

Generative Product Recommendations for Implicit Superlative Queries

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Abstract

In Recommender Systems, users often seek the *best* products through indirect, vague, or under-specified queries, such as “*best shoes for trail running*”. Such queries, also referred to as *implicit superlative queries*, pose a significant challenge for standard retrieval and ranking systems as they lack an explicit mention of attributes and require identifying and reasoning over complex factors. We investigate how Large Language Models (LLMs) can generate implicit attributes for ranking as well as reason over them to improve product recommendations for such queries. As a first step, we propose a novel four-point schema for annotating the best product candidates for superlative queries called **SUPERB**, paired with LLM-based product annotations. We then empirically evaluate several existing retrieval and ranking approaches on our new dataset, providing insights and discussing their integration into real-world e-commerce production systems.

1 Introduction

Superlative queries are common in product search as users seek products with the highest degree of one or more attributes to satisfy their needs. While some superlative queries can be handled by existing retrieval systems (Kumar et al., 2024; Zhang et al., 2015) through attribute-based filtering (e.g., “the largest M2 Pro with 32 GB RAM”), others can pose challenges to the existing solutions. Specifically, in this paper, we study the problem of product ranking and recommendation for *implicit superlative queries*, where the desired product attributes are not explicitly stated. These queries often involve aspects that require common sense knowledge of the product (Bos and Nissim, 2006; Scheible, 2007). This problem is further compounded by users creating vague and under specified search queries, either due to a lack of knowledge about certain entity features or the search spanning implicit dimensions,

Queries	Query Type	Ranking Criteria
<i>toys</i>	Expecting Relevant Products	No Superlative criteria.
<i>highest rated toy for 3-year olds</i>	Objective Superlative	<i>Single Objective Criteria:</i> highest rating
<i>best toy for my 3-year nephew who loves the Flintstones</i>	Implicit Superlative	<i>Multiple & Implicit Criteria:</i> highly-rated, overall positively-reviewed, suitable for a male child, likes Flintstones, dinosaurs, etc.

Table 1: Types of queries along with the criteria of each. **SUPERB** focuses on implicit superlative queries.

frequently leading to query-product mismatches. For example, a query such as “*the best toy for a 3 year old girl*” requires gauging the best products across several implicit attributes. Therefore, to effectively serve such a query, product recommendations should consider popular toy standards like ASTM F963, quality, non-toxic materials, and bright, engaging colors — attributes that are often unknown to end users. With a plethora of product options available on e-commerce platforms, identifying the best products to meet customer needs requires additional product category and world knowledge. Users would then compare multiple products across these attributes before purchasing the best product that fits their needs (Vedula et al., 2022, 2023).

Existing ranking pipelines (Reddy et al., 2022) rely on traditional relevance labels like ‘Highly Relevant’ vs ‘Irrelevant’ or ESCI (Exact, Substitute, Complement, Irrelevant), and are typically designed for highly objective queries. They do not capture the nuances of product quality and the subjective expectations of “best” products for a given need. Even when presented with highly relevant recommendations, users generally rely on a variety of sources, including reviews, blogs, discussion portals, and other online content, to obtain the best. In such a scenario, Large Language Models (LLMs) trained on vast amounts of data from diverse sources can act as sources of common-sense and world knowledge. They have been exposed to extensive text sources and have demonstrated success in modeling global opinions in various do-

*Work done at Amazon.

mains (Santurkar et al., 2023) and predicting user preferences (Kang et al., 2023). LLMs can leverage their knowledge to offer expert insights beyond the basic product descriptions, thereby enabling search and ranking based on external knowledge.

We hypothesize that LLMs possess the capability to perform multi-objective optimization over implicit attributes that match user preferences. Hence, LLMs could play a pivotal role in recommending products for superlative queries by (i) offering comprehensive knowledge across multiple product dimensions, and (ii) addressing the inherent subjectivity associated with such queries.

Our work aims to investigate the research question: *Can LLMs effectively rank and recommend the “best” products?* To that end, we propose a four-level labeling scheme for superlative queries – **SUPERB** with LLM-based annotations, and evaluate retrieval effectiveness across multiple traditional and LLM-based ranking pipelines. To our knowledge, this is the first work to explore implicit superlative queries for product recommendation. Specifically, we make the following contributions:

- We investigate the challenges in answering superlative queries, and define a four-level labeling scheme for relevance ratings.
- We introduce **SUPERB**,¹ **Superlatives** with **Best** relevance annotations, a schema of superlative queries, and pair them with LLM-based annotations using four different ranking approaches i.e., **pointwise**, **pairwise**, **listwise** and **deliberated** prompting.
- We evaluate the retrieval effectiveness of multiple ranking pipelines against **SUPERB**.

