AI in Product Management

Prof. Zillur Rahman
Department of Management Studies
Indian Institute of Technology, Roorkee

Lecture- 8
Enhancing Quantitative Research with AI

Welcome to this NPTEL online certification course on artificial intelligence in product. In Module 8, we will see how to enhance quantitative research with AI. In Module 7, we have seen how to analyze qualitative data with AI. Now, we will look at quantitative research and how it can benefit from the use of AI. So, this is Part 2, and we are here on Module 8.

This is the module overview. So, we will start with the introduction and discuss the role of AI in quantitative research. Then we will discuss the tools for conducting quantitative research using AI, explain the benefits of using AI for quantitative research, and then discuss the ethical considerations of using AI in quantitative research. These ethical considerations are always important whenever we use artificial intelligence for any purpose. So, to introduce the use of quantitative research using AI.

First, what is quantitative research? Quantitative research in the field of product management refers to the systematic, empirical investigation of observable phenomena with the help of statistical, mathematical, and computational techniques. It is a research method that focuses on quantifying the collection and analysis of data. So, we have talked about qualitative, and now we are talking about quantitative.

So, both these methods show how they can benefit from the use of AI and how it can be used for the purpose of product management. So, product management involves planning, developing, marketing, and launching a product. Quantitative research plays a crucial role in each of these stages. It helps product managers understand market trends, customer needs, and product performance, enabling them to make data-driven decisions.

For instance, product managers may use quantitative research to analyze user behavior data, identify patterns, and understand how users interact with the product. This can inform product development, feature prioritization, and marketing strategies. Quantitative analysis has long been a cornerstone of decision-making in product management. With the rapid advancements in artificial intelligence and machine learning, the process of

quantitative analysis has been revolutionized, enabling more accurate predictions, faster insights, and improved decision-making.

Now, let us look at the role of AI in enhancing quantitative analysis. So, we start with data processing. AI can handle large volumes of data efficiently, enabling faster processing and analysis compared to traditional methods. This capability is essential in today's data-driven environment, where organizations often deal with extensive datasets that require quick turnaround times for insights.

So, the first step in this process is automation of data cleaning. AI algorithms can automate the data cleaning process, identifying and correcting errors or inconsistency in large data sets. This reduces manual efforts and enhances the quality of the data being analyzed. Then comes real-time data handling. AI systems can process streaming data in real time.

allowing organizations to make immediate decisions based on the most current information available. This is particularly useful in sectors like finance and e-commerce, where timely insights can lead to competitive advantage. So, the first was data processing. The second is analytics. predictive analytics.

Machine learning algorithms are central to predictive analytics, which involves identifying trends and forecasting future behaviors based on historical data. The first thing that it does is pattern recognition. AI models learn from historical data to identify patterns and relationships among variables. For instance, in retail, predictive analytics can forecast future buying patterns by analyzing past consumer behavior. helping business optimize inventory and marketing strategies.

Next is continuous learning. AI-driven predictive models continuously improve as they are exposed to new data. This iterative learning process enhances their accuracy over time, ensuring that predictions remain relevant even as market conditions change. Now, what are the tools for quantitative research using AI? The first thing we will talk about is Linear Discriminant Analysis, or LDA, an approach used in supervised machine learning to solve multi-class classification problems.

LDA separates multiple classes with multiple features through data dimensionality reduction. Whenever there is a requirement to separate two or more classes having multiple features efficiently, the LDA model is considered the most common technique to solve such classification problems. For example, if we have two classes with multiple

features and need to separate them efficiently, classifying them using a single feature may show overlapping. So, see Figure 8.1, this is

Figure 8.1, where we are showing overlapping. To overcome the overlapping issue in the classification process, we must increase the number of features regularly. For example, let us assume we have to classify two different classes having two sets of data points in a two-dimensional plane, as shown in Figure 8.2. So, here we have the x-axis, and here we have the y-axis. However, it is impossible to draw a straight line in a 2D plane that can separate these data points.

Efficiently by using linear discriminant analysis. We can dimensionally reduce the 2D plane into the 1D plane. Using this technique, we can also maximize the separability between multiple classes. So, what we are doing is reducing the 2D plane into a one-dimensional plane. LDA can be applied to tackle complex problems and help organizations make better decisions, such as

customer segmentation for effective marketing. Managers must be able to categorize diverse customer bases. LDA is pivotal in segmenting customers, enabling product managers to tailor their product design for different customer groups. The outcome is a more personalized shopping experience, increasing customer loyalty and sales. The next is quality control in manufacturing products. Producing high-quality goods while minimizing defects is a fundamental challenge. Sensor data from machinery can be used with LDA to identify patterns associated with defects. By detecting irregularities in real-time, manufacturers can take immediate corrective action, improving product quality and reducing wastage. The next tool is Partial Least Squares Discriminant Analysis, that is, PLSDA.

