Issues in Information Systems
Volume 25, Issue 4, pp. 236-251, 2024

DOI: https://doi.org/10.48009/4_iis_2024_119

Deep learning based simulation for new product demand estimation

Adesh Kumar, *The University of Texas at Austin, adeskuma@utexas.edu*
Pankaj Nagpal *, *Arkansas State University, pnagpal@astate.edu*
*Corresponding author

Abstract

Increasingly, the manufacturers and third-party sellers sell their products online at large e-commerce platforms. A good forecast is necessary to avoid resource wastage in the form of over-production or underserved demand. Sensing the demand for a new product on e-commerce platforms in the presence of other competitive products requires techniques beyond traditional forecasting methods. Typical e-commerce platforms, being a two-sided marketplace, need to make a trade-off between showing very relevant and trusted products versus exploring new selections. As customers heavily rely upon organic search functionality for product discovery, the demand forecasting for products depends upon signals from search algorithms. In this paper, we propose an end-to-end Deep Learning (DL) based solution to estimate new product demand. Our design science research (DSR) approach involves the use of search ranking algorithm and its features to simulate the impressions of new products in the presence of existing products and vice versa. This approach helps to estimate demand using simulated search funnel metrics to bake in competitive characteristics of other products.

Keywords: deep learning, simulation, new products, cold start, product recommendation

Introduction

Several e-commerce platforms are two-way marketplaces where end customers buy products listed by sellers. The dominant channels for product discovery of the products are organic search and sponsored ads. However, discovery of new products on e-commerce platforms is a challenging problem due to heavy reliance of search functionality for product discovery as it is optimized to surface already established products (Cao & Zhang, 2017). The ranking algorithms in e-commerce platforms use historical customer actions such as clicks, purchases on the products as proxy for relevance.

These historical signals are either absent or limited for new products, and hence the discovery of new products is improbable via search algorithms. We rely on the intuition that demand of any product on e-commerce platform is highly correlated with impressions on the same and similar products. Hence, the important features for demand forecasting model in a two-side marketplace setting are search funnel metrics - impressions, cart-adds, clicks, and purchases. As these features are not accrued for new products, the demand forecasting for the new products is a nontrivial problem. Therefore, the mechanism of launching a new product on e-commerce platform requires a solution that addresses the missing feature values of search funnel metrics used in the conventional demand forecasting model in order to get high confidence demand estimates for new products (Abou et al., 2022). An established method of estimating the demand for a new product is the Delphi method using human judgement. This method appeals less when new product demand is to be estimated at scale in context of a two-sided marketplace (Dai & Huang, 2021). The alternative method of test marketing that requires to launch the new products in a limited capacity is both time consuming, operational heavy, and prone to make incorrect decisions.

Design science research is an “important paradigm of Information Systems (IS) research” (Gregor & Hevner, 2013) with publications in Issues in Information Systems (Bovee et al., 2020).With the passage of time, this valuable method was less understood. Design science papers such as Gregor and Hevner (2013) have redefined the method. Earlier papers such as Hevner and Park (2004) had defined the method, and also delineated the steps in the design science method. Unlike the behavioral science method, which is concerned with theory development and theory testing, the design science method endeavors to create novel artifacts (Hevner & Park, 2004). We utilize the guidance in these key papers related to design science research. Hevner & Chatterjee (2010) also provide direction to research on design science. Based on these papers, we set to design a better method for new product demand estimation.

Background and artifact

In the retail industry, two-sided marketplaces such as Walmart, Amazon, eBay, etc. enjoy more than 40% market share [https://www.statista.com/statistics/274255/market-share-of-the-leading-retailers-in-us-e-commerce/]. These marketplaces aggregate the demand at their real estate, i.e. brick-and-mortar stores and websites, and fulfil it with a large selection of products that are sourced from manufacturers or third-party sellers. In addition to foot traffic, the customers visit their websites to make purchases. In online settings, customers reveal their intention for purchases in the form of search queries. Based on various product features, the underlying ranking algorithms display the most relevant products to the end customers. The listing of search results is dynamic with response to a customer’s queries and depends upon several factors such as timing, customer’s location, product availability, pricing, etc. (Santu et al., 2017). Due to marketplace dynamics, the search funnel metrics such as clicks, views, purchases at product and query level have proven to be significant features in demand forecasting models.

