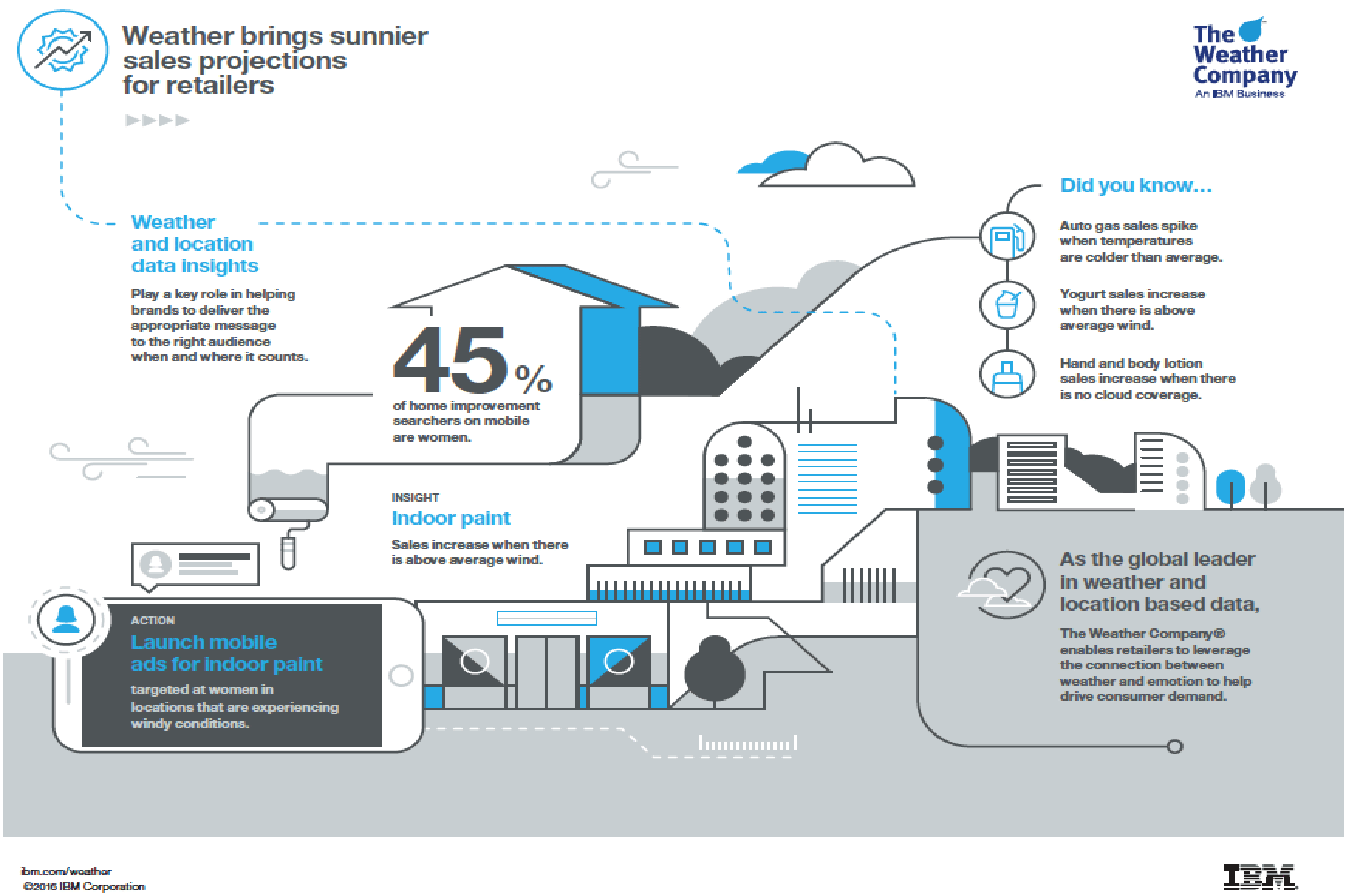

Figure: Weathering demand

Source: IBM Weathering demand.com

Analysing buying patterns

- One important area where retailers benefit from machine learning is to evaluate purchasing trends and patterns to recognize and plan for customized virtual bend-selling and upselling incentives.