It is a dimensionality reduction and classification technique that is particularly useful for handling complex and highly correlated data in product management. PLSDA can be leveraged in several ways to guide decision-making and strategic development, especially when product managers deal with high-dimensional datasets and need to make sense of the relationships between various factors. There are several areas where PLSDA can be useful. One is classifying customer groups. PLSDA is useful for segmenting customers into distinct groups based on multiple characteristics, such as

Demographics, purchase behavior, and preferences. It is particularly effective when the variables are numerous and correlated. By identifying latent structures in the data,

PLSDA helps product managers categorize customers more accurately. Next comes targeting. Once customer segments are classified,

Product managers can tailor marketing strategies, offers, and communication to specific customer groups, improving the relevance of outreach and increasing customer satisfaction. Identifying Key Product Attributes: PLSDA helps in understanding which product features or attributes are most important in differentiating customer preferences or product outcomes. By modeling the relationships between product features, and customer choices, PLSDA can reveal which characteristics drive the most engagement or satisfaction. Prioritizing development efforts: Managers can use the insights from PLSDA to focus on the features that matter most to different customer segments.

Allowing for more efficient resource allocation in product development. Fifth is classifying product types: PLSDA can be used to differentiate between competing products by identifying key characteristics that distinguish a company's products from those of competitors. This helps product managers position their products effectively in the market by highlighting unique selling points. The next is strategic positioning: The technique can reveal which product attributes resonate most with target customers and how these attributes compare with competing products, enabling product managers to make data-driven decisions on branding and positioning. Classifying user behavior: PLSDA can be applied to classify users based on their engagement with the product. For example, it can help differentiate between high-engagement and low-engagement users by identifying which product features or behaviors are associated with high levels of user interaction. Improving user retention: By understanding the differences between engaged and disengaged users, product managers can make targeted improvements to features or user flows to increase retention and overall product usage. Decision trees, as we have already discussed in Module 4, a decision tree is a flowchart

Like a structure used to make decisions or predictions. It consists of nodes representing decisions or tests on attributes, branches representing the outcome of these decisions, and leaf nodes representing final outcomes or predictions. Each internal node corresponds to a test on an attribute. Each branch corresponds to the result of the test, and each leaf node corresponds to the class label or a continuous value.

Decision trees are a type of supervised machine learning algorithm used to categorize or predict outcomes based on a series of questions. In the context of product management, a decision tree could represent different stages in launching a new product, with each

branch representing a different outcome—high demand or low demand—and each leaf representing the final decision based on those outcomes, such as launch product or delay launch. Consider an example. An e-commerce company is trying to predict whether a customer will churn or not.

This is based on various factors such as age, purchase history, and website engagement. As an AI, the decision tree would ask various questions, such as: Is the customer under 30 years old? Or has the customer made a purchase last month? Based on the answers, the decision tree algorithm will navigate through the decision path. The AI decision tree algorithm will then make a prediction, such as: Yes, the customer is likely to churn, or no, the customer is likely to stay. Thus, AI decision trees can assist researchers in unraveling complex consumer behavior patterns and identifying influential factors that drive market trends.

Businesses can gain valuable marketing insights, enabling them to make data-driven strategic decisions. Next is K-Nearest Neighbors (KNN), which we have also talked about earlier. It is a versatile machine learning algorithm used for both classification and regression tasks. The k-nearest neighbor algorithm is a non-parametric model that operates by memorizing the training datasets without deriving a discriminative function from the training data. It predicts responses from new data based on similarity with known data samples. KNN search is pivotal in applications like image recognition, fraud detection, and recommendation systems.

Such as music apps and song suggestions. KNN represents a paradigm shift from keyword-centric searches to those driven by similarity and context. For example, suppose we have an image of a creature that looks similar to a cat and a dog, but we want to know whether it is a cat or a dog. This is the KNN classifier. Here we have an input value, and this is the predicted output.

For this identification, we can use the KNN algorithm, as it works on a similarity measure. The KNN model will find the similar features of the new dataset to the cats and dogs images and, based on the most similar features, it will categorize it as either a cat or a dog. So, KNN can have various applications in product development, such as grouping customers. KNN classifies customers into different segments based on their behavioral or demographic data.

