Rethinking E-Commerce Search

Haixun Wang
Instacart, Inc.
USA
haixun.wang@instacart.com

Taesik Na
Instacart, Inc.
USA
taesik.na@instacart.com

Abstract
E-commerce search and recommendation usually operate on structured data such as product catalogs and taxonomies. However, creating better search and recommendation systems often requires a large variety of unstructured data including customer reviews and articles on the web. Traditionally, the solution has always been converting unstructured data into structured data through information extraction, and conducting search over the structured data. However, this is a costly approach that often has low quality. In this paper, we envision a solution that does entirely the opposite. Instead of converting unstructured data (web pages, customer reviews, etc) to structured data, we instead convert structured data (product inventory, catalogs, taxonomies, etc) into textual data, which can be easily integrated into the text corpus that trains LLMs. Then, search and recommendation can be performed through a Q/A mechanism through an LLM instead of using traditional information retrieval methods over structured data.

1 Introduction
E-commerce search primarily operates in the “structured data” domain, with the objective of finding the most relevant products in a product database. While the database contains textual attributes such as product names and descriptions, it is predominantly a structured dataset containing records with attributes such as brand, price, size, weight, and other product-specific features such as gluten-free, screen resolution, etc.

1.1 Challenges in E-Commerce Search
E-commerce search presents two fundamental challenges. The first is understanding the user intent behind short search queries, and the second is understanding products in the catalog, which requires world knowledge or a product knowledge base.

1.1.1 Query Understanding
In classic information retrieval, the challenge of query understanding is largely the challenge of extracting information from the query and map it to database attributes such as brand, product name, and other features such as organic.
But even for a search query as simple as “red wine $40”, most e-commerce search engines fail to understand the intent behind the search. As shown in Fig 1, over the years, Amazon returned a variety of products other than red wine. A red-colored pair of shoes, because the color of the shoes or pants turned out to be “wine red.” The system also failed to understand $40 is an approximate price constraint, and returned pants of waist size 40. These are well-known issues for query understanding, but in practice, there are numerous edge cases that require specialized algorithms and models. As a result, query understanding remained largely an unsolved problem in industrial e-commerce search systems.

### 1.1.2 Document (Product) Understanding

Each product in the product database (catalog) has attributes such as name, description, price, and so on. It is not easy to find the most relevant products for a given query through term-based IR methods. Recent development in embedding-based retrieval [Zhang et al., 2020; Huang et al., 2020; Xie et al., 2022] has improved semantic matching, but it is still difficult to answer queries such as “healthy snacks for kids,” or “alternatives to ice cream.”

Clearly, E-commerce search is a knowledge-intensive task. Providing customers with recommendations, ideas, and inspiration requires knowledge outside of the product database. E-commerce companies such as Amazon and Baidu invest heavily in developing product knowledge graphs with the goal of learning everything there is to know about their products.

Unfortunately, building such product knowledge graphs has had limited success to date. At least two obstacles exist. First, modeling such knowledge explicitly in a product knowledge graph necessitates the creation of a very complex schema or ontology, which makes accessing such knowledge challenging because algorithms must navigate the complex schema or ontology. Second, it is difficult to develop a general-purpose algorithm that can convert unstructured data about any
product into a structured format, because each product type may require the development of algorithms that identify patterns that are specific to that product type.

1.2 A New Vision for E-Commerce Search

E-commerce search is a knowledge-intensive task. As shown in Fig 2, its success relies on the seamless integration of structured data (e.g., the product catalog), semi-structured data (e.g., taxonomy and ontology), and unstructured data (e.g., customer reviews, web articles, etc.)

In fact, this problem is more general than e-commerce search, as it applies to any task that involves querying against a database, while some critical knowledge for answering such queries resides in data of heterogeneous types outside of the database.

For such problems, the traditional approach is to collect all the relevant data and convert them into a structured form such that they can be indexed, retrieved, and ranked for search. The challenge is that the data could be massive, and the cost of information extraction could be prohibitively expensive.