- presenting consumers the most appropriate goods depending on their actions at the time.

- With AI and artificial intelligence technologies, it's simple to look how powerful tools they are for distributors:
  - Reading and hearing to information.
  - Knowing and growing from it.
  - Quickly and reliably.
  - Suggesting the better move without specific programming.

Analysing traffic patterns

- The use of deep learning to forecast patterns in retail foot traffic is that another important area of technology being developed by retailers.

- Through integrating video and audio from real-time traffic with digital fingerprinting from shopper's smartphones, sensors can detect in-store foot traffic.

- Significant progress has been made thanks to innovations such as deep learning, retail foot traffic monitoring and analysis.

- Some vendor solutions conduct a profound learning process that allows us to predict congestion.

Assortment planning

- The aim of assortment planning is to make the right product picks and order the right quantities to meet market demand.
- The business changes once a fashion season is finished.
- The excess inventory is often sold at heavily discounted prices at this point.
- The first step in the preparation of the collection is to understand the basics.
- Second, retailers also try to make their scheduling easier.
- We would combine stores with similar characteristics instead of planning for each store.

Why assort management is important

- Eliminate guess work.
- Feed the right stores.
- Get better information.

Eliminate guess work

- The main principle of proper planning for the assortment is to focus the decisions on information rather than guesses.
- This approach makes you nearer to the real variety of units for a particular style that you need to purchase.

Feed the right stores

- Overall sales has something to do with what customers want, it is just an indication of a place's traffic attracting ability.

- Each contact point of the customer is different.

- To get the best order amounts for each product based on what your customers need, you need to use assortment scheduling.

- Using product scheduling to customize the orders often increases customer experience, because consumers are more probable to find in-store what we need.

Get better information

- Increasing the preparation of assortments means improving the performance and amount of useful data that can affect the assortments tremendously.

- Proper variety planning puts things together so that before they go to visual merchandising, you can see assortments in one place.

- This is important before it's too late to catch issues.

Assortment planning to drive supply chain

- An end-to-end supply chain will work to schedule the:
  - Production.
  - Inventory.
  - Sales.
  - Margins necessary.

- It is possible for manufacturers to use market trend data and retailer requirements to modify their inventory levels.

Retail analytics

- The retail industry's that challenge is that the database and modelling resources that once served them well are no longer up to the task with ever larger data sets.

- Many players in the retail space use recommendation engines that apply scale-based deep learning.

- The inclination at that slow pace is to consider what is available as opposed to what is required.

- This capitulation is a failure treatment. To draw on insights found in their consumer analytics, the modern retailer needs to process large amounts of retail information in real time.

- For example, assume a consumer moves with a basket of goods in a store and the individual items contain RFIDs. Using a request, the retailer can make additional purchasing recommendations based on the composition of the basket as the consumer heads for checkout.

Domestic forecasting

- Demand forecasting is one of supply chains main concern. This aimed at maximizing inventory, reducing costs and rising customer loyalty, revenue and income.

- When competition among retailers on the market is growing day by day, companies concentrate on more anticipating analytical methods to lower their expenses and improve their profitability and profits.

- When consumers are unable to find the products they are looking for in the store, they can move to another competitor or buy replacement goods.

- It is very important to have an efficient supply predictive analytics and supply tracking program for successful operations planning in view of rivalry and monetary restrictions in the wholesale sector.

- Conventional techniques of predicting are predicated on methods to regression predicting.

- DL approaches have produced better predictions and outcomes in many research studies than conventional machine learning algorithms.

Case study: Forecasting seasonal footwear demand using ML

- Overview of retail fashion industry.

- The clothing sector has changed tremendously over the last several centuries, particularly since the advent of e-commerce. Customer’s flavour has been the main factor of clothing materials supply.

- The ongoing change in the behaviour of customers has resulted in smaller life cycles of goods and more unpredictable demand.

- Clothing companies need to create overriding methods that can be modified to the continuous improvements in the sector with all these challenges.

- Such methods include advertising as a tool to create supply and electronic capacity as enablers of growth, such as e-commerce and mobile apps.

- It is also important to establish deferral techniques by conducting components or semi-finished products in allocation facilities or warehouses to offer flexibility and give the business additional time to see stronger transmissions on the market.