By finding the K-nearest neighbors that are the most similar customers, managers can group customers who exhibit similar purchasing habits, engagement levels, and

preferences. Content-based recommendations, product features such as size, color, and category can be used to train a KNN model to recommend similar products to customers. What a customer has already liked or purchased. This improves user engagement and satisfaction with relevant product suggestions. Competitor analysis can be used to compare product pricing with competitors by identifying similar products in the market based on features, quality, or target demographics.

Product managers can then adjust pricing strategies by understanding how similar products are priced in the market. Dynamic pricing models can help in dynamic pricing by evaluating how similar products are priced at different times, allowing for more competitive and data-driven price adjustments. The next is feature usage analysis. So, product managers can use KNN customer data to identify the most valuable product features by grouping users based on their feature usage.

Product managers can see which features are frequently used by similar users and prioritize future product development based on this insight. The next is random forest, which is a commonly used machine learning algorithm that combines the output of multiple decision trees to reach a single result. So, these are multiple decision trees and then a final result is reached. Its ease of use and flexibility have fueled its adoption, as it handles both classification and regression problems.

Again, you can see Module 4 for more details. So, random forest models can be applied to various product management tasks. One such task is user behavior prediction, predicting how users will interact with your product. This can guide feature development and personalization efforts. A/B testing analysis assesses the impact of product changes and A/B tests more accurately by using random forests to analyze user behavior data.

Customer segmentation: Segmenting your user base based on behavior and preferences can inform targeted marketing and feature customization. Demand forecasting: Estimate product demand to optimize inventory management and ensure product availability. Anomaly detection: Identifying unusual user behavior that may indicate security breaches or technical issues. Now, let us look at some of the benefits of quantitative research using AI. The first of these benefits is speed and efficiency.

AI can process and analyze large datasets much faster than human researchers, significantly reducing the time required to complete research projects. This rapid processing enables quicker insights and decision-making. The second benefit is

scalability. AI systems can handle vast amounts of data, allowing researchers to conduct studies on a much larger scale than traditional methods would permit.

This scalability is crucial for obtaining representative samples. In market research. The third is enhanced data analysis. AI algorithms excel at identifying patterns and trends within complex datasets that might be missed by traditional analysis methods. This capability leads to more accurate forecasting and prediction.

The fourth is complex strategy management. AI can manage and integrate multivariable analysis that would be challenging for human analysts, allowing for a deeper exploration of relationships between different factors in research. Next comes adaptive learning. AI models can adapt to new data inputs over time, improving their accuracy and relevance as they learn from ongoing research findings.

As they learn from ongoing research findings, this adaptability ensures that insights remain current and actionable. Bias reduction. AI helps mitigate certain biases that may affect human researchers by relying on data-driven approaches rather than subjective interpretation. This leads to more objective insights.

The next thing that we have to talk about today is the ethical concerns of quantitative research using AI. So, the first such consideration is bias and discrimination. AI systems can perpetuate and amplify biases present in the training data. If historical data reflects systematic inequalities, AI algorithms can produce biased outcomes, leading to discriminatory practices.

This is particularly concerning in fields like education, where biased algorithms can adversely affect marginalized groups. Second is privacy concerns. The extensive data collection required for AI systems raises significant privacy issues. Sensitive information may be collected, stored, and analyzed without adequate consent or transparency. leading to potential misuse of personal data. The lack of transparency is another ethical concern of quantitative research using AI. Many AI algorithms operate as black boxes, making it difficult for researchers to understand how decisions are made and how conclusions are drawn.

This lack of transparency can undermine trust in research findings and accountability for the outcomes produced by AI systems. Informed consent. Obtaining informed consent from participants becomes more complex when using AI technologies. Participants may

not fully understand how their data will be used or the implications of AI analysis, raising ethical dilemmas regarding autonomy and agency. Accountability and responsibility.

The use of AI in research. Blurs the line of accountability. It can be challenging to determine who is responsible for errors or biases in AI-generated findings, whether it is the developer, researcher, or institution involved. This ambiguity complicates ethical accountability in research practices. Next is the impact on human judgment.

Over-reliance on AI could diminish the role of human judgment in interpreting research results. Researchers might accept AI-generated conclusions without critical analysis, potentially leading to flawed interpretations and a lack of nuanced understanding of complex issues. Next is the ethical use of synthetic data. When researchers use synthetic data generated by AI models, ethical concerns arise regarding the representation and validity of this data. Researchers must clearly disclose the use of synthetic data and its implications for research outcomes.

So, to conclude this module, we have discussed the concepts and tools for conducting quantitative research using AI. We have learned about the benefits of using AI for quantitative research. And finally, we have also learned about the ethical considerations of using AI in quantitative research. These are some of the references from which material for this module was taken. Thank you.