Our contributions highlight the importance of addressing superlative queries in recommendation systems, an area that has been largely overlooked. By introducing **SUPERB**, we enable the development and evaluation of systems capable of understanding and fulfilling these high-expectation queries, ultimately improving the user experience and enhancing product recommendations.

2 Related Work

We now discuss related work to place our contributions in context.

¹ <https://github.com/emory-ir1ab/SUPERB>

2.1 LLMs for Ranking and Recommendation

LLMs have been successfully applied for ranking and recommendation (Yue et al., 2023). Early pointwise ranking approaches (Nogueira et al., 2019) fine-tuned BERT (Devlin et al., 2019) and T5 (Raffel et al., 2020) with query-document pairs, and showed improved performance across a variety of benchmarks (Craswell et al., 2021; Thakur et al., 2021). Pointwise approaches (Ma et al., 2024) ranked items based on scores predicted for individual documents, while pairwise approaches (Qin et al., 2024) prompted models with the query and two documents to compare and rank. Others (Pradeep et al., 2023a,b; Sun et al., 2023) explored a listwise ranking strategy by prompting with a list of documents and generating a ranked list of document IDs. These three paradigms were also examined in the context of recommender systems (Yue et al., 2023).

2.2 LLMs for Relevance Labelling

After showing promise in predicting searcher preferences (Thomas et al., 2024), LLMs have been extensively used in generating relevance labels (Faggioli et al., 2023; Yan et al., 2024; MacAvaney and Soldaini, 2023; Mehrdad et al., 2024; Dhole and Agichtein, 2024a; Dhole et al., 2025). As compared to human evaluation, automated relevance labeling is faster and more scalable.

2.3 Prompting Approaches

Apart from standard prompting approaches, deliberative prompting (Li et al., 2023; Zheng et al., 2024) approaches like Chain-of-Thought (Wei et al., 2022) and scaling inference time compute (Snell et al., 2024; Guo et al., 2025) have successfully improved the performance of LLMs. These methods involve the model generating related information, such as reasoning chains or explanations, to elucidate the reasoning process before arriving at an answer. Our deliberated prompting approach, discussed in Section 5.2 is on similar lines, where we seek to regurgitate implicit attributes so as to make them explicit and help in arriving at the appropriate best label.

2.4 Superlative Search Queries

Much of the research related to superlatives has focused on applications in question answering, opinion mining, and sentiment analysis. A recent study (Kumar et al., 2024) focused on ranking over

objective superlatives where the dimensions to compare against (also referred to as the comparison set (Pyatkin et al., 2024)) are often explicitly provided. However, superlative queries often have implicit, vague and complex dimensions, as we explore in this work.

3 Implicit Superlative Queries

We now formalize the type of superlative queries that we seek to address. We define implicit superlative queries as those which (i) *seek the highest degree of one or more attributes or features of a product*; and (ii) *are implicit in nature*. These queries involve preferences which are generally popular, subjective, and not just based on quantifiable attributes. E.g., the superlative query, “*best toy for my 3-year nephew who loves the Flintstones*”, requires an implicit understanding that the user might be looking for a good quality toy which is well-rated and reviewed, reasonably priced, age appropriate, and relates to characters or properties of the show “The Flintstones”. The superlative query “*shoes most suited for marathons*” involves understanding that the user is interested in running shoes and possibly in attributes like cushioning, stability, and durability, which are important for long-distance running. Addressing such implicit superlative queries would therefore require (i) inferring key hidden attributes, (ii) world knowledge or a general understanding of concepts, and (iii) being able to reason and compare across different related products and ensure that the necessary attributes are of the highest degree. Table 1 shows a summary and examples of targeted queries.

4 The SUPERB Relevance Scheme

We design a novel four-category relevance taxonomy to rank, recommend, and evaluate the retrieved product candidates for superlative queries.

- **Overall Best (3)**: reserved for products that excel across a broad spectrum of parameters including quality, user experience, value for money, innovation, aesthetics, and environmental impact, among others. Products in this category represent the best of what is available in the market, meeting or exceeding all the expected criteria.
- **Almost Best (2)**: includes products that perform exceptionally well for most criteria but may fall short in one or a few aspects. These products are generally considered top-tier but

lack one or more elements that would elevate them to the Overall Best status.

- **Relevant But Not the Best (1)**: captures products that are suitable for certain contexts or specific needs but do not represent the best available option across the board.
- **Not Relevant (0)**: products that do not align well with the user’s query or fail to meet the basic standards expected in their category, making them generally not recommended.

