AI in Product Management

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Lecture- 15
Market And Category Analysis with AI

Welcome to this NPTEL online certification course on artificial intelligence in product management. Now we will talk about module 15. In this, we will talk about market and category analysis with the use of AI. So now we are talking about part 4, which is category management and customer analysis using AI, and we are talking about this module. To give you an overview of this module, we will start with the introduction to market and category analysis.

Then we will discuss AI-driven strategies for category management profitability, describe the use of AI in category factors, and then explain the role of AI through trend analysis in facilitating environmental analysis. So, the introduction to market and category analysis. For either new or existing products, product managers must ask whether the category of interest is sufficiently attractive to warrant new or or continued investments by their company, current competitors, and potential new entrants. The product portfolio approach popularized by the Boston Consulting Group uses the market growth rate to indicate attractiveness.

Other models utilize a two-dimensional strategic grid consisting of market attractiveness and business position. However, since we are studying product management, the kind of analysis to be done here is described as product category analysis. Product category defines a set of competitors against which one most often competes on a daily basis. While this may seem to be a narrow definition, a product manager can adapt the analysis presented in this module to the definition of product category or industry most appropriate for the circumstances. An essential component of the marketing planning process is an analysis of a product's potential to achieve a desired level of return on the company's investments.

An analysis of this type not only assesses financial opportunities but also provides ideas about how to compete better given the structural characteristics of the category. The characteristics of the product category rarely point in the same direction. For example, Ford chose to purchase Jaguar because of the considerable brand equity in the name. And because Ford management believed the brand gave the company an instant entry into the luxury car market field.

Besides the product managers for the manufacturing or service provider, another interested party in this analysis is the distribution channel. Since more channel members, particularly retailers, are interested in the profitable management of entire product categories, clearly retailers will give more space and/or selling time to those categories that are attractive, which means faster inventory turnover, greater total profit, and less space for categories that are unattractive. Thus, the kind of analysis described in this module will also be relevant to And probably is also being performed by the channel members in the distribution system.

The following are the important factors summarized in Figure 15.1 in assessing the underlying attractiveness of a product category. The three main areas of inquiry include the first is basic aggregate factors, category factors related to major participants, and the environmental factors. So, this is the summary, the category attractiveness summary. So, first we start with the aggregate category factors that include things like category size, category growth, stage in the product life cycle, sales cyclicity, seasonality, and profits. The second is category factors that include threats of new entrants, bargaining power of buyers, bargaining power of suppliers, current category rivalry, pressures from substitutes, and category capacity.

The third is environmental factors. Technological, political, economic, regulatory, and social. Now let us start with the first one, which is aggregate market factors. So the first thing here is the category size. It is measured in both units and monetary values and is an important determinant of the likelihood that a product will generate revenues to support a given investment.

In general, larger markets are better than smaller ones. Besides having more market potential, large categories usually offer more opportunities for segmentation than smaller ones. Therefore, both large firms and entrepreneurial organizations might find large markets attractive. Large markets, however, tend to draw competitors with considerable resources, thus making them unattractive for small firms. For example, in the soft drink category, Coca-Cola and PepsiCo

spent $240 million in the first six months of 2003 on advertising alone, supporting Coke, Diet Coke, Pepsi, and Diet Pepsi, and this did not include money spent on promotion.

Thus, absolute size by itself is not sufficient to attract new or continuing investments. The next is market growth. It is the key market factor advocated by various planning models, not only is current growth important, but growth projections over the horizon of the plan are also critical. Fast-growing categories are almost universally desired due to their ability to support high margins and sustain profits in future years. However, like large categories, fast-growing ones also attract competitors. In technology-based markets, fast growth often means dramatic shifts in market share and the virtual disappearance of rival products. Thus, growth brings

The prospect of increasing revenues, but also a dynamic market structure in terms of competitors. Then comes the product life cycle. A general assessment of the attractiveness of a category at each stage of the life cycle is an important determinant of category attractiveness. In the introduction phase, Both the growth rate and the size of the market are low, thus making it unattractive for most prospective participants who would rather wait on the sidelines for a period of time.