Demand forecasting methods

- Market forecasts are highly complex in the garment and shoes sector leading to:
  - Unpredictable market.
  - High variability.
  - Stock-keeping Unit Intensity (SKU).
  - Temporary and trend products.
  - Brief life cycles and lack of cultural data.

- Current predicting techniques typically only take a single variable or at most a few factors into consideration, so that portion of the variability in the predicting system remains unknown while trends can be uncovered.

Predictor variables in demand forecasting

- Many prevalent sorts of details utilized in supply predicting is POS information or onshore records.

- which is commonly utilized in conventional regression predicting and advanced machine learning techniques.

- For instance, in creating a Demand Signal Registry (DSR) for a quickly-operating material product company (FMCG), Rashad and Spraggon (2013) observed that the main significant factors in influencing production from the many factors analysed are:
  - Year.
  - Month.
  - Weekday.
  - Holidays.

Traditional techniques v/s machine learning techniques

	Traditional Forecasting	Machine Learning Forecasting
Number of predictor variables	Single or a few	Unlimited
Data source	Mainly demand history	Multiple
Algorithms	A number of single-dimension algorithms	An array of integrated algorithms
Manual data manipulation and cleansing need	High	Low
Data requirements	Low	High
Technology requirements	Low	High

Figure: Traditional techniques v/s machine learning techniques

Source: https://docplayer.net/102535491-Forecasting-seasonal-footwear-demand-using-machine-learning.html