We design such a fine-grained system for multiple reasons. Fine-grained labels have been found to be more advantageous than simplistic binary choices (Zhuang et al., 2024). In addition, they facilitate nuanced evaluations and provide comprehensive feedback. For example, differentiating between **Overall Best** and **Almost Best** might be less obvious when purchasing standard office supplies, where basic functionality is adequate. However, this distinction becomes essential when selecting infant car seats, where the highest safety and technology standards are vital.

5 Dataset Construction

We now describe how we generate superlative queries and pair them with products labeled with annotations from our schema.

5.1 Creation of Superlative Queries

For generating superlative queries, we employ the Amazon Shopping Queries dataset (Reddy et al., 2022), which consists of search queries each annotated with up to 40 potential items with ESCI relevance judgements.²

Inspired by LLM-based reformulation approaches (Yang et al., 2023; Dhole and Agichtein, 2024b; Dhole et al., 2024), we prompt the Claude-Sonnet (Anthropic, 2024b) LLM with tailored few-shot instructions, to reformulate these shopping queries into their superlative counterparts. We then select queries paired with at least five products with the **Exact** ESCI label. We consider all the products of such queries for subsequent **SUPERB** annotations.³ We generate a total of 35,651 superlative queries from 1,825 original queries. The complete prompt is shown in Appendix Table 6 and some of the generated queries are shown in Table 2.

²Exact (3), Substitute (2), Complement (1), Irrelevant (0)

³Products of the highest relevance might not necessarily be the **Overall Best** option.

Query	Superlative Queries
“running shoes”	“best running shoes for flat feet” “best running shoes for rocky terrain”
“diaper backpack”	“best diaper backpack for twins”, “most comfortable diaper backpack for back pain”

Table 2: Examples of generated superlative queries.

5.2 Creating Relevance Annotations

We adopt four methods for annotating the retrieved product candidates with an LLM: **pointwise**, **pairwise**, **listwise** and **deliberated** prompting. In the **pointwise** approach, we prompt the model with a superlative query q and the description of a product p_1 , to generate a single annotation label b_1 that corresponds to a category in our schema, along with an explanation E (Eq. 1).

$$(q, p_1) \rightarrow \mathbf{M} \rightarrow b_1 + E \quad (1)$$

In the **pairwise** approach, we want the model \mathbf{M} to compare a product p_1 to another product p_2 . Hence, we prompt \mathbf{M} with the additional description p_2 and force it to generate two labels b_1 and b_2 for both products as shown (Eq. 2).

$$(q, p_1, p_2) \rightarrow \mathbf{M} \rightarrow b_1 b_2 + E \quad (2)$$

In the **listwise** approach, we expand the context to $N - 1$ additional products. We hypothesize that providing a context of other products would help the model make accurate judgements in inferring the necessary attributes. Besides, it is more efficient as compared to the pointwise approach as it can process multiple products simultaneously and generate category labels for each (Eq. 3).

$$(q, p_1, \dots, p_N) \rightarrow \mathbf{M} \rightarrow b_1 b_2 \dots b_N + E \quad (3)$$

Unlike traditional relevance ranking, where pairwise and listwise evaluations seek to generate a ranked list of document ids, our pairwise and listwise evaluations provide additional information through other products, by expecting the ‘best’ labels for 2 or multiple products. The pairwise and listwise approaches allow gauging the properties of other related product(s) for generating the category label of a product. We do not explicitly force the model to select the highest category (i.e., Overall Best) in these scenarios.

$$q \rightarrow \mathbf{M} \rightarrow a_q \quad (4)$$

$$(q, a_q, p_1) \rightarrow \mathbf{M} \rightarrow b_1 + E \quad (5)$$

Query: best infant stroller for park walks

Deliberate

Generated Attributes:

- Lightweight and compact for easy maneuverability
- Large wheels with good suspension for smooth rides on different terrains
- Ample storage space for carrying baby essentials
- Reclining seat for baby’s comfort
- Adjustable canopy for shade and sun protection
- Easy one-hand fold for convenient transportation
- Brakes for safety
- Durable and sturdy construction

Figure 1: Attributes generated through deliberated prompting for a superlative query.

We also employ a two-step **deliberated prompting** strategy inspired by previous studies (Wei et al., 2022; Li et al., 2023; Zheng et al., 2024), which asks the model to deliberate and reason before generating the final answer. We first generate a set of attributes a_q characterizing the best features of products, and then use them to prompt the model to generate the final taxonomy label (Eq. 4-5). These attributes serve as potential dimensions for the model to compare against in the subsequent pointwise step. Figure 2 shows an example of the label generation process with deliberated prompting.