When market growth and sales start to take off, the market becomes more attractive. In the maturity phase, the assessment is unclear. While the growth rate is low, the market size could be at its peak. So, this is the classical pattern for soft drinks, fast foods, and many other consumer packaged goods.

Large dollar volumes with slow growth. Finally, the decline phase is usually unattractive, so most competitors flee the category. The next is sales cyclicity. Many categories experience substantial inter-year variations in demand. High capital-intensive businesses such as automobiles, steel, and machine tools are often tied to general business conditions.

And therefore, suffer through peaks and valleys of sales as gross domestic product varies. AI-powered sales cycle forecasting offers businesses the tools to make smarter, data-driven decisions that improve overall performance. AI algorithms, through intense learning, can process vast amounts of data and uncover hidden patterns. These algorithms learn from the data over time. Continuously refining their predictions and adjusting as market conditions evolve. Some typical applications of AI algorithms in forecasting include time series analysis, sentiment analysis, and demand forecasting. The next is seasonality, that is, intra-year cycles in sales, which is generally not viewed positively. For example, in the last few years, the toy industry has reduced its reliance on the Christmas period to generate most of its sales.

Such seasons with business tend to generate price wars because there may be few other opportunities to make substantial sales. So, AI can be used to predict seasonality by analyzing large amounts of data to identify patterns and trends. AI can be especially useful in situations where traditional methods might struggle, such as when predicting Subtle seasonality or fluctuations in demand during special events. Then comes profits. While profits vary across products or brands in a category, large inter-industry differences exist. These differences in profitability across industries are actually based on a variety of underlying factors. Differences can be due to factors of production, that is, labor versus capital Intensity and raw material, manufacturing technology, competitive rivalry, to name a few. Thus, product categories that are technically low in profitability are less attractive than those that offer higher returns. A second aspect of profitability is that it varies over time.

Variance in profitability is often used as a measure of industry risk. Semiconductors offer abnormally high returns when demand is good. But concomitant poor returns when demand slumps. Therefore, product managers must make a risk-return trade-off, evaluating the expected returns against the variability in those returns. Now, let us look at the AI-driven strategies for category management profitability.

AI automates tasks such as data analysis, market segmentation, and demand forecasting, which streamlines and simplifies the work of category managers. It also allows the creation of innovative strategies and campaigns that are relevant to customer needs. AI analyzes price elasticity and suggests optimal prices for products, which affects the maximization of profitability. AI can significantly enhance pricing strategies by analyzing price elasticity. AI algorithms can

scrutinize historical sales and pricing data to identify factors that influence product demand. This empowers category managers to set optimal prices that maximize profitability and cater to customer needs. AI models can accurately predict future demand based on various factors, including seasonal trends, marketing campaigns, and economic conditions. This enables category managers to optimize inventory levels, preventing stockouts or overstocking. So, AI tools can analyze individual customer profiles and purchasing habits to offer personalized pricing, boosting customer satisfaction. AI algorithms can analyze sales, profitability, and margin data for individual products to identify underperforming items. This allows category managers to optimize product assortment, focusing on products with high profit potential.

AI-powered pricing automation involves dynamically adjusting prices in real time based on various factors, such as competitor pricing, product demand, and inventory availability. This automation saves category managers time and resources while ensuring optimal pricing. So, these are practical applications of AI in category management. So, Walmart predicts product demand and optimizes inventory levels. Amazon personalizes product prices for each customer based on their purchase history and preferences.

P&G analyzes price elasticity and sets optimal prices for its products. Coca-Cola develops personalized marketing campaigns and optimizes product distribution. Unilever analyzes online reviews and customer feedback to improve products and services. The second type of factors is category factors. Although the aggregate factors just described are important indicators of the attractiveness of a product category, they do not provide information about underlying structural factors affecting the category.