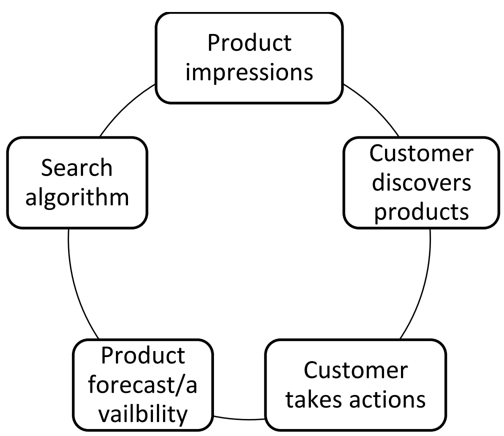

Figure 1: Search impression dependent demand cycle

For e-commerce platforms, the search algorithms are the most important technological components that drive revenue (Li, 2024). The forecasting process, as depicted in **Figure 1**, leverages customer actions such as clicks, cart-adds, purchases, reviews, etc. as some of the important features. As these e-commerce platforms provide a huge selection of products (billions of products), it is difficult to estimate a high confidence forecast at SKU level. In e-commerce setting, the hierarchical forecasting method is well-accepted method to have a high confidence forecast at high product categories/groups and then trickled down at product type, brand, and SKU level (Bandara et al., 2019; Ren et al., 2020). As demand at an e-commerce platform can be inferred from keywords used by end customers, the search funnel characteristics such as keyword volume, clicks, cart-adds, and purchases are key features used in the forecasting process (Mitra et al., 2022). For e-commerce platforms, the discovery of new products is a challenging problem due to ranking algorithm bias and established product demand cannibalization which are described in the section that follow.

Ranking algorithm bias

E-commerce platforms use ranking algorithms to surface relevant products for customer queries. These models are called Learn to Rank (LTR) models. However, most of the e-commerce platforms suffer from various type of biases that favor established products, making the discovery of a new product difficult (Baeza-Yates, 2018). There are many reasons for these biases:

Sample bias: Sample bias is mainly related to the method of obtaining training data. When the sampling method systematically favors the selection of certain type of products (e.g. established products), the ranking model is biased in favor of these products. When new products are not represented with enough examples in the training dataset, the trained LTR models will not capture the patterns related to new products. This will result in lower position of new products in search results, reducing the visibility of these new products.

Objective function bias: LTR models are trained to optimize the objective function, which represents the relevance score for query and set of candidate products. When LTR model use features such as engagement metrics, the new products are ranked lower due to the absence of historical customer engagement. In machine learning parlance, new products suffer from missing value problem on key relevance metrics.

Feature bias: LTR models use the features capturing the historical relationship between query and product based on the temporal data. When a model gives higher weight to temporal behavioral features, the model will have a negative bias for new products as those behavioral correlations are missing for new products.

In our solution, we have proposed to address the biases in LTR models with feature engineering while using the existing ranking model already deployed in production in an e-commerce setting.

Established product demand cannibalization

Another challenge related to new product discovery is demand cannibalization i.e. demand shift from established products to new products. If customers are buying established products, then introducing new products in the list of search results would negatively impact the sales of existing products. Many e-commerce platforms have tried to address this problem with personalized experience to customers. New products appeal to a certain segment of customers who are willing to take the risk of trying out new products. The basic premise to address cannibalization concern is to identify and serve customer segments with personalized product recommendations. The reaction to novel product varies across customer segments. The highly attractive customer segments for new products are the ones are comfortable to shop around various e-commerce platforms for their product needs. Serving the need of these customers would enhance new product discovery without impacting the sales of existing popular products. In the long run, new products bring more customers to e-commerce platform hence increasing size of the pie. This paper does not delve into personalization algorithms, but e-commerce platforms use customer segmentation, A/B testing, and reinforcement learning frameworks to understand the personalization needs of different sets of customers. Reinforcement learning algorithms (Q. Cai et al., 2018) techniques such as multi-arm bandit are used to explore the policies determining the customers and situation to show new products.

Literature review

Forecasting demand for new products is more challenging compared to existing products, as there is no historical sales data available to indicate future demand patterns (van Steenbergen & Mes, 2020). Traditional forecasting methods, relying solely on past sales data, are not applicable for new product launches. Several quantitative methods have been proposed to forecast demand for new products by leveraging available information beyond historical sales data alone. Further summaries are provided in Appendix A.

Smirnov and Sudakav (2021), and R. A. Trihatmoko et. al (2018) proposed a method to transfer knowledge from previous launches. Machine learning techniques like Random Forests, Gradient Boosting, and Neural Networks can combine data on product characteristics, descriptions, prices, etc. with sales patterns of previously launched similar products to predict demand profiles for new products. These data-driven approaches learn current and future demand based on the past product introductions. This technique is recommended when the product launch is a recurring phenomenon within the organization. Also, the implicit assumption is that the type of the new products is of same category as previous launches and the learning from the previous launches can be extrapolated for the new launch.

Van Steenbergen and Mes (2020) proposed an innovative method, demand pattern-based similarity, to estimation the demand for new products. Methods like DemandForest use k-means clustering to group products with similar demand patterns, then apply ensemble models like random forests and quantile regression forests to forecast total demand and demand distributions for new products based on their characteristics. The train and test phase of the demand forest model is provided below:

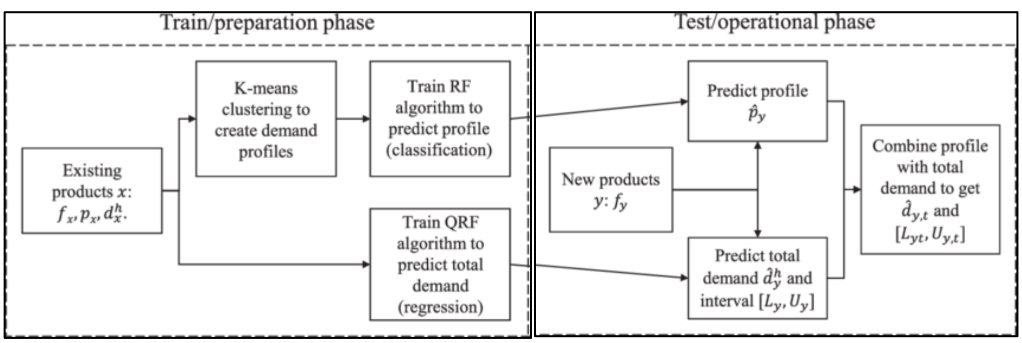

Figure 2: DemandForest model for predicting demand profile for a new product. Source: Forecasting demand Profile of new products (van Steenbergen & Mes, 2020)

This method is suitable for complementary products where demands are highly correlated. For example, the longitudinal/temporal demand pattern of new vitamin D supplement is correlated with the demand pattern of vitamin B12 as customers generally include these two vitamins in their diet together.Both Smirnov and Sudakav (2021), and Van Steenbergen and Mes (2020) proposed to use the auxiliary sources for demand sensing for new products in a specific category. Transferring knowledge from auxiliary data sources like social media, online reviews, or other product domains can provide useful signals to forecast demand for completely new product categories. This approach is used for the online datasets to generate a demand profile for a product category. This method is same as a driver-based forecasting model that rather utilize social media and online review signals as features. The process of extracting the features from the social media data is cumbersome and prone to noise. The general method to code the features from social media data is to model topics of interest using NLP techniques. With the help of Topic model along with sentiment model, the demand for a particular category can be estimated.

$$D_t = \sum_{i}^{n} \beta_i * f(T_{i,t}, S_{i,t})$$

*Where β_i is a coefficient for topic **i**, and $T_{i,t}$ is volume of traffic related to **i** topic at time **t**, and $S_{i,t}$ is sentiment score for topic **i** at time **t.** And D_t is demand at time* **t.**

Swaminathan and Venkitasubramony (2024) explored the hybrid and qualitative approaches for new product demand forecasting. They observed that combining machine learning with traditional statistical methods or qualitative expert judgments in a hybrid approach can further improve new product demand forecasting accuracy. Techniques like the Delphi method and market research provide complementary information. Overall, the literature highlights machine learning and hybrid methods as promising approaches to tackle the challenging problem of forecasting demand for new products by leveraging all available data sources beyond just historical sales. Proper quantification of uncertainty in demand forecasts is also crucial for inventory and operational planning (Abou et al., 2022).

The existing literature are focusing mainly on demand forecast without considering the presence of competitive products and cannibalization of existing product demand. We think the simulation-based approach would be more suitable to estimate the demand of new products with higher confidence as it allows to make several trade-offs related to competitive dynamics among hundreds of products available at online platforms. The simulations are useful tools widely adopted in industry to observe behavior of complex systems when running real experimentations are expansive, resource intensive, and time consuming (Lamé & Dixon-Woods, 2020), (Saikou Y. Dialla, 2016).

Summary and discussion

The key contribution of this paper is to provide a cost-effective framework to estimate the demand of new products at an e-commerce marketplace. The framework uses end-to-end product discovery funnel via search functionality, rather than relying on historical patterns, and highly expensive and time-consuming test marketing methods. In the absence of historical data for a new product, the existing methods rely on historically correlated proxies such as historical demand of similar products to estimate the demand for the new product. Our proposed approach uses simulation of search functionality with appropriate adjustments for new products, and hence does not suffer from the oversimplification present in other approaches. Moreover, our solution simulates product discovery via search functionality, and hence provides the flexibility of testing several marketing scenarios in an offline setting (such as availability of competitive products, or price changes). This flexibility is essential to understand demand estimates with a changing competitive landscape.

Simulation based approach

New product forecasting is a challenging problem in the retail space. Forecasting models in e-commerce setting uses product impressions. However, the impressions of the new product are unknown. High confidence imputation of new product impressions in forecasting model would result in a high confidence estimate for new products. To solve this cold start problem for new products, two process steps (Figure 1) need to be adjusted simultaneously: 1) discovery of new products in search and 2) demand forecasting and availability of new products. The proposed simulation framework (Figure 3) has following components to solve this problem end-to-end:

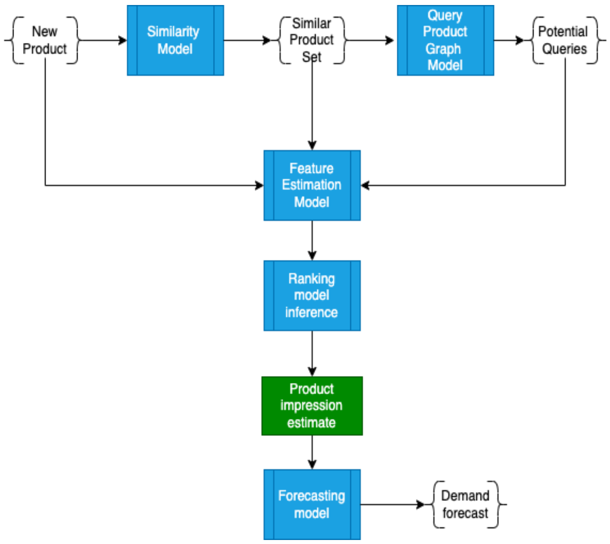

Figure 3: High level design of proposed framework

Product similarity model

The crucial component in our solution design is the product similarity model to identify products that are semantically similar to the new product. Generally, the product attributes are stored in a mix of unstructured data such as text (product title, product description, etc.), images (as product images), and structured fields such as brand name, seller's name, geography etc. To build an algorithm to identify similar products, we propose to train a Deep Learning (DL) model with multi-modal inputs (text, and images) to summarize the high-dimensional product information to small dimensional embedding vectors (Kornblith et al., 2019; Hsiao & Li., 2014) encapsulating semantics of products. Figure 4 shows the architecture of the DL model that predicts the price of the product based on the unstructured and structured input data. For similarity algorithm, each product is passed through the DL model so that low dimensional embedding for each product can be extracted while final prediction (i.e. price) is discarded (Punia & Shankar, 2022a).

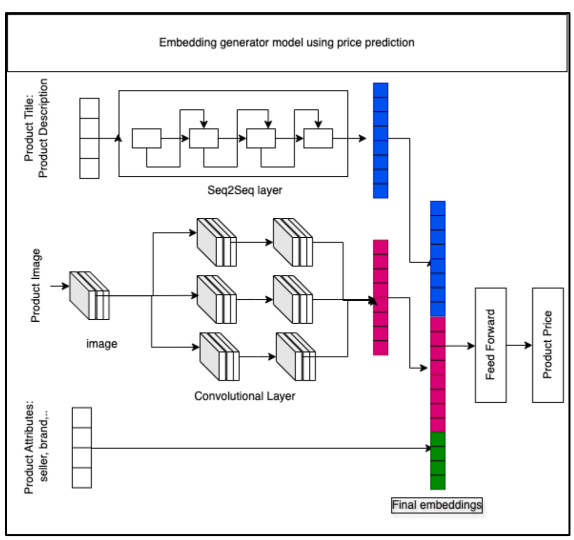

Figure 4: DL learning model architecture

The loss function for DL model is:

$$\mathcal{L}(\mathrm{w}) = \frac{1}{2}\sum_{i}^{n}(price_i - prediction_i)^2$$

Where w is models' parameters and N is number of examples in training dataset. The DL model estimates the price conditioned on X features:

$$\mathrm{E}(price/X) = func(X)$$

Based on the embeddings from the similarity model, the algorithm identifies the existing products that are similar to new products. We propose to use cosine similarity measurement. The cosine similarity between product A and B can be calculated with following formula:

$$Cosine\ Similarity = \frac{\boldsymbol{E_A} \cdot \boldsymbol{E_B}}{||\boldsymbol{E_A}||\ ||\boldsymbol{E_B}||}$$

Where $\boldsymbol{E_A}$ and $\boldsymbol{E_B}$ are embeddings for product A and product B.

Algorithm for selecting the similar products

Input: ***S*** as set of products, ***N*** new product, ***E*** embedding matrix

Initialize: ***L*** <- empty list
Loop: for each product **s** ∊ ***S*** set of products:
    if similarity ($\boldsymbol{E_S}, \boldsymbol{E_N}$) > threshold:
    Add ***s*** in ***L***
Output: **L**

Relevant Queries for New Product

As customers majorly use search queries to identify products for their purchase intent, we need to find potential queries that customers would likely use for discovery of the new product. As we get a list of similar products from previous step, we can find the associated potential queries related to the new product with graph data representing query and products. Queries and products are two types of nodes and clicks/purchases volume are edges in graph network (Figure 5). From the list of the similar products identified from the previous step, we take one hop walk on the graph along high weight edges to arrive at the potential queries. The edge weight represents strength of association between products and queries. Among all of the queries connected to a product in the graph, high-weighted queries are used by customers to discover the new product.

Figure 5 illustrates how P1 and P2, which are similar products for new product, searchable via queries Q1, Q2, Q3, and Q4. The edges between products and queries represent the weighted combination of the customer actions such as clicks, adds, purchases, reviews etc. (W. Cai et al., 2021).

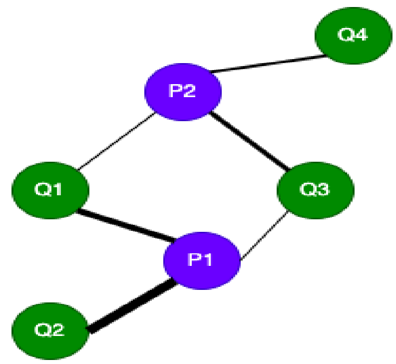

Figure 5: Graph representation of query and product mapping. P1 and P2 are two similar products for a new product. The thickness of edge between two nodes represents the degree of customer actions on a product for a query

To select the potential queries for new product, the detection algorithm should traverse from similar product nodes to next query nodes. The algorithm will select only those queries with edge weight more than a threshold.