In this paper, we envision a solution that is the direct opposite of what the e-commerce industry has done in recent decades. Rather than converting all information into a structured form and then conducting search over a database, we convert all structured and semi-structured data into text and then answer queries through a large language model (LLM) trained over the text.

The following is the rationale for our new approach. First, answering questions like “healthy snacks for kids” or “alternatives to ice creams” requires world knowledge, which is difficult to capture in product knowledge graphs but readily available in pre-trained LLMs like GPT-3 [Brown et al., 2020]. Second, LLMs provide a text-to-text interface [Raffel et al., 2020], eliminating the need for a separate query understanding system. Third, as we will see, while converting structured data to text is not trivial, the relevant structured data for any specific task such as e-commerce search is not only limited in size and variety, but also well understood due to the presence of a schema. Therefore, we can focus on developing algorithms to properly convert structured data into additional text for training LLMs.

1.3 Paper Organization

This position paper envisions a new solution for E-commerce search. Section 2 describes the motivation and design of a new architecture for information retrieval. Section 3 discusses how to better represent the database IDs. In Section 4, we propose methods to convert structured and semi-structured data to annotated text. Section 5 discusses fine-tuning strategies for LLMs and inference time use cases. Section 6, discusses research direction. We discuss related work in Section 7 before we conclude in Section 8.
Figure 2. The success of e-commerce search requires the integration of structured, semi-structured, and unstructured data.
2 A Database and LLM Powered IR System

In this section, we describe the architecture of our envisioned solution for e-commerce search. Fig 3 shows the architecture of the classic information retrieval system, the model-based system, and our database and LLM-powered system.

The classic information retrieval system, as shown in Fig. 3(a), employs an index-retrieve-then-rank architecture. It requires the development of many for query understanding, retrieval, and ranking, which results in modern IR systems being comprised of a disparate mix of heterogeneous models (e.g., one model used to learn document representations, another for document understanding, and yet another for ranking) [Metzler et al., 2021]. Moreover, the architecture does not support the incorporation of the world knowledge required to understand queries or documents.

Metzler et al. [2021] envisioned a model-based architecture for information retrieval on the web. As shown in Fig. 3(b), with a single LLM replacing modules for indexing, retrieval, and ranking, the model-based approach directly provides end-to-end solutions to all kinds of information needs ranging from search to summarization and question answering. The model-based architecture is attractive as it greatly simplifies the IR system, but it faces a number of practical obstacles.

1. An LLM is trained over a text corpus. The model is designed to handle a sequence of tokens instead of structured data, where complex relationships exist among data items.
2. The model-based approach replaces the traditional index in the IR system. As a result, it does not have knowledge about the universe of document identifiers, and cannot refer to supporting documents in the corpus it is trained over.
3. Search engines such as Google index billions of new pages every day. It is difficult to continuously update an LLM with such a large amount of data.

In contrast to web search, IR systems for applications such as e-commerce are centered on structured databases such as product catalogs. On the one hand, a good e-commerce experience for customers requires world knowledge about the products in addition to product specifics in the database, which makes pre-trained LLMs extremely useful as it can provide such knowledge through a unified text-to-text interface. Furthermore, unlike web search engines that must index billions of new pages every day, the structured databases are much limited in size, which are more feasible to be consolidated into or synthesized with LLMs.

On the other hand, the model-based approach is insufficient to support applications such as e-commerce engines. First, because e-commerce search is based on a product catalog, we need a mechanism to consolidate knowledge in the database to the LLM in the training or fine-tuning process. Second, the model must be able to perform database lookups in order to provide product specifics to the customer. In particular, information such as product price and availability that is constantly changing over time is not suitable to be consolidated into the LLM during training or fine-tuning, which makes the ability to refer to records in the database during runtime critical.