In e-commerce settings, sellers sometimes exaggerate claims in product descriptions. Making the LLM generate and reason on key useful product attributes prevents the model from providing a biased category judgment based on the seller’s description, but instead generate a well-rounded, unbiased categorization in line with the LLM’s common sense knowledge. In each of the methods, we also force the model to generate an explanation to improve model performance (Wei et al., 2022) and also aid human evaluation. Figure 1 shows sample generated attributes for a superlative query. We describe the corresponding instructions in Table 13 in the Appendix.

Queries	Best Annotations
2,230	29,218
Best Label	Number of Examples
Overall Best	8,564
Almost Best	10,100
Relevant But Not the Best	8,342
Not Relevant	2,212

Table 3: Category label distribution of SUPERB.

Retrieval Pipeline	P@5	P@10	P@20	nDCG@5	nDCG@10	nDCG@20
BM25	.206	.163	.125	.219	.213	.235
RM3	.214	.180	.139	.219	.219	.243
BM25 Top K + Pointwise Reranking	.226	.163	-	.205	.198	-
RM3 Top K + Pointwise Reranking	.208	.180	-	.199	.210	-
BM25 Top K + Listwise Reranking	.262^α	.192 ^α	.125	.278^α	.259^α	.264^α
RM3 Top K + Listwise Reranking	.248	.201^α	.140	.245	.241	.254

Table 4: Performance metrics for different ranking pipelines. α denotes significant improvements via a paired t-test with Holm-Bonferroni (Holm, 1979) correction (p -value < 0.05) over BM25.

Retrieval Pipeline	P@10	P@50	nDCG@10	nDCG@50
BM25-Top 100	.154	.079	.205	.279
BM25-Top 100 + Window (5, 2)	.185^α	.084^α	.241^α	.309^α
BM25-Top 100 + Window (20, 10)	.198 ^α	.082 ^α	.240	.302 ^α
BM25-Top 200	.196	.079	.205	.279
BM25-Top 200 + Window (20, 10)	.262	.088	.259	.328

Table 5: Comparing different retrieval pipelines for the long context setting. α denotes significant improvements via a paired t-test with Holm-Bonferroni (Holm, 1979) correction (p -value < 0.05) over BM25.

We use deliberated prompting to generate a large number of (query, product, best-label) triplets, which we refer to as **SUPERB**. We generate a total of 29,218 triplets corresponding to 2,230 randomly sampled unique superlative queries. The label distribution is shown in Table 3. Most of the labels are concentrated in the **Almost Best** and **Relevant But Not the Best** categories, with fewer in the **Not Relevant** category. This is expected as annotations were performed over products that were human-rated as **Exact**, albeit with respect to the original non-superlative queries.

6 Methods

We perform our analysis in a constrained setting where the item description is limited to 512 tokens in length. This is useful for low latency applications. We then use **SUPERB** for evaluating the following ranking pipelines:

- (i) **BM25**: We use BM25 as our baseline.
- (ii) **RM3**: We also employ a pseudo-relevance feedback baseline RM3 (Abdul-Jaleel et al., 2004).
- (iii) **BM25/RM3 + Listwise Re-ranking**: Here, we re-rank the results of the first stage BM25 and RM3 through a listwise ranking approach. We force the model to generate a ranked list of product IDs in the style of RankGPT (Sun et al., 2023) (Eq. 6).

$$(q, p_1, \dots, p_N) \rightarrow \mathbf{M} \rightarrow r_1 \dots r_N + E \quad (6)$$

where r_j is the index of a product ranked j .

- (iv) **BM25/RM3 + Deliberated Pointwise Re-ranking**: Here, the model is forced to generate a schema label for each item along with a confidence score, when given a query and estimated product attributes. The final ranked list is obtained by first sorting using the labels, and resolving ties first by confidence scores, and then by the BM25 scores. This can also be seen as a black-box counterpart of pointwise ranking approaches which provide confidence through logit probabilities. The confidence scores range between 1 and 9 (Eq. 7-8).

$$q \rightarrow \mathbf{M} \rightarrow a_q \quad (7)$$

$$(q, p_1, a_q) \rightarrow \mathbf{M} \rightarrow b_1 + c_1 + E \quad (8)$$

- (v) **BM25 + Sliding-Window for long contexts**: We also analyze the case where we use **longer product descriptions**, and when there are a **large number of products in the context**. In that case, employing a listwise strategy can be detrimental as LLMs have been known to show bias towards specific positions of text in the context (Liu et al., 2024), while employing a pointwise strategy would involve excessive inference calls. Also, in practice, we observe that LLMs find it hard to generate 100 or 200 item IDs at once, hindering their ability to re-rank items properly. We hence evaluate such queries using a sliding-window approach with BM25, introduced in RankGPT (Sun et al., 2023).