Methodology

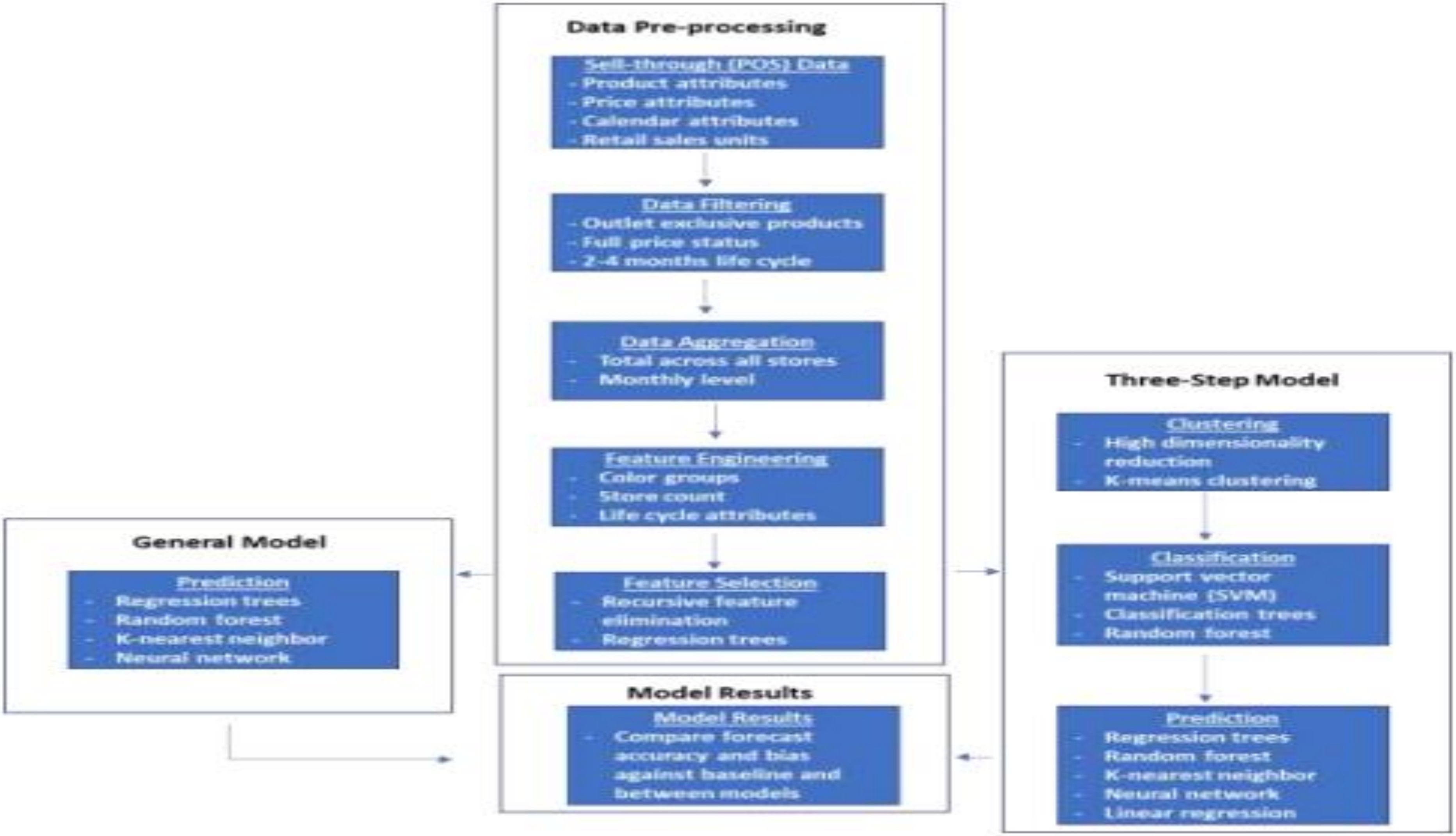

Figure: Methodology

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Machine learning techniques used

- Supervised learning techniques.
- Unsupervised learning techniques.
- Scope and granularity of data.

Supervised learning techniques

- Guided training presents a program with document which has specified performance parameter.

- The program "learns" how to measure this quality for new documents where the performance is uncertain.

- The concept of controlled teaching method utilized is given here:
  - Reversion and category trees.
  - Random forests.
  - Neural networks.
  - K-Nearest Neighbour (k-NN).

Unsupervised learning techniques

- Instead of predicting an output value, unsupervised learning attempts to learn patterns in information.

- The meaning of each unattended teaching method used as follows is defined:
  - K-Means clustering.
  - Stochastic Neighbour Embedding (t-SNE).

Scope and granularity of data

- Two forms of content are gathered by the organization: Sell-in information (batch) and sold from data (POS).

- The collected POS content included:
  - Brand characteristics.
  - Schedule characteristics.
  - Shop attributes.
  - Cost and advancement characteristics.
  - Sales units from 115 retail outlet stores at the regular type location level.

- Although the purpose of this venture is on supporting the determination of each design to purchase from the supplier throughout the year, the content are consolidated to the point at this choice. i.e. at the monthly price, throughout all stores.

List of attributes from the aggregated data by month at the style level

Variable category	Variable	Description
Meta Data	Style	Unique style number of each product
Meta Data	Style Description	Description of the style
Calendar	Year	Fiscal year
Calendar	Month	Fiscal month
Product Attributes	Color	Color code
Product Attributes	Basic Material	Type of upper material
Product Attributes	Gender	Gender or age group description
Product Attributes	Category	Product family
Product Attributes	Sub-Category	Classic vs modern
Product Attributes	Retail Outlet Sub-Department	Basic vs. seasonal
Product Attributes	Cut	Ankle height
Product Attributes	Pillar	Product sub-brand
Product Attributes	Product Class	Product main feature
Price and Promotion	Price Status	Full-price vs mark-down
Price and Promotion	Manufacturer's Suggested Retail Price (MSRP)	Ticket price
Price and Promotion	Average Unit Retail (AUR)	Actual selling price
Sales Units	Retail Sales Units (Target variable)	Retail sales units

Feature selection and engineering

- In preparation for constructing the template, many features have been updated or removed. Under the colour classification.
- There are many different findings, some of which are very similar.
- Component and class are identical to one-to one connection attributes, i.e. They are entirely associated with one another.
- Since seasonal models are launched with limited lifecycles at various periods of the year.
- Their prices are assumed to rely on the development characteristics in relation to the schedule characteristics.
- Revenue are not only linked to the schedule month in which the sale takes place, but also to the month in which the item is released.