Our ultimate goal is to integrate databases and LLMs into a unified infrastructure for information retrieval, with the LLM acting as the single, consolidated model that responds to all types of users’ information needs about a set of entities, and the database managing the facts about the entities, including those that are constantly changing.

Specifically, Fig 3(c) illustrates the architecture behind our vision. In the case of e-commerce search, the database stores products and other types of entities (e.g., brands, manufacturers, etc).
Figure 3. Classic information retrieval (left), model-based information retrieval [Metzler et al., 2021] (middle), and our proposal, a database+LLMs based information retrieval system (right).

We convert the content of the database into textural descriptions, and inside the descriptions, we embed the IDs of the entities. We call such descriptions “annotated” texts, and we combine them with other text corpora to train an LLM or use them to fine-tune a pre-trained LLM. Essentially, the LLM is trained or fine-tuned with text whose vocabulary has been expanded with IDs. During search, the LLM responds to users’ information needs with answers that contain IDs of the relevant entities. Using the IDs, we perform database lookups to retrieve every fact about those entities, including information that changes constantly.

To implement the vision described above, we need to answer three questions.

1. How do we create universal IDs for database entities such that they can best connect databases with LLMs?
2. How do we convert content of the database to annotated texts (descriptions with embedded IDs)?
3. How do we train or fine-tune LLMs with the annotated texts?

We discuss possible solutions to these questions in Sections 3, 4, and 5, respectively.

3 Universal IDs

To integrate databases and LLMs into a unified IR infrastructure, we add IDs of database records as distinct texts in the text corpus to train or fine-tune LLMs. The LLMs will then respond to user questions with text that contain such IDs, with which we can perform database lookups to retrieve facts about those database records.

The question is how can we best represent the database IDs in text. The most straightforward way is to represent an ID as is. For example, suppose a record in a product catalog contains the following information: {ID:123, name: Milk with Reduced Fat, category: Milk, brand: Lucerne, price: $10, available: Yes}, where 123 is the ID of the record.

ACM SIGIR Forum 6 Vol. 57 No. 2 – December 2023
We may create a textual description of the product with 123 embedded directly in the description. For example: “123 is a Lucerne brand milk with the name Milk with Reduced Fat.”

There are two potential problems with the above approach. First, the ID space could be too large. A product catalog may contain millions of items, which means we need to add millions of unique tokens into the vocabulary, whereas the current vocabulary of GPT contains about 50K tokens. Still, this is much better than the web search scenario envisioned by the model-based approach [Metzler et al., 2021], as Google indexes over 30 billion web pages. A possible solution is to use hierarchical IDs. For e-commerce search, we can leverage the product taxonomy to create hierarchical IDs. In the previous example, instead of 123, we may use Milk/123 as the ID, assuming the product taxonomy has only one level.

The second issue is more subtle. A token such as 123 may already encode some rich knowledge. If we use it as an identifier of a product, the LLM may associate the prior knowledge with the product. A possible solution is to use a rare token that does not have any prior meaning as IDs [Ruiz et al., 2022]. We can generate a rare token using a random sequence of characters. For example, rather than using the original ID 123, we may pick a rare random sequence of characters such as [K#^&*] to denote the product, and all we need to do is to maintain a [K#^&*] ↔ 123 mapping when we need to perform database lookups.

4 Unifying All Data into Annotated Texts

In this section, we describe possible ways of converting structured and semi-structured data to “annotated text,” that is, textual description of entities in the (semi-)structured data with embedded IDs.

Consider a column in a relational table or an edge in a taxonomy or an ontology. Each column/edge denotes either an attribute value or a relationship with another entity. We create a set of templates for every column in every database table and every edge in the taxonomy/ontology.

4.1 Manually Created Templates

For example, consider the product catalog where each record is about a product, and it has columns such as name, brand, manufacturer, etc. We may create the following templates:

Name (attribute):

- [ID] is [Name].
- The name of [ID] is [Name].
- ...