We choose the Claude-Haiku (Anthropic, 2024a) model for our experiments since it is beneficial to evaluate smaller models for production pipelines. We use the PyTerrier (Macdonald and Tonello, 2020) library with the PyTerrier-GenRank (Dhole, 2024) plugin for designing the retrieval and re-ranking pipelines, and computing precision ($P@k$) and nDCG metrics. The complete prompts are shown in Tables 16 and 17. We perform a paired t-test with Holm-Bonferroni correction (Holm, 1979) to gauge significance.

7 Results and Analysis

As shown in Table 4, we find that the listwise ranking approach is able to rank the best products significantly better as compared to other approaches across all metrics. The listwise scores are better for queries with larger nDCG values of BM25 meaning they benefit from an initial ranked list as shown in Appendix Figure 4. Pointwise approaches also help marginally with $P@10$ compared to BM25.

We also show the results for top-100 and top-200 items with long descriptions in Table 5. We find that employing a listwise approach in a sliding window fashion significantly improves retrieval effectiveness over the baseline BM25 retrieval across all metrics. In some cases, we observe modest improvements compared to BM25, highlighting the difficulty of handling superlative queries, which is inherently challenging due to ambiguities and the need for extensive world knowledge. This complexity underscores the hardness of the task for traditional retrieval models. LLMs provide a natural baseline for tackling this issue, given their vast repository of world knowledge, enabling them to approximate knowledge bases and better handle the nuances of superlative queries.

We now examine some error cases in the listwise approach to further explore performance. By analyzing queries where the methods perform well or poorly, we can gain insights into the model’s behavior. The relative performance by nDCG@10 is summarized in Figure 4 in the Appendix.

Both BM25 and LLM perform well: Queries like “*most versatile baby carrier for all terrains*” (nDCG@10 of 0.756 and 0.756, respectively) and “*Best of montreal album for summer road trips*” (0.787, 0.951) show strong performance for both approaches. These queries are specific, and the attributes are commonly matched both lexically and

semantically to product descriptions.

Both BM25 and LLM perform poorly: For queries such as “*Most durable kids plates not plastic*” (nDCG@10 of 0.024 and 0.016, respectively) and “*most gentle water wipes for baby’s skin*” (nDCG 0.066 and 0.054, respectively), both approaches struggle. In these cases, challenges like negation, tokenization errors, and specific attributes may contribute to poor performance.

LLM outperforms BM25: Queries like “*most modern LG refrigerators to complement minimalist kitchen decor*” or “*most stylish child safety harness to match toddler’s outfits*” involve interpreting nuances related to style, versatility, and aesthetics, where LLMs arguably excel i.e. recognizing global preferences and broader contexts, enabling them to rerank products with less tangible attributes.

BM25 outperforms LLM: Many BM25-favored queries have clear, well-defined criteria, such as “*safest bottle warmer for preserving nutrients*” (nDCG 0.508 vs. 0.264); “*most flexible rv caulking sealant for easy application*” (nDCG 0.619 vs. 0.474). We speculate that BM25 excels with queries containing specific product terms and common words as it performs well without advanced reasoning, while LLMs might over-generalize.

8 Conclusion

This work studied superlative queries with implicit attributes, which are typically more complex compared to other query types since ranking products for them requires inferring attributes, placing other products in context, and using commonsense and world knowledge to determine the best ones. We present **SUPERB**, a **4-point schema** to spur further progress in developing product ranking pipelines for superlative queries. We also propose **pointwise, deliberated pointwise, pairwise, and listwise** methods to label superlative queries over it and re-rank retrieved products, using an LLM as the backbone.

Our experiments show that LLMs can rank the best items, improve ranking when provided with initial ranked lists, and can also be sensitive to them. In addition, our methods are applicable to rank superlative queries in other item and document ranking settings. The listwise approach is preferable for lower budgets, while the deliberated point-wise approach can be preferred for better

quality annotations. We believe that our study can drive further research on superlative search queries.

Our work highlights key considerations for deploying an LLM-based product ranking system into production. While a listwise approach effectively ranks multiple items at once, it can be inefficient due to lengthy item descriptions. In contrast, a pointwise approach is faster, especially with parallel processing. Sliding window methods and query reformulation are also viable alternatives. Generating attributes and explanations clarifies label assignments, boosting user trust and satisfaction.