List of attributes for feature selection

Variable Category	Variable	Description
Meta Data	Style	Unique style number of each product
Meta Data	Style Description	Description of the style
Calendar	Year	Fiscal year
Calendar	Month	Fiscal month
Product Attributes	Color Group	Color code
Product Attributes	Basic Material	Type of material
Product Attributes	Gender	Gender or age group description
Product Attributes	Category	Product family
Product Attributes	Sub-Category	Classic vs. modern
Product Attributes	Cut	Ankle height
Product Attributes	Product Class	Product main feature
Price and Promotion	Manufacturer's Suggested Retail Price (MSRP)	Ticket price
Price and Promotion	Average Unit Retail (AUR)	Actual selling price
Lifecycle	Lifecycle	The total number of months in the lifecycle of a style
Lifecycle	Lifecycle Month	The number of months since product launch
Lifecycle	Lifecycle Start Month	The month at which the lifecycle started
Store	Store Count	Number of stores selling a style
Sales Units	Retail Sales Units (Target variable)	Retail sales units

Dataset partitioning

- Table: Overview of datasets generated for the general model.

Dataset	Months of sales	Number of Styles	Number of records
Training	36	578	1796
Validation	18	195	560

- Table: Overview of datasets generated for the three-step model.

Dataset	Months of sales	Number of Styles	Number of records
Training	35	539	1558
Validation	19	201	591
Testing	3	58	155

Model building

- General model.

- Three-step model.

Three step model

Process Name	Variable Name	Variable Category
Clustering	Lifecycle	Lifecycle
	MSRP	Price and Promotion
	Average AUR	Price and Promotion
	Average Store Count	Store
	Retail Sales Units	Sales Units
Classification	Lifecycle	Lifecycle
	MSRP	Price and Promotion
	AUR	Price and Promotion
	Store Count	Store
	Fiscal Year	Calendar
	Fiscal Month	Calendar
	Lifecycle Month	Calendar
	Lifecycle Start Month	Calendar
	Color Group	Product
	Basic Material	Product
	Gender	Product
	Category	Product
	Cut	Product
	Cluster Number	Cluster

K-means clustering

- After arranging the data and reducing the information dimension to just two elements.
- we operated the grouping method k-means to segment the information files into group scope.
- Classification:
  - At the end of the segmentation process, group details are allocated to the documents of both testing and verification sets.
  - The class engines were the classification characteristics as well as the statistical qualities.

Three steps followed in classification

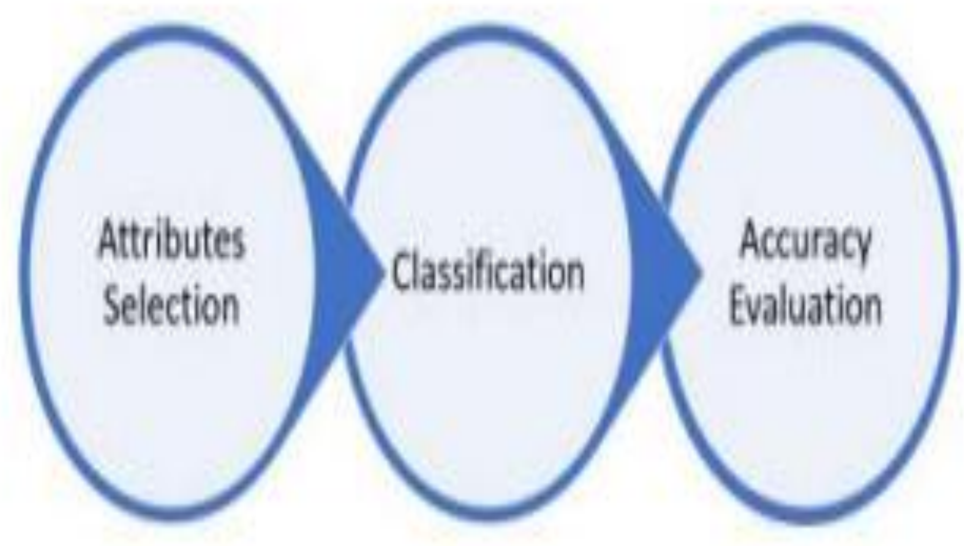

Figure: the three sub-steps followed in classification

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Three sub-steps in prediction