Organic (boolean attribute):

- [ID] [Name] is ([Organic]==true? organic: not organic).
- ([Organic]==true? [ID] is considered healthy as it is organic.)
- ...

Brand (foreign key):

- The brand ID of [ID] is [Brand].
- [ID] [Name] of brand [Brand] is manufactured by [Manufacturer]
- ...

In the above templates, we use [ ] to denote a column in a relational table. Note that each template may refer to multiple columns, as shown in the last template.

For any entity in the relational table, we can instantiate descriptions using the templates. For example, for a given product {ID:123, name: Milk with Reduced Fat, category: Milk, brand: Lucerne, price: $10, available: Yes}, we may instantiate the descriptions by following the templates. Here are some results:

- The name of [P123] is Milk with Reduced Fat.
- [P123] Milk with Reduced Fat is organic.
- The brand ID of [P123] is [B456]
- ...

Note that there is no need to instantiate a description using every template for an attribute or a relationship, since they are more or less equivalent, and LLMs have the ability to understand the semantics. The reason to have multiple templates and randomly sample from them is to avoid bias.

4.2 Query Based Templates

The templates described above are designed to describe an entity one attribute or one relationship at a time, but a relational table contains important information and knowledge that only manifests if we examine the data in a more holistic way.

We propose to create templates based on database queries. Each query has a meaning behind it, and through templates, we will express such meanings in natural language. To a certain extent, this could be considered the reverse of the Text-to-SQL [Katsogiannis-Meimarakis and Koutrika, 2023] effort.

We are particularly interested in database queries that contain joins and aggregates, which enable us to express more complex information. For example, joins help us connect grocery ingredients and recipes, and products and complementary products, etc. As an example, we can generate descriptions such as “A glass of [P103] Reduced fat Lucerne Milk contains about 140 calories,” which comes from the result when we join the product table with a nutrition table (and calculate calories based on servingSize and fatCaloriesPerServing).

The user engagement data is critical to e-commerce search. To generate natural language descriptions from user engagement data, we will use templates based on aggregate and group-by queries. This allows us to convey in natural language information such as “how frequently a product is purchased”, “which products customers purchase together”, etc. The resulting annotated text may look like these:

---

Here we use [P123] to denote the token we choose for the entity of ID 123. As described in Section 3, there are multiple options to create such tokens.
- The top 5 items customers purchase after searching for ‘milk’ at Instacart are [P101], [P102], ..., and [P105].
- Over 1,000 customers buy [P001], [P022], and [P042] together every day in California.
- ...

<table>
<thead>
<tr>
<th>Prompt</th>
<th>Could you use five different ways to describe the following product in English? Please make it sound natural, and please embed the id in each description.</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>{</td>
</tr>
<tr>
<td></td>
<td>“id”: [P123],</td>
</tr>
<tr>
<td></td>
<td>“name”: “Lucerne Milk with Reduced Fat”,</td>
</tr>
<tr>
<td></td>
<td>“description”: “the best milk in the world”,</td>
</tr>
<tr>
<td></td>
<td>“brand”: “Lucerne”,</td>
</tr>
<tr>
<td></td>
<td>“feature”: “organic, gluten free, and kosher”,</td>
</tr>
<tr>
<td></td>
<td>“price ($)”: 3.00</td>
</tr>
<tr>
<td></td>
<td>}</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>LLM Response</th>
<th>1. Check out the Lucerne Milk with Reduced Fat, product ID [P123]. It’s touted as the best milk in the world, and it’s organic, gluten free, and kosher. Plus, it’s only $3.00! You can see what it looks like on the Instacart website.</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>2. For just $3.00, you can enjoy the world’s best milk, Lucerne Milk with Reduced Fat. It’s organic, gluten free, and kosher. You can find it under the product ID [P123] on our website, where you can also view its image.</td>
</tr>
<tr>
<td></td>
<td>3. Have you tried the Lucerne Milk with Reduced Fat? It’s product ID [P123] and it’s known as the best milk in the world. It’s organic, gluten free, and kosher, and it’s only $3.00. You can see its image on our website.</td>
</tr>
<tr>
<td></td>
<td>4. The Lucerne Milk with Reduced Fat, product ID [P123], is not just any milk. It’s the best milk in the world, and it’s organic, gluten free, and kosher. Plus, it’s only $3.00. Check out its image on our website.</td>
</tr>
<tr>
<td></td>
<td>5. If you’re looking for the best milk in the world, try the Lucerne Milk with Reduced Fat. It’s organic, gluten free, and kosher, and it’s only $3.00. You can find it on our website under the product ID [P123].</td>
</tr>
</tbody>
</table>