A classical model developed by Porter in 1980 considers five factors. We will see that in Figure 15.2 in assessing the structure of the industry. So, this is Porter's five forces analysis. One is the threat of new entrants, two is the bargaining power of buyers, three is the bargaining power of suppliers, four is the amount of intra-category rivalry, and the fifth is the threat of substitute products or services. Now, let us look at each one of them.

So, we are talking about the threat of new entrants. The first thing here that we will talk about is barrier analysis. AI can assess the ease with which each competitor can enter the market by evaluating factors like technological advancements, patent data, and capital requirements. Automation of market entry scenarios. AI can simulate market entry scenarios to predict how new competitors might impact existing players.

Helping businesses prepare and adjust their categories accordingly. The second is the bargaining power of buyers. Let us look at the customer insight. AI can process customer data to understand buying patterns, preferences, and price sensitivity. This enables businesses to tailor

their products to meet customer expectations, thereby reducing the buyer's power. Personalization at scale: AI can offer personalized experiences to large customer bases, strengthening customer loyalty and diminishing their bargaining power by creating value through customization. Supplier analytics: AI can analyze supplier performance data, track their reliability, and predict price fluctuations, helping businesses negotiate better terms or identify alternative suppliers. Supply chain optimization.

AI can optimize supply chain management by forecasting demand, managing inventory more efficiently, and reducing dependence on powerful suppliers. The third is the amount of intra-category rivalry. And the first factor here is AI for market analysis. AI-powered tools can analyze vast amounts of data. such as competitors' pricing, marketing strategies, product launches, and customer sentiment. This allows companies to assess the intensity of competition and adjust their strategies in real time. The second is predictive analytics: AI can predict market trends

Competitor behavior and industry growth patterns enable businesses to stay ahead of competitors by making data-driven decisions. Then comes the threat of substitute products or services. Let us look at product innovation. AI can drive innovation by identifying opportunities to improve products or develop new ones that offer superior value compared to substitutes. Monitoring substitute trends, AI can analyze consumer preferences and trends to detect the rising popularity of substitute products. Enabling businesses to innovate or differentiate before substitutes become a major threat. Next comes the environmental analysis.

Environment refers to the external factors unrelated to the product, customers, and competitors that affect marketing strategy. The vulnerability of a product category to changes in the environment is an unattractive characteristic, but virtually all product managers must deal with this. Environmental factors fall into five groups: technological, political, economic, regulatory, and social. These factors should be examined to assess category attractiveness and to determine if any forecasted changes occur. Dictate changes in strategy.

So, now how is AI used for trend analysis? Trend analysis, as a technique to identify and analyze temporal patterns in collected data, has evolved significantly with the integration of AI and has become a cornerstone for developing innovative solutions and optimizing decision-making processes. It is a critical analytic methodology widely recognized for interpreting recognizable patterns within diverse data sets and is extensively applied across various sectors such as economics, finance, and marketing. To leverage AI in trend forecasting, the integration of precise machine learning algorithms is indispensable.

This algorithm rigorously scrutinizes historical data, identifies patterns and trends, and forms the backbone of intelligent forecasting. However, the selection of the algorithm is pivotal. Each machine learning algorithm comes with its unique set of merits and challenges, necessitating a careful choice that aligns impeccably with the specific needs and goals of businesses. The key ML algorithms used in trend analysis are neural networks.

Neural networks, inspired by the human brain, function excel in recognizing complex patterns and long linear relationships in data, making them indispensable for forecasting trends in diverse and dynamic environments. Their ability to learn and adapt makes them particularly suited for deciphering intricate data structures and optimizing predictive accuracy in trend analysis. Support vector machines operate by categorizing data into distinct classes, maximizing the margin between them. This precision in classification renders SVM highly effective in trend forecasting, enabling businesses to make sharp, informed distinctions between different potential outcomes.