Addressing superlative queries in product recommendation systems is essential, particularly for the next generation of interactive shopping assistants (Vedula et al., 2024; Li et al., 2025) and generative recommender systems (Senel et al., 2024). This becomes even more relevant as information-seeking and product search systems grow closer together (Kuzi and Malmasi, 2024). These superlative queries capture user intent to find the best possible items, an aspect often overlooked in current systems. Introducing **SUPERB** allows for the development and assessment of recommendation pipelines capable of handling high-expectation queries, helping systems address this unmet need.

Limitations

LLMs have a tendency to average out preferences and often aligning to the majority of the users making them apt for our use case, as shoppers frequently tend to buy the best products unanimously for instance, following viral trends or popular recommendations provided by bloggers.

However, there are other types of superlative queries that could be subjective and depend on user preferences. It would be interesting to see how such user preferences could be incorporated in ranking the best. We envisage various ways our work could be extended to achieve this – through traditional techniques like relevance feedback, conversational interactions, and understanding cultural contexts (Dhole, 2023; Mitchell et al., 2025). Besides, users often make use of public reviews, blogs and ephemeral trends to guide their purchase decision (Hsu et al., 2013; Wilson et al., 2024). Hence incorporating public reviews and other external information through retrieval augmentation could be an interesting line of subsequent study.

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Appendix

Given a query, generate multiple diverse superlative versions of the same which require common sense inference. The reformulated superlative queries should provide additional context for which common sense knowledge is required. The context should be related to the item in the original query in various ways and should seek the highest degree of some related aspects. For instance, if a user is looking for a mouse pad, she might be interested in the best one which best complements the color of her laptop, or may require the most suitable one for painful wrists, etc. The context should require generally understood knowledge and common sense and it should not depend on objective criteria like highest rated or cheapest. Some examples of superlative queries are “Best booster chairs to make mealtime hassle-free for my toddler”, “most user-friendly diaper pail to make my life as a new mom easier”, “most suitable lawnmower for rocky areas”, “most stylish and modern changing table pad to complement my nursery decor”, “Smoothest-riding 2 seater stroller for twin toddlers”, “Best diaper genie for sparking a child’s creativity”, “Highest quality epoxy resin for creating stunning wood art pieces”, You should not try to change the type of the product which the user is asking for. Only if the product explicitly mentions a single product, you should change it to make it more generalized (for instance, Amazon \$100 gift card can be changed to \$100 gift card and so on). Do not generate anything else except for one body of JSON and do not explain yourself. Do not include double quotes while generating the superlatives.

Provide your output in the form of a JSON.

Input Query: LEGO kit

```
{{
  "superlatives": [
    "best LEGO kit for chess players",
    "best lego kits for marvel fans",
    "most impressive lego kits for my friend who is fascinated about India",
    "best lego kit to encourage my toddler to learn astronomy",
  ]
}}
```

Input Query: black halter beaded satin long gowns sequin

```
{{
  "superlatives": [
    "Trendiest black halter beaded satin long gowns with sequins for an Afro-themed fashion parade",
    "Best halter beaded satin long gowns to match my husband’s black silk coat",
    "Most casual black halter satin long gowns with sequins helpful ",
    "most suitable black halter beaded satin long gowns sequin for a date night"
  ]
}}
```

Input Query: armani exchange glasses

```
{{
  "superlatives": [
    "best glasses with bold and trendy frames",
    "best glasses which can be used for office and at parties",
    "best retro look armani exchange glasses",
    "most suitable armani exchange glasses for travelling to dubai and mexico" ,
    "best armani exchange glasses that blend seamlessly with my red jeans",
  ]
}}
```

Input Query: {query}

Table 6: Prompt used for Superlative Query Generation

Based on the item description and some of its reviews, your internal knowledge about all the features of such types of items, and a user’s given shopping query, you should classify the item into one of the taxonomy categories:

User Query: {query}
 Item Description: Title: {title} Description: {description}
 User Query: {query}

- Categories:
3. Overall Best: The item meets the following criteria: The item is overall best in its category on various parameters – excellence in quality, user experience, value for money, innovation, aesthetics, environmental impact, market position, safety, versatility, processing speed, user rating, etc..
 2. Almost Best: The item scores high on most or majority of the parameters except for a few. Most users would consider this as item as the best..
 1. Relevant But Not Best: The item is suitable in certain contexts but not the best option..
 0. Not Relevant: The item is generally not recommended as it is not relevant to the user’s query..