Algorithm for Top k queries for

Input: ***L*** as set of similar products, ***N*** new product, ***G*** graph dataset, threshold, k

Initialize: ***Q*** <- empty list
Loop: for each product **l** ∈ ***L*** set of products:
    Loop: for each edge of $\boldsymbol{e_i} \in Wt(\boldsymbol{q_i}, \boldsymbol{l})$:
        if ($\boldsymbol{e_i}$ > threshold) and (len Q <=***k)***:
            Add $\boldsymbol{q_i}$ in ***Q***

Output: ***Q***

Feature estimate for new product

We propose handling of missing values (imputation) only for the important features selected by LTR models. Several methods can be used to estimate the key features for a new product based upon similar product set (Naina et al., 2020). We propose to have a simple feature aggregation of customer actions upon the set of similar products related to new product N.

$$\widehat{\text{feature}}(\text{q}, \text{N}) = \frac{\sum_i^n feature(q, S_i)}{\sum_i^n 1}$$

$S_i \in$ set of similar products related to new product N.

In theory, we are estimating the prior value of the features. The posterior values of the features are updated based on real customer actions on new product impressions. The general technique to get the posterior value is Bayesian regression model.

Ranking Model Inference

A standard scientific technique to get relevant recommendations for a user is collaborative filtering (Yu et al., 2021). Collaborative filtering is more appropriate when the query intention of user is unstated and implicit. When user intentions are explicit, Learn-to-Rank algorithms are state-of-the-art scientific approaches, generally called rankers in the industry. The rankers are apt at providing ranked recommendations over a large candidate set of interest. To obtain an unbiased rank of new products based on prior key feature values, we need to get ranker inference on a pair of query and associated product set that includes new products. The inference step provides a sorted list of products including new and established products for a given query. The mathematical formulation of ranking model is as follow:

$$rank(q, p_i) = \varphi(\beta_j, \gamma_j, \widehat{f_{(q,p)}})$$

Where β_j , γ_j are model's parameters and $\widehat{f_{(q,p)}}$ is predicted features for new product when P is new product. After inference from ranking model, we have the following dataset: (***q,p,r***) where ***q*** is query, ***p*** is product, and ***r*** is rank of product ***p*** for query ***q*** (Santu et al., 2017).

Product Impression estimates

The impression estimate is received from a simple linear model conditioned on product rank and other features along with query features. The query and product features are modeled as follows:

$$\widehat{Imp_{p,q}} = f(\beta_0, \beta_1, \beta_2, \beta_3)\{\boldsymbol{r}, \boldsymbol{f}(\boldsymbol{p})\, \boldsymbol{f}(\boldsymbol{q})\}$$

$\widehat{Imp}$ is an estimate of the impressions for product ***p*** for query ***q***. β_1 is coefficient for rank, β_2 are coefficients for product features, and β_3 are coefficients for query features. The impressions of product p are aggregated as following:

$$Imp_p = \sum_q \widehat{Imp_{p,q}}$$

Design science result: Forecasting model for new product

The simulated forecast for new products and other affected products is estimated using the existing forecasting model having product impressions as a key feature. There are several machine learning techniques for demand forecasting solely based on historical demand such as ARIMA models, deep learning based models (Salamai et al., 2022), and collaborative filtering (Punia & Shankar, 2022b), however our approach uses a driver based models (Smirnov & Sudakov, 2021). The formulation of the forecasting model is:

$$\mathcal{F} = \sum_m \beta_m * \mathrm{X}_m$$

Where X_m = variable variant m and β_m is the coefficient of m variable. One of the features in X_m is impressions for the product. The demand forecast of new product is estimated from the product level multi-variate model conditioned on several features rather than relying solely on historical trend. More often, the demand at category level such as 'shoes' needs to be estimated first for planning purposes. Hierarchical demand forecasting models are generally used where the features are aggregated at category or location level. The change in demand at category level can be estimated with help of features such as share (%) of new products, product age distribution, and price ratio of new products versus old products etc. in the hierarchical models.