**Figure 4.** Using LLMs such as ChatGPT to automatically generate descriptions of database records in natural language.
4.3 LLM Generated Templates

We have described how to manually create templates that can be instantiated in natural language. If the database contains a large number of tables with a complex schema, manually creating templates may be a time-consuming process, and the resulting templates may lack diversity.

We can also use LLMs such as ChatGPT to automatically generate templates. Fig. 4 shows an example, where ChatGPT is asked to generate a set of descriptions for a database record and the descriptions must embed the ID of the record. As we can see the diversity of the descriptions is quite high. The idea is not to invoke ChatGPT to describe every record in a database table. Rather, we can convert the descriptions that ChatGPT generates for a few records to templates and then use the templates to generate natural language descriptions of each record.

We may also use ChatGPT to generate query-based templates. However, directly using SQL as input to ChatGPT hasn’t produced good results. Instead, we can ask ChatGPT to describe the results of the SQL queries. In other words, we convert this problem to the problem in Fig. 4.

5 System Architecture

Once we convert all the structured data into non-structured data as natural language text, we ingest it into LLM with a traditional language modeling approach. During training, our goal is to transfer the knowledge learned from our database to a LLM while maintaining semantic and syntactic properties of language in the LLM. Once fine-tuning is complete, the model becomes proficient in using domain-specific e-commerce world knowledge in conjunction with information obtained from a database. This enables us to utilize the model as a retrieval and recommendation engine during inference, with product IDs seamlessly integrated into the model itself.

5.1 Training

We envision that the model-based search can be realized by fine-tuning an LLM with a language modeling (LM) objective using the annotated texts converted from structured data. Multi-task learning using specific task identifiers [Metzler et al., 2021; Raffel et al., 2020] can also be utilized to train a model, but fine-tuning an LLM with an LM objective using texts has several benefits.

- It doesn’t require any labeled data, whereas the previous approach [Metzler et al., 2021] requires some supervision. While labeled data (e.g., positive relationships between a query and products) can be utilized, it is not employed for supervised learning in our case. Instead, we first transform labeled data into natural language text format, as outlined in Section 4, and then train a model with self-supervised learning.
- The use of LM objectives is a highly effective method for transferring knowledge, mirroring the objectives employed in pre-trained LLM training.

Figure 5 (a) depicts the process of training a LM. We start with a pre-trained LLM and fine-tune the model with the annotated texts obtained from the methods described in Section 4. We optionally inject general world knowledge useful for the e-commerce domain as additional examples to encourage the model to retain world knowledge specific to the e-commerce domain and linguistic syntax and semantics of the language in the LLM. This step allows us to naturally transfer domain.
Figure 5. Example of how an LLM can be used during training and inference time. (a) shows training time where an LLM learns knowledge generated from a relational database and database queries. Optionally, the model can learn richer domain-specific world knowledge through distillation. (b) shows inference time behavior. The example on the top shows a model that performs a search retrieval, where the model shows relevant, alternative, and commonly purchased items as product IDs. Retrieved product IDs are then processed for final multi-objective ranking and business logic. The example in the middle shows that the model recommends replacements for a specific product ID. The last example shows that the model recommends next search suggestions given a search history.

knowledge to the LLM through an innate ability to learn and memorize. During training, the model memorizes product IDs as novel vocabularies while also establishing correlations between these new concepts and the pre-existing world knowledge embedded in the model.