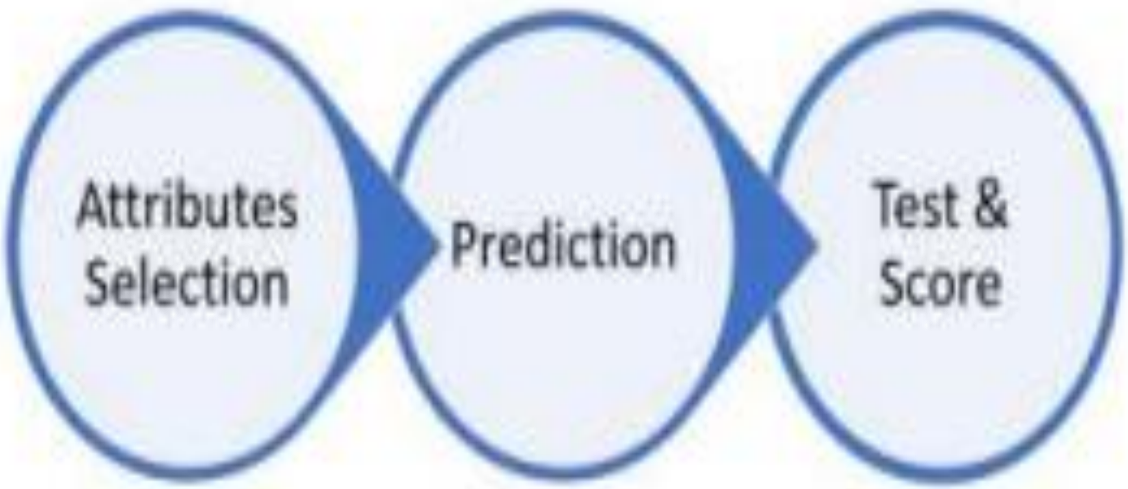

Figure: The three sub-steps followed in prediction

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Performance measurement

- For our predictive models, we used two performance metrics: predictive accuracy and bias. To measure predictive precision, we utilized:
  - Weighted Mean Absolute Percentage Error (WMAPE).
  - Weighted Mean Percentage Error (WMPE).

- We eventually utilized equation 3 to determine the expected discrimination in a specific manner.

- Equation 1: $$\text{Absolute Forecast Error} = |\text{Forecasted Sale} - \text{Actual Sales}|$$

- Equation 2: $$\text{Forecast Accuracy (WMAPE)} = \frac{\sum_{i=1}^{n} |\text{Forecasted Sales} - \text{Actual Sales}|}{\sum_{i=1}^{n} \text{Actual Sales}}$$

- Equation 3: $$\text{Forecast Bias (WMPE)} = \frac{\sum_{i=1}^{n} \text{Forecasted Sales} - \text{Actual Sales}}{\sum_{i=1}^{n} \text{Actual Sales}}$$

Results

- General model: The template with 12 parameters culminated in the smallest failure as shown in figure depending on the effects of reciprocal function removal.

Importance Rank	Attribute	Attribute Category
1	Store Count	Store
2	Month	Calendar
3	Lifecycle Month	Lifecycle
4	Gender	Product
5	AUR	Price and Promotion
6	Year	Calendar
7	Basic Material	Product
8	MSRP	Price and Promotion
9	Color Group	Product
10	Lifecycle	Lifecycle
11	Cut Description	Product
12	Product Class Description	Product