Random forests aggregate multiple decision trees to construct robust predictive models. Their ensemble approach enhances reliability and accuracy in trend forecasting by mitigating the risk of overfitting providing a balanced and diversified perspective on emerging trends. Next come the Bayesian networks. Bayesian networks employ probabilistic graphical models to represent the statistical dependencies among a set of variables.

This brings a nuanced understanding of probability to trend analysis, allowing for the incorporation of uncertainty and variability in predictions, refining the anticipatory intelligence of businesses. How does AI for trend analysis work? AI in trend analysis transforms the approach to identifying and predicting market trends using advanced data analytics, predictive modeling, and adaptive learning algorithms. By employing large language models with access to extensive data repositories, businesses can extract key patterns essential for developing dynamic market strategies. This approach significantly improves the capacity to analyze large volumes of data.

The AI algorithm architecture integrates various components to optimize the trend analysis process that we will see in Figure 15.3. So this is Figure 15.3, and it is about AI-driven architecture to optimize the trend analysis process. So we have these data sources: market data feeds, consumer behavior analytics, economic indicators, competitor activity, and news and events. Now, this goes to data pipelines, embedded models, and vector databases, and then it all goes to Z brain of orchestration, and then it moves on to large language models. Here is a step-by-step breakdown for this trend analysis solution architecture. The first is the data source.

Trend analysis relies on diverse data sources to accurately predict market movements. This data includes market data feeds, real-time and historical data on market prices, volumes, and movements across various sectors and geographies. Consumer behavior analytics provide insights into consumer purchase patterns, preferences, and feedback collected through CRM systems and social media channels. Competitor activity includes information on competitors' product launches, market campaigns, and market share changes. News and events include real-time news streams and global events information that could impact market trends. The second is data pipelines.

Data from the above sources is routed through pipelines that handle ingestion, cleaning, and structuring, preparing it for detailed analysis. The third is the embedding model. The prepared data is then processed by an embedding model. This model transforms the textual data into numerical representations called vectors, which AI models can understand.

Widely used models for this purpose come from providers like OpenAI, Google, and Cohere. The fourth is the vector database. The generated vectors are saved in the vector database, which facilitates efficient querying and retrieval. Examples include Pinecone, Weaviate, and PG vector. The fifth is the application programming interface (APIs), plugins, and tools such as SERP, Zapier, and Wolfram, which connect different system components, enabling additional functionalities like external data access or specific analytical tasks.

Then comes the orchestration layer. The orchestration layer is critical in managing workflows. Z-Ware is an example of this layer that simplifies prompt chaining, managing interactions with external APIs by determining when API calls are required, retrieving contextual data from vector databases, and maintaining memory across multiple LLM calls. Ultimately, this layer generates a prompt or series of prompts that are submitted to a language model for processing.

The role of this layer is to orchestrate the flow of data and tasks, ensuring seamless coordination across all components of the AI-driven trend analysis system. The seventh is query execution. The data retrieval and generation process begins when the user submits a query to the trend analysis app. Users submit queries about market trends, consumer behavior, or competitor analysis to the trend analysis app. The eighth one is LLM processing. Once received, the app transmits the query to the orchestration layer. This layer will retrieve relevant data from the vector database and LLM cache, then send it to the appropriate LLM for processing. The choice of LLM depends on the nature of the query. The next comes output.

The LLM generates an output based on the query and the data it receives. The insights generated by the LLMs can be trend forecasting, market analysis reports, and strategy recommendations. Trend analysis app insights are delivered to the users through an app specifically designed for trend analysis, providing businesses easy access to actionable data. Feedback loop: user feedback on the LLM's output is another important aspect.

of the architecture. This feedback is used to improve the accuracy and relevance of the LLM output over time. The twelfth is agent. AI agents step into this process to address complex problems, interact with the external environment, and enhance learning through post-deployment experiences. They achieve this by employing advanced reasoning, planning, strategic tool utilization, and leveraging memory, recursion, and self-reflection.