5.2 Inference

Once we train the model, we utilize the model as a retrieval and recommendation engine to perform various tasks as shown in figure 5 (b). Similar to conventional prompt engineering, we can leverage the model with various configurations such as zero-shot, few-shot, and fine-tuning as in [Brown et al., 2020]. The examples in figure 5 (b) show how to use the model in a zero-shot
setting. We show search retrieval, product replacement, and personalized search suggestions as example use cases. To generate answers with specific product IDs, we need to be clear and precise with the LLM. We list several prompts below.

- **Search retrieval**: Show relevant products for ‘milk’, provide alternatives for ‘milk’ and commonly purchased items at Costco. List with product IDs and organize answers.
- **Product replacement**: Show replacements for [P001]. List with product IDs.
- **Personalized search suggestion**: Products to buy next: yeast baking, pickling salt, pasta noodles.

By using the prompts outlined above, we expect that the LLM will generate responses in a pre-defined manner. Upon generating the output, as illustrated in Figure 5 (b), we extract information using simple text manipulation techniques or an additional entity linking model. Instructing the LLM to output in JSON format is also a common practice to enforce desired formatting. Following this, we obtain the most up-to-date information, including pricing and availability, by connecting to a real-time updated database. Additional ranking and business logic can be applied, and the final results are presented to users.

## 6 Research Directions

There are numerous obstacles that need to be overcome in order to realize our vision in a production environment. We shall delve into several issues that are worth exploring in the subsequent sections.

### 6.1 Latency Optimization

The primary obstacle to implementing model-based search in a production environment is latency. Since language models generate output responses token by token, the latency of the output is heavily influenced by the length of the response being generated. We explore several approaches to overcoming this challenge in the following section.

#### 6.1.1 The Encoder Based Approach

An encoder based model with fine tuned classification heads can generate output with a single inference. In this approach, the model generates a probability score for each class (a product in e-commerce) simultaneously.

Using the LLM trained with unstructured data integrated with the product IDs as described in section 5.1, the model can be further fine-tuned with supervised tasks. The last projection layer that was used for token generation is removed, and an aggregation layer is added, often incorporating pooling methods, to produce refined representations. Finally, a head with an output size that matches the number of classes (products) is added to create a classification model, as depicted in Figure 6.

Figure 6 shows several tasks that can be performed with an encoder based approach. We show the T5 [Raffel et al., 2020] model approach as an example where task identifiers can be used to perform multiple tasks using a single model. For the search relevance task, we treat this problem
Figure 6. Example of how a single model can be used for multiple tasks with an encoder model approach. This example shows a model that performs a search relevance task, complementary product suggestion, and substitute product recommendation.

as a multiclass-multilabel classification task, where \# of classes = \# of product identifiers. For a single query, we can map multiple relevant product IDs, and can feed into the model. A sample training example is shown in the following.

- **“[Query] milk”: ([P001], 0.4), ([P006], 0.3), ([P123], 0.2), . . . , ([P234], 0.1)**

“[Query]” indicates the task is a search relevance task, where labels can be soft or hard (we can utilize previous user engagement history as soft labels).

Another task can be complementary product suggestions. Given a product, we predict multiple complementary products that can go well together. This problem can also be solved as a multiclass-multilabel classification task, and below is a sample training example.

- **“[Complementary] [P001]”: ([P006], 0.8), ([P123], 0.9), . . . , ([P234], 0.7)**

Here, “[Complementary]” represents the task as a complementary product suggestion.

Next task shown in the figure is substitute product recommendation where it is very similar to complementary product suggestion task in terms of input and output types but with a different task identifier. The task identifier used for this task is “[Substitute]”.