Please classify the item into one of the four types. You should return a number between between 3 (Overall Best) and 0 (Not Relevant) followed by an explanation on the next line justifying why that category of best is suitable.

Table 7: Pointwise Prompt Used For Best Annotations

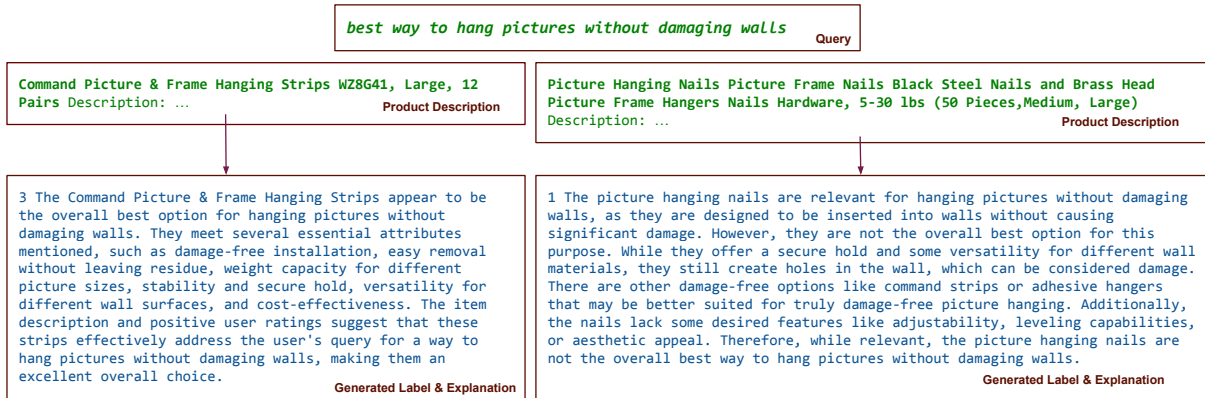


Figure 2: Sample generated label and explanation using the deliberated pointwise approach.

A Evaluating the Best Product Judgements

To evaluate the efficacy of the **SUPERB** labels from the above methods, we perform a human evaluation to record the agreement with the model’s labels. In-house domain experts performed the annotation. For each superlative query, the product descriptions, the corresponding category labels and their explanations from the pointwise, pairwise and listwise methods are presented to the annotator, who may agree with none, some, or all of the LLM generated labels.

As shown in Table 8, in our first phase of human evaluation, we find that the pointwise approach is more often preferred over listwise and pairwise approaches. During the process of annotation, we find that the pairwise approach tends to narrow its focus on attributes presented in the single product in the context, often misjudging necessary attributes. In the pointwise and listwise approaches, this seems to be less of a concern.

	Pointwise	Pairwise	Listwise
Agreement Rate	66.36%	44.86%	60.75%

Table 8: Comparing the three best labelling approaches over 107 random superlative queries.

In the second phase of human evaluation, we use the best strategy of the first phase, i.e., pointwise, and

measure the effects of deliberation over a separate set of queries. We find that deliberated prompting is preferred more often than its non-deliberated counterpart, as shown in Table 9, and making the attributes explicit helps assign better quality annotations.

	Without	With Deliberation
Agreement Rate	75.23%	78.90%

Table 9: Effect of deliberation on pointwise prompting for 109 random superlative queries.

Effect of Increasing the Number of Products: We measure the listwise ranking performance while increasing the number of input products K . As shown in Figure 3, we find that the listwise approach increases the likelihood of picking the best product as we provide more products in the context, and then tends to stagnate after a large K . The pointwise approach’s performance remains almost the same.

As shown in Table 10, we also shuffle the product order from the first stage retriever and evaluate how sensitive the listwise re-ranker is to the initial order. Shuffling the top-20 products in three different random orders causes drastic performance drops in each, i.e. listwise re-ranking benefits from an initial ranked list and improves upon it.

Listwise	BM25	seed1	seed2	seed3	RM3
nDCG@10	.259	.147	.143	.141	.241

Table 10: Listwise reranking performance when the top-20 products are placed in context with initial rankings from BM25, random and RM3 orderings. The listwise re-ranker is highly sensitive to the order provided by the first stage retriever.