LLM cache tools like Redis, SQLite, and GPT Cache are used to cache frequently accessed information, improving AI systems' response times. The fourteenth is logging or LLM ops. Throughout this process, LLM operations, tools like Weights and Biases, MLflow, Helicon, and PromptLayer help log actions and monitor performance. This ensures the LLM operates at peak efficiency and evolves consistently through ongoing feedback mechanisms. The fifteenth is validation.

A validation layer is employed to validate the LLM output. This is done through tools like Guardrails, Rebuff, Guidance, and LMQL to ensure the accuracy and reliability of the information provided. Sixteenth is LLM APIs and hosting. LLM APIs and hosting platforms are essential for executing analysis, performing trend analysis tasks, and hosting the applications.

Depending on the requirements, developers can select from LLM APIs offered by companies such as OpenAI and Anthropic or opt for open-source models. Similarly, they can choose hosting platforms from cloud providers like AWS, GCP, Azure, and CoreWeave or opt for open-aided clouds like Databricks, Mosaic, and AnyScale. The choice of LLM APIs and cloud hosting platforms depends on the project needs and preferences. Now, we will look at AI techniques used in trend analysis.

So, the first is predictive analysis. Predictive analysis rooted in data mining, machine learning, and statistical methodologies transform vast data sets into actionable business insights by mapping probabilities based on historical data. Although it does not forecast the future, it indicates what is likely to happen, vital for identifying potential customer behavior and market trends.

It involves scanning various information sources like market research and customer feedback, and employing monitoring and early warning systems on key indicators. After defining specific problems via frameworks like Csmart or OKR, relevant data is assessed, and predictive models are built. validated, and meticulously evaluated before real-time deployment and monitoring. Thus, predictive analytics enable businesses to identify trends, navigate uncertainties, and strategize effectively by providing probable insights based on past occurrences. The next is data mining. Data mining is a crucial subfield connecting statistics and AI, employing mathematical algorithms to extract hidden patterns and unidentified correlations within large datasets, providing valuable insights into future occurrences and trends. It involves the process of data collection, cleaning, pattern identification, and knowledge visualization and communication.

Methods like regression for predicting numeric outcomes, and clustering for grouping similar data, enhance trend analysis by revealing concealed patterns and insights crucial for informed decision-making and strategic planning in various industries. Data mining, therefore, serves as a sophisticated tool for navigating vast information, identifying unseen trends, and enabling data-driven decisions in the business landscape. So, this is the large language processing text, audio, video. and then we have predictive analytics, influencer marketing, competitive edge, personal data security, and sentiment analysis.

Large language processing serves as a pivotal technology in trend analysis by empowering machines to comprehend and interpret human language, allowing for in-depth exploration of trends in voluminous text data from diverse sources like social media and news outlets. Through NLP, Analysts can categorize and discern patterns and emerging trends within large datasets. Significantly impacting sectors like media, where rapid identification and organization of trending topics are crucial. Techniques like latent Dirichlet allocation and latent semantic analysis are integral to extracting current data from the sea of information.

Improving content organization and aiding in effective information retrieval. Sentiment analysis is another essential component of NLP in trend analysis, permitting Deciphering sentiments within text and providing businesses with a refined understanding of consumer sentiments and perceptions about brands, products, or services. This process enables businesses to quickly adopt strategies and operations based on evolving consumer trends and preferences. The next is named entity recognition, that is, NER.

By recognizing and categorizing entities like names and locations within text, It plays a critical role in real-world trend detection by identifying the frequency and context of mentions related to various entities in text data, offering insights into prevailing trends and topics of interest. Further, part-of-speech tagging assists in elucidating the relationship between words in text, allowing for a more accurate extraction of trends from textual data. In video broadcasting, content analytics uses NLP to cluster videos into coherent topics based on user comments, utilizing techniques like singular value decomposition. Moreover, anomaly detection in NLP aids in recognizing outliers in text data.