Figure: List of Attributes selected for model building

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Results

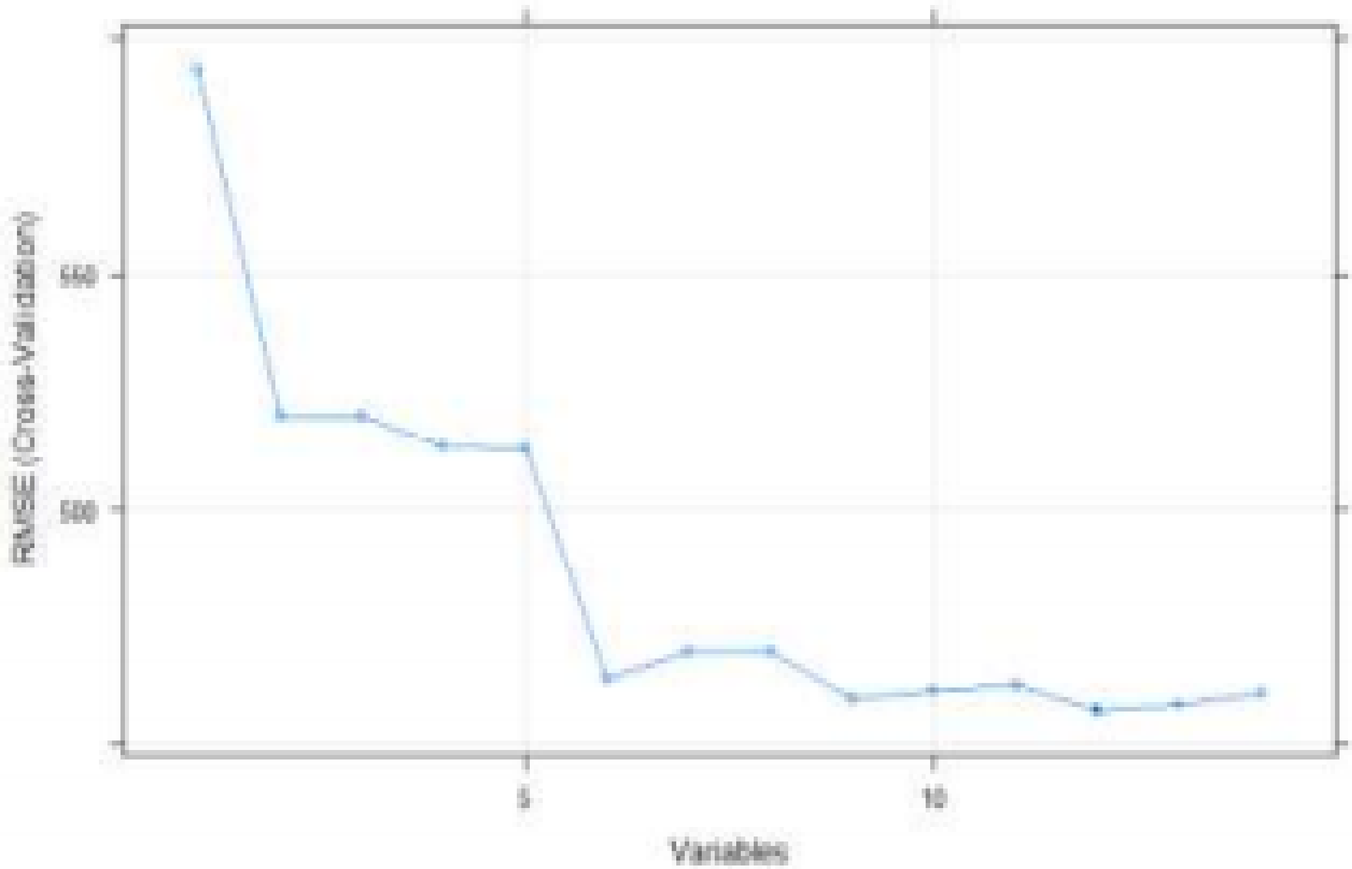

Figure: Cross validation error by number of attributes

Source: https://docplayer.net/102535491-Forecasting-seasonal-footwear-demand-using-machine-learning.html

Three step model

- The stages followed in the three-step model:
  - Clustering.
  - Classification.
  - Prediction.

Clustering and classification

- We used the profile score to access the variety of groups that matched our tests.
- The silhouette points in data groups are a type of perception and accuracy checking.
- Table: The silhouette score for different k number of clusters.

Number of Clusters	Silhouette Score
2	0.378
3	0.422
4	0.481
5	0.469
6	0.487
7	0.489
8	0.463
9	0.441
10	0.427

Prediction

- Testing the forecasting formulas on both verification and trial sets resulted in quite distinct quality algorithms tests.
- Both datasets, the predictability of the ensemble approaches was much smaller.
- Overall, relative to the validation sample, the test group had slightly better predictive reliability and worse predictive bias.

Machine learning for supply chain management

- Operational inefficiencies in supply chain management can often lead to potential reductions in sales, rising costs, and poor customer service–ultimately reducing profits.