Once we fine-tune the model, the inference for the encoder model approach becomes faster compared to the generative language model. We simply use a desired task identifier with a query (a search term or a product ID text), perform a single inference of the model, and obtain the final probability scores for all product IDs from the model. The parsing and entity linking used for the generative model approach can now be replaced with top K selection logic to get the final candidate product IDs for each task. Based on the requirements of each domain, we perform the final ranking and present the results to the users.
The benefit of using an encoder-based approach is that it has predictable inference time complexity since it can directly produce product IDs as results using a single inference. Single inference per task is advantageous, leading to lower run-time costs. However, this approach has several drawbacks.

- A supervised learning dataset is necessary for each task in a multi-task learning process. This can pose a significant challenge, especially for cold start products.
- The number of classes in the output layer increases as more product IDs are added, which can result in practical challenges during implementation.
- It is not scalable since each classification model has to be trained with new training objectives whenever we need a different task.

One can utilize both the benefits of generative language model and classification model. For the most popular tasks, we can utilize the encoder model approach for faster inference while we can quickly prototype new applications with the generative approach.

Most production machine learning models are based on the encoder model, as it still necessitates strict latency requirements for deployment in production. However, with the continuous improvement of computing resources, the latency of the generative language model is also improving. It will be intriguing to see how this develops in the future.

### 6.1.2 Model Compression

Another research direction to optimize the latency of the models is model compression. At a high level, model compression aims to optimize inference time latency either by (1) knowledge distillation [Gu et al., 2023; Agarwal et al., 2023; Jha et al., 2023], which involves training a smaller model with the rich knowledge found in a larger model, (2) pruning [Ma et al., 2023; Zhang et al., 2023], which involves removing redundant computations, or (3) quantization [Liu et al., 2023; Kim et al., 2023a,b; Lin et al., 2023], which involves approximating computation. Given the intense competition to host in-house LLMs using cost-effective methods, it will be interesting to observe the progression of these lines of research.

### 6.2 Personalization

Personalization has been a crucial subject in e-commerce applications, and many related studies have employed sequence modeling to enhance the comprehension of user intent in the search or recommendation arena [Li et al., 2021; Pancha et al., 2022]. We anticipate that all of these approaches can be applied concurrently with LLM, enabling the utilization of world knowledge in LLM and sophisticated user modeling.

As demonstrated in Figure 7, we can leverage LLM to personalize search. The concept involves incorporating past user engagement data as input to the prompt and allowing LLM to generate a response. The feature store, as depicted in the figure, comprises user-level features such as prior purchases, which are integrated into the prompt. Once the LLM generates a response, it can be used as input for further personalization. A conventional user sequence model can be employed to deliver accurate predictions. The example in the figure illustrates a zero-shot configuration, but we can adopt few-shot learning and/or fine-tuning approaches to achieve more sophisticated outcomes.
The above example shows how to personalize search by incorporating user engagement history in the prompt for a LLM. When a user issues a query, user engagement signals like past orders can be retrieved from a feature store, then those are provided as a context in the input prompt. This is especially useful for broad intent queries like 'breakfast' when there are many relevant items, it helps retrieve better personalized items. After the LLM response, further personalization can be applied using another ML models. Other applications can also follow similar prompt engineering to personalize the experience.

### 6.3 Catastrophic Forgetting

Product information in e-commerce keeps getting updated, we need to continue to ingest the updated and new data into the model. Whenever the new information needs to be ingested, we can perform fine-tuning the model with the new data. As the size of the database grows, however, we might encounter a catastrophic forgetting problem [French, 1999] where we completely forget the old data that has been used for training the model. In order to ensure we don’t encounter catastrophic forgetting problems, we might want to use a big enough model in order for the model to contain all the information. However, the absence of a clear guideline makes it difficult to determine the right model capacity based on the size of the data. A number of methods [Lange et al., 2019; Ahn et al., 2019; Nguyen et al., 2019; Serrà et al., 2018] have been proposed to address this issue, but most of the research has focused on small or simulated environments.