Thus detecting deviations from prevailing trends and forecasting evolving patterns. Visual representation tools like word clouds offer intuitive insights into the prevalence and relevance of words and themes within a corpus, further assisting trend analysis. In summary, organizations can identify, understand, and leverage trends by employing NLP's diverse capabilities and transforming how they interact and gain insights from contextual data in real time. Deep learning and neural networks: the role of deep learning and neural networks in trend analysis is progressively gaining prominence, with hybrid deep neural network algorithms such as TreeNet emerging as potent tools for predicting trends in time series data. One striking aspect of employing deep learning in trend analysis is its capability to predict the forthcoming value in a series and the entire trend, therefore offering an enriched, more holistic insight into the data.

This approach of using piecewise linear representation or trend lines renders a more accurate depiction of the underlying dynamics of non-stationary and dynamic time series, which is paramount in predicting significant changes in data. While enhancing the understanding of trend semantics, this representation is also pivotal for decision-makers. The Time Series Analysis Analyzing trends in time series data is crucial for insightful decision-making within artificial intelligence. Time series data, a sequence of data points measured over time, aids industries in predicting patterns and strategizing.

The three significant components of a time series are trends, seasonality, and remainder, with the trend indicating systematic long-term change. Trends can be deterministic, predictable through mathematical functions, or stochastic, unpredictable, and changing randomly over time. Detecting trends involves using unit root tests like the augmented

Dickey-Fuller and the KPSS test. Managing trends entails utilizing a differencing approach. Through multiple steps to model how the series evolve over time, understanding and aptly handling these trends in time series data enables the refinement of predictive models, improving their reliability and efficiency in drawing forecasts and insights from the data.

The next comes sentiment analysis. Sentiment analysis Trend analysis works primarily by leveraging sophisticated algorithms and models to extract and quantify emotional tones from a vast array of text data, enabling the identification of prevailing attitudes, opinions, and emotions related to a specific object over a defined period. This process provides critical insights into the temporal progression of public sentiment, highlighting fluctuations and shifts that might signify emerging trends or patterns.

In a typical workflow, the first step is to aggregate relevant contextual data from diverse sources like social media, online forums, news articles, and review sites. This data is then meticulously cleaned and pre-processed to remove noise and convert the text into a format suitable for analysis. Next, advanced NLP techniques, often employing ML models, are applied to the refined data to identify and categorize sentiments as positive, negative, and neutral. Techniques like word embedding and neural network modeling enable the conversion of textual information into numerical data, facilitating the evaluation of sentiment polarity and intensity within the gathered content.

Following the determination of sentiment values, statistical and data analysis methods are utilized to observe and interpret trends in sentiments over time. The time series analysis of sentiment scores can reveal patterns and fluctuations in public opinion, indicative of evolving trends, shifts in perceptions, and emerging phenomena in the scrutinized domain. The final step usually involves visualizing the resultant sentiment trends through graphs, charts, and other illustrative tools, allowing for a more intuitive and insightful interpretation of the data.

The visualization aids in making informed and strategic decisions, identifying opportunities, and understanding the overarching sentiment landscape in real time. The integrated synergy of data collection, sophisticated NLP techniques, statistical analysis, and intuitive visualization in sentiment analysis paves the way for a deeper understanding of societal and consumer trends, enabling entities to stay abreast of changing preferences, opinions, and behaviors in an ever-evolving environment. So, to conclude this module, we have discussed the concept of market and category analysis. We have discussed AI-driven strategies for category management profitability, understood the use of AI in analyzing category factors,

and learned about the role of AI through trend analysis in facilitating environmental analysis. And these are some of the references from which the material for this module was taken. Thank you.