- There are many uncertainties in the order-to-cash cycle, a key process in supply chain management.
  - Insufficient stock to meet demand.
  - Distribution of shortages and technical difficulties n enormous order backlog.
  - Request variance n stakeholder contact gaps.
  - Variation of stock quality levels.
  - Varied consumer performance indicators end.
  - Distribution of non-ordered goods.

Recommended architecture for machine learning models

- Creating models to recognize system gaps and predict the probability of return orders and shipment delays needs case-specific information such as:
  - Customer profile and demographics.
  - Order and shipping data.
  - Brand acceptance.

- Introduce and equip the data analytics platform with machine learning and visualization capabilities capable of embedding massive out-of-the-box data volumes.

- Identify the root cause of return orders by combining different data sources such as pricing, shipping and order booking.

- Predict whether shipments are likely to be delivered on time using data relating to invoice, transport and shipment.

Machine learning models use case

- An example can explain the effect of using an OTC ML approach.
- The optimized the data model for a marine shipping business after collecting data on chemical products orders for one year, and examined two specific business scenarios.
- The organization collected relevant data to identify problems with late deliveries and trained the ML model to determine the leading cause in the categories of 'defects’, resulting in returned products.
- Predictive model can help businesses to identify pre-emptively which orders are likely to be returned, act proactively, and accelerate the delivery of orders.

Checkpoint (1 of 2)

Multiple choice questions:

1. What is the purpose of performing cross validation?
   a) To assess the predictive performance of the model
   b) To judge how the trained model performs outside the sample on test data
   c) Both a and b
   d) None of the above

2. Why is second order differencing in the time series needed?
   a) To remove stationary
   b) To find the maxima or minima at the local point
   c) Both a and b
   d) None of the above

3. When performing regression or classification, which of the following is the correct way to process data?
   a) Normalize the data → PCA → training → answer
   b) PCA → normalize PCA output → training
   c) Normalize the data → PCA → normalize PCA output → training
   d) None of the above

Checkpoint solutions (1 of 2)

Multiple choice questions:

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Checkpoint (2 of 2)

Fill in the blanks:

1. __________________ is a systematic approach to sourcing, storing, and selling inventory—both raw materials (components) and finished goods (products).
2. __________________ encompasses a variety of statistical techniques from data mining, predictive modelling, and machine learning, that analyse current and historical facts to make predictions about future or otherwise unknown events.
3. __________________ is a process whereby products are selected and planned to maximize sales and profit for a specified period of time.
4. __________________ is a field of predictive analytics which tries to understand and predict customer demand to optimize supply decisions by corporate supply chain and business management.

Checkpoint solutions (2 of 2)

Fill in the blanks:

1. **Inventory management** is a systematic approach to sourcing, storing, and selling inventory—both raw materials (components) and finished goods (products).
2. **Predictive analytics** encompasses a variety of statistical techniques from data mining, predictive modelling, and machine learning, that analyse current and historical facts to make predictions about future or otherwise unknown events.
3. **Assortment planning** is a process whereby products are selected and planned to maximize sales and profit for a specified period of time.
4. **Demand forecasting** is a field of predictive analytics which tries to understand and predict customer demand to optimize supply decisions by corporate supply chain and business management.

Question bank

Two mark questions:

1. What is inventory management?
2. What is demand forecasting in retail industry?
3. Define retail analytics.
4. Define K-Means clustering.

Four mark questions:

1. Explain some use cases of inventory management.
2. With an example explain the applications of machine learning in retail analytics.
3. Write importance of machine learning in supply chain management.
4. Explain the benefits of predictive analytics to retailers in terms of intelligent inventory management.

Eight mark questions:

1. Briefly explain the applications of machine learning in inventory management.
2. Explain with an example applications of machine learning in inventory management and retail analytics.

Unit summary

Having completed this unit, you should be able to:

- Understand inventory management
- Gain knowledge on the machine learning use cases in inventory management
- Understand the benefits of predictive analytics to retailers in terms of intelligent inventory management
- Learn about the applications of inventory management with machine learning
- Understand the machine learning techniques for analysing buying patterns
- Gain knowledge on make use of machine learning algorithms for retail analytics
- Understand the demand forecasting methods