Evaluation Framework

Generally, forecast quality is evaluated with the accuracy metric (Wei et al., 2017). The overall framework has several machine learning solutions to arrive at the total forecast, hence performance of each component should be measured separately. As the solution provides the ability to simulate the product impressions, the accuracy of impression prediction is important. The product embeddings for measuring the similarity among products is extracted through price prediction model. The evaluation metric for this model is Root Mean Squared Deviation (RMSD), defined as:

$$RMSD = \sqrt{\frac{\sum(price_i - \widehat{prediction}_i)^2}{N}}$$

For evaluation of quality of the embeddings for product similarity task, we can create a golden dataset with following structure ($product_1$, $product_2$, similarity label) and generate the following contingency table:

		Predicted	
		Similar	*Non-Similar*
Actual	*Similar*	TP	FN
	Non-Similar	FP	TN

The evaluation metrics are precision and recall which are defined as follows:

$$Precision = \frac{TP}{TP + FP}$$

And

$$Recall = \frac{TP}{TP + FN}$$

Where TP = True Positive, FN = False Negative, FP = False Positive, and TN = True Negative

Discussion

This is a novel approach to estimate the demand for a new product without making changes to existing system components such as ranking model or forecast models. This approach allows us to bake in the competitive dynamic of the marketplace while estimating the demand for new products and its impact on the existing products. The proposed framework cleverly provides ways to understand the impact of new product position relative to established products in search results, generally known as ranking biases (Baeza-Yates, 2018). Essentially, this approach is best suited when estimating unrestricted and unbiased demand for the new product is needed to make launch decisions. This framework helps estimate the lower bound of new product demand when product discovery is not biased.

The approach to de-biasing the discovery of the new product is a separate research topic which had many other techniques not discussed in this paper. The novelty of this approach is to use deep learning models to get the semantic embedding of product features in low dimension space. Combined with graph network between query and product, this approach estimates the missing values on key features for new products.

Finally, the estimated impressions based on new product ranking in search results helps in obtaining a high confidence demand estimate for new products. The future direction of our research is to provide a reduced variance of the demand estimates from this framework. Another interesting research area is to combine the state-of-the-area Active Learning approaches for new product demand forecasting (Zhu et al., 2020). Active Learning will allow to fine-tune the overall algorithm with a limited number of product launches.

Implications for practice

In this paper, we propose a novel methodology for estimating the demand for new products using end-to-end simulation of product discovery mechanism. However, it requires us to build several AI and machine learning based components. The two critical components i.e. similarity algorithm and feature estimation models should be reassessed for accuracy periodically. As mentioned in the evaluation section, the performance of product embeddings in identifying similar products needs to be reassess periodically with a fresh golden dataset. Generally, organizations set up a human annotation mechanism to get the golden dataset. In this case, the human annotators are experts who are trained to judge the similarity between two products on pre-defined dimensions such as product functionality, brand, product category, product images, price, etc. Similarly, the accuracy of ranking model's features for new product needs to be assessed with real user interaction data on new products launch on an e-commerce website. This can be achieved by comparing the real feature values of new products n-days after the launch on the e-commerce website.

Limitations

This approach estimates the demand for new products mainly based on product discovery via search functionality. This could raise a concern that discovery of new product will negatively impact established products. Our research briefly touched upon the need for personalized recommendations to quell this concern. However, we have not added the scientific approach to enable personalized recommendation in search algorithm. In practice, increased selection of products on e-commerce websites along with the right discovery mechanism will result in two important business metrics, i.e. increased traffic of new users and increased time spent on e-commerce website; as both new and existing users will explore more products on the website. The discovery of products is not only limited to search functionality, but is also achieved via product recommendation mechanisms used for cross-sell and up-sell, e.g. 'people viewed this product also considered other products' or 'people bought this product also bought other complementary products. The increased overall engagement of users on e-commerce website should recoup the lost (cannibalized) demand of established products via search functionality in the long run. Our current approach does not account for any other discovery mechanism, mainly to reduce the complexity of the overall solution.

Conclusions

The launch of new products on an e-commerce website is a costly affair from an operational point of view. Launching the product for testing in the market is not only expensive but also fraught with under-estimating the demand, if it is not done for long period of time. On the other hand, the methods to estimate demand of new product using pre-launch data is faulty as it does not consider the competitive dynamics of other products. Our approach that uses a state-of-the-art AI solution is highly scalable across all type of products. It is a robust framework to estimate the demand for new products without actually launching a product on an e-commerce website. Our solution allows the marketer to simulate the discovery of the new product via search functionality and provide a lower bound (i.e. a conservative estimate) of demand.

References

Abou, E., #1, M., #2, Z., Agarwal, R., & Abedin, B. (2022). Uncovering Barriers in Forecasting Uncertain Product Demand in the Supply Chain. In *Int. J Sup. Chain. Mgt* (Vol. 11, Issue 6). http://excelingtech.co.uk/

Baeza-Yates, R. (2018). Bias on the web. *Communications of the ACM*, *61*(6), 54–61. https://doi.org/10.1145/3209581

Bandara, K., Shi, P., Bergmeir, C., Hewamalage, H., Tran, Q., & Seaman, B. (2019). *Sales Demand Forecast in E-commerce using a Long Short-Term Memory Neural Network Methodology*. http://arxiv.org/abs/1901.04028

Bovee, B. S., Jernejcic, T., & El-Gayar, O. (2020). A GAMIFICATION TECHNIQUE TO INCREASE ENGAGEMENT IN ASYNCHRONOUS ONLINE DISCUSSIONS. *Issues in Information Systems*, *21*(3), 20–30. https://doi.org/10.48009/3_iis_2020_20-30