An alternative approach to managing this is to restrict the volume of data we need to ingest. Rather than considering product IDs as separate documents, we can use internal taxonomies as unique documents for broad information intake. These taxonomies are typically much smaller in size compared to individual products. By treating the search and recommendation task at the taxonomy level, the amount of information the LLM needs to learn will be considerably reduced, thereby addressing the catastrophic forgetting issue. The study of catastrophic forgetting in LLMs continues to be a fascinating and demanding area of research.

### 7 Related Work

Our proposed approaches try to incorporate external (e-commerce) data into LLM as data storage. Since the model understands embedded knowledge, it can be directly used to generate output responses without external help during inference time. The runtime convenience comes at the expense of training the model.

As discussed in earlier Section 6, continuous update with training can lead to problems like catastrophic forgetting and language drift. In order to address these problems, there have been
several efforts [Liu, 2022; Chase, 2022; Gun et al., 2020; Lewis et al., 2020; Nakano et al., 2021] to decouple external data ingestion and output generation without training the model. The idea here is to use LLM to generate output responses using the external data as context. This is referred to as retrieval augmented generation (RAG) [Lewis et al., 2020]. They try to overcome the limitations of a fixed context window used in LLM. Since we cannot give our entire database as input prompt, all the approaches involve fetching the data, augmenting and refining it. Since refinement is a lossy process, it is possible that the input prompt may not capture all the essential context which is vital for output generation. This can be a critical issue especially for e-commerce applications where there are many relevant contexts (products) for any given task. When there are many documents in need of refinement, additional LLM calls for refinement can cause latency increase. Although there are limitations in the above approach, it will be interesting to see the progress of research trying to decouple data ingestion and output generation process.

Text-to-SQL parsing [Katsogiannis-Meinarakis and Koutrika, 2023] is an area of research that tries to transform natural language questions into their corresponding SQL statements, based on data provided by relational databases. Conceptually this is similar to what the current e-commerce engine is doing, but it has limitations. The tasks that can be performed with SQL statements are confined by SQL syntax and database schema, it becomes difficult to perform queries that require common knowledge (e.g. what are relevant product IDs that are good for Christmas?). SQL cannot generate meaningful responses without having explicit knowledge embedded in databases. Keeping the explicit knowledge as a knowledge graph in the database can be a solution, but it is not scalable. Use of knowledge in LLM right from the retrieval of documents can make complex tasks achievable.

8 Conclusion

The two biggest challenges for e-commerce search are understanding queries and leveraging world knowledge to match queries and products. Large language models are not only powerful in query understanding, but they also possess a vast amount of world knowledge. Still, databases are a critical component of the e-commerce infrastructure as they manage accurate and sometimes time-changing facts about the products. This position paper examines how the strengths of database systems and large language models can be synthesized to create information retrieval systems that better support e-commerce search. We believe the solution is to convert structured and semi-structured data such as the product catalog, taxonomies, and ontology to natural language text and train a language model, which is used as an end-to-end solution for e-commerce search. This is a clear departure from previous e-commerce search approaches that focus on converting unstructured data such as product descriptions, customer reviews, web pages, etc. to structured data through a costly information extraction process and using a myriad of algorithms and machine learning models to support a complex system with separate modules for indexing, retrieval, and ranking.
References


Yuxian Gu, Li Dong, Furu Wei, and Minlie Huang. Knowledge distillation of large language models, 2023.


Jeonghoon Kim, Jung Hyun Lee, Sungdong Kim, Joonsuk Park, Kang Min Yoo, Se Jung Kwon, and Dongsoo Lee. Memory-efficient fine-tuning of compressed large language models via sub-4-bit integer quantization, 2023a.


Zechun Liu, Barlas Oguz, Changsheng Zhao, Ernie Chang, Pierre Stock, Yashar Mehdad, Yangyang Shi, Raghuraman Krishnamoorthi, and Vikas Chandra. Llm-qat: Data-free quantization aware training for large language models, 2023.