Cai, Q., Filos-Ratsikas, A., Tang, P., & Zhang, Y. (2018). Reinforcement mechanism design for e-commerce. *The Web Conference 2018 - Proceedings of the World Wide Web Conference, WWW 2018*, 1339–1348. https://doi.org/10.1145/3178876.3186039

Cai, W., Song, Y., & Wei, Z. (2021). Multimodal Data Guided Spatial Feature Fusion and Grouping Strategy for E-Commerce Commodity Demand Forecasting. *Mobile Information Systems*, *2021*. https://doi.org/10.1155/2021/5568208

Cao, X., & Zhang, J. (2017). *Prelaunch Demand Estimation*. https://web-docs.stern.nyu.edu/

Dai, Y., & Huang, J. (2021). A Sales Forecast Method for Products with No Historical Data. *2021 IEEE 6th International Conference on Cloud Computing and Big Data Analytics, ICCCBDA 2021*, 229–233. https://doi.org/10.1109/ICCCBDA51879.2021.9442603

Gregor, S., & Hevner, A. R. (2013). Positioning and presenting design science research for maximum impact. In *MIS Quarterly: Management Information Systems* (Vol. 37, Issue 2, pp. 337–355). University of Minnesota. https://doi.org/10.25300/MISQ/2013/37.2.01

Hevner, A., & Chatterjee, S. (2010). *Design Research in Information Systems* (Vol. 22). Springer US. https://doi.org/10.1007/978-1-4419-5653-8

Hevner, A., & Park, J. (2004). *Design Science in Information Systems Research Article* (Vol. 8). https://www.researchgate.net/publication/201168946

Jen-hao Hsiao, & Li-Jia Li. (2014). *ON VISUAL SIMILARITY BASED INTERACTIVE PRODUCT RECOMMENDATION FOR ONLINE SHOPPING* (IEEE). International Conference on Image Processing .

Kornblith, S., Norouzi, M., Lee, H., & Hinton, G. (2019). *Similarity of Neural Network Representations Revisited*.

Lamé, G., & Dixon-Woods, M. (2020). Using clinical simulation to study how to improve quality and safety in healthcare. In *BMJ Simulation and Technology Enhanced Learning* (Vol. 6, Issue 2, pp. 87–94). BMJ Publishing Group. https://doi.org/10.1136/bmjstel-2018-000370

Li, L. (2024). *Research on Personalized Recommendation System for E-Commerce Products Based on Collaborative Filtering Algorithm*. 876–880. https://doi.org/10.1109/eebda60612.2024.10485710

Mitra, A., Jain, A., Kishore, A., & Kumar, P. (2022). A Comparative Study of Demand Forecasting Models for a Multi-Channel Retail Company: A Novel Hybrid Machine Learning Approach. *Operations Research Forum*, *3*(4). https://doi.org/10.1007/s43069-022-00166-4

Naina, R. H., #1, M., Abu, N., #2, B., Khirzan, M., Rahman, B. A., Asiah, S., Shahid, M., & Borhan, H. (2020). Modelling the Predictors and Outcomes of Supply Chained of Brand Experience: Evidence from the Chained Fast Food Brand. In *Int. J Sup. Chain. Mgt* (Vol. 9, Issue 5). http://excelingtech.co.uk/

Punia, S., & Shankar, S. (2022a). Predictive analytics for demand forecasting: A deep learning-based decision support system. *Knowledge-Based Systems*, *258*. https://doi.org/10.1016/j.knosys.2022.109956

Punia, S., & Shankar, S. (2022b). Predictive analytics for demand forecasting: A deep learning-based decision support system. *Knowledge-Based Systems*, *258*. https://doi.org/10.1016/j.knosys.2022.109956

Ren, S., Chan, H. L., & Siqin, T. (2020). Demand forecasting in retail operations for fashionable products: methods, practices, and real case study. *Annals of Operations Research*, *291*(1–2), 761–777. https://doi.org/10.1007/s10479-019-03148-8

Saikou Y. Dialla, C. J. L. J. J. P. R. G. (2016). *Simulating complex service systems, WSC'16, Winter Simulation Conference, Arlington, VA, December 11-14, 2016.* (IEEE).

Salamai, A. A., Ageeli, A. A., & El-Kenawy, E. S. M. (2022). Forecasting e-commerce adoption based on bidirectional recurrent neural networks. *Computers, Materials and Continua*, *70*(3), 5091–5106. https://doi.org/10.32604/cmc.2022.021268

Santu, S. K. K., Sondhi, P., & Zhai, C. (2017). On application of learning to rank for e-commerce search. *SIGIR 2017 - Proceedings of the 40th International ACM SIGIR Conference on Research and Development in Information Retrieval*, 475–484. https://doi.org/10.1145/3077136.3080838

Smirnov, P. S., & Sudakov, V. A. (2021). Forecasting new product demand using machine learning. *Journal of Physics: Conference Series*, *1925*(1). https://doi.org/10.1088/1742-6596/1925/1/012033

Swaminathan, K., & Venkitasubramony, R. (2024). Demand forecasting for fashion products: A systematic review. In *International Journal of Forecasting* (Vol. 40, Issue 1, pp. 247–267). Elsevier B.V. https://doi.org/10.1016/j.ijforecast.2023.02.005

van Steenbergen, R. M., & Mes, M. R. K. (2020). Forecasting demand profiles of new products. *Decision Support Systems*, *139*. https://doi.org/10.1016/j.dss.2020.113401

Wei, J., He, J., Chen, K., Zhou, Y., & Tang, Z. (2017). Collaborative filtering and deep learning based recommendation system for cold start items. *Expert Systems with Applications*, *69*, 1339–1351. https://doi.org/10.1016/j.eswa.2016.09.040

Yu, J., Shi, J., Chen, Y., Liu, W., Liu, K., & Xie, Z. (2021). Enhancing Collaborative Filtering Recommendation by User Interest Probability. *2021 4th International Conference on Artificial Intelligence and Big Data, ICAIBD 2021*, 525–529. https://doi.org/10.1109/ICAIBD51990.2021.9459028

Zhu, Y., Lin, J., He, S., Wang, B., Guan, Z., Liu, H., & Cai, D. (2020). Addressing the Item Cold-Start Problem by Attribute-Driven Active Learning. *IEEE Transactions on Knowledge and Data Engineering*, *32*(4), 631–644. https://doi.org/10.1109/TKDE.2019.2891530

Appendix A
Summary of Literature

Paper (Authors and year)	Key findings	Implications for our paper
Cao and Zhang (2017)	Paper proposes a cost-effective method with high external validity for new product demand estimate leveraging price sensitivity of new product products.	Using price of the product as main feature for simulation exercise. For product embeddings, we proposed to use product price as outcome variable.
Dai and Huang (2021)	Propose to build the sales trend model using the similar products identified based on the several features. The basic idea is that the sales of new product will closely follow the trend of the similar products after launch.	Identifying the similar products could help for new product demand estimation.
S. Gregor et al. (2013)	Impact of design research	Conceptual design
A. Hevner et al. (2004)	Design science in information system	Systems for simulation
A. Hevner et al. (2010)	Design science in information system	Systems for simulation
Santu et al. (2017)	Paper discusses a few Learn-to-rank models used in search function for e-commerce. These models use the user feedback signals such as click rates, add-to-cart ratios, order rates, and revenue as features.	For new product, if we estimate the priors of these user feedback features, we can estimate the impressions and other search funnel metrics.
Bandara et al. (2019)	E-commerce platform contains large numbers of related products, in which the sales demand patterns can be correlated. Building hierarchical forecasting at category and store level aggregation.	(1) Related product's sales will be correlated at e-commerce platforms. (2) The SKU level forecast just based on the historical sales have high variation. (3) highlights the cannibalization effect at SKU level within product categories.
Ren et al. (2020)	The main focus of the paper is to engage extraction of the features from user-generated data for forecasting. This paper also proposes to use the reviews and social media data for forecasting as another alternative source for external signals.	(1) Our approach aligns with the proposal of using the user-generated data as features to forecast the demand. (2) As the new products don't have any historical sales, we proposed to use the snapshot of user-generated features to predict new product demand.

Mitra et al. (2022)	This paper provides a detailed list of different type of forecasting models used in retail industry and their applicability in various scenarios. The paper also provides the demand forecasting model's evaluation metrics.	Our proposed approach has 3 sequential systems with their individual uncertainties. In future, we should measure the uncertainty of entire solution together and proof that our solution will also reduce the forecasting uncertainty.
Cai et al. (2018)	This paper highlights reinforcement learning use cases in ecommerce two-sided marketplace. The proposed approach highlights how reinforcement learning algorithm can be used in search results.	We proposed to use reinforcement learning based approach to deal with cannibalization concerns due new product discovery.
Steenbergen and Mes (2020)	This paper highlights how not having historical data making forecasting for new products difficult. It proposes that the new product would have same demand pattern as similar product in a same profile (category).	Our approach is influenced by this paper which proposes an end-to-end process of demand forecasting of the new product. We have some components of DemandForest in our solution.
Smirnov and Sudakov (2021)	This paper highlights the importance of feature engineering in the forecasting of new product. The proposed feature engineering requires the domain understanding.	It is related to use the impressions of products in the forecasting model as an additional feature.
R. A. Trihatmoko et al. (2018)	This paper provides an overview of new product introduction framework for an FMCG company. This proposed approach uses both quantitative and qualitative inputs for demand forecasting.	Literature overview
Swaminathan and Venkitasubramony (2024)	This paper highlights the qualitive methods to incorporate the expert opinion in new product forecast. This also delves in various machine learning techniques to model the demand in this industry.	Literature review
Kornblith et al. (2019)	This paper highlights various Deep Learning models to extract the product embeddings to estimate the similarity between two products.	In our paper, we have used cosine similarity based on the simplicity of its formulation.
Hsiao and Li (2014)	This paper shows how E-commerce companies use visual feature presentation from DL models to detect the similar products.	We also proposed to use the product images as high dimensional features in price prediction model.