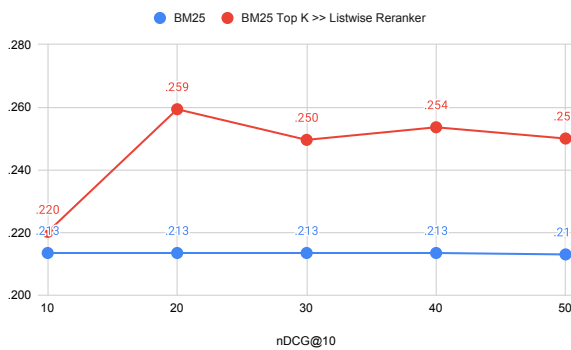


Figure 3: Listwise ranking consistently improves the best ranking for different values of K .

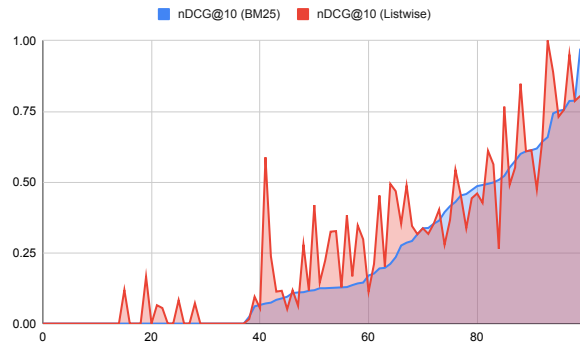


Figure 4: Listwise scores rank better than BM25 for almost all queries. Moreover, LLMs when employed in a listwise fashion benefit from an initial ranked list as queries with higher BM25 scores tend to get better improvements from the listwise approach.

B Effect of Query Reformulation

To reduce inference latency for such scenarios, we also investigate incorporating LLM-based reformulation i.e. employing the LLM during query generation rather than during reranking. Specifically, we introduce two types of **query reformulations** to generate (i) *keywords*: this is accomplished by generating generic query expansion terms which are related to the query (ii) *attributes*: we use the above estimated ideal attributes for expanding the query.

Results: We find that employing keyword and attribute-based reformulated queries helps improve overall retrieval effectiveness, as compared to the original queries. Attribute-based reformulation improves recall and MAP across all retrieval settings.

We find that by employing keyword and attribute based reformulated queries helps improve overall retrieval effectiveness, as compared to the original queries. Attribute based reformulation improves recall and MAP across all retrieval settings. Table 11 presents the details.

Queries	BM25			BM25 + Window (20,10)		
	MAP	R@50	nDCG@50	MAP	R@50	nDCG@50
SUPERB (Raw)	.152	.358	.279	.168	.372	.302
+ Keyword based QR	.155	.371	.291	.172	.383	.31
+ Attribute based QR	.156	.382	.291	.176	.389	.311

Table 11: Comparison of Query Reformulation with BM25 over superlative queries.

Based on the following descriptions of multiple items and a user’s shopping query, you need to classify each item into one of the taxonomy categories:

User Query: {query}

Item 1 Description: Title: {Title 1} Description: {Item Description 1}

Item 2 Description: Title: {Title 2} Description: {Item Description 2}

...

...

Item N-1 Description: Title: {Title N-1} Description: {Item Description N-1}

Item N Description: Title: {Title N} Description: {Item Description N}

User Query: {query}

Classification Categories:

3. Overall Best: The item meets the following criteria: The item is overall best in its category on various parameters – excellence in quality, user experience, value for money, innovation, aesthetics, environmental impact, market position, safety, versatility, processing speed, has been rated highly, etc..
2. Almost Best: The item scores high on most or majority of the parameters except for a few. Most users would consider this as item as the best..
1. Relevant But Not Best: The item is suitable in certain contexts but not the best option..
0. Not Relevant: The item is generally not recommended as it is not relevant to the user’s query..

Please rank each item into one of the four types. First, return the rankings as numbers separated by ‘ ’ where each number ranges between between 3 (Overall Best) and 0 (Not Relevant). And then provide a short explanation as to why you assigned the best categories. You should start your answer with only the rankings (i.e. 3 2 2 0 and so on) and not a description. Ensure that the number of rankings is equal to the number of items shown i.e. exactly 25.

Table 12: Listwise Prompt Used For **SUPERB** Annotations. It provides multiple additional items as context.

Given a user seeking the best item, define the ideal requirements for satisfying the user query by returning a list of attributes which are essential for that item. For instance, if the user is seeking the best laptop for his 15 year old son, the attributes could be a large RAM, the best GPUs (maybe from NVIDIA or AMD), good speakers etc. You should try to come up attributes which are essential for the perfect or the best item as well as which satisfy the user query. Return your output as a json. Do not generate anything else. {query}

Table 13: Deliberation Step used for Generating Attributes

Based on the following descriptions of two items, their reviews, and a user's shopping query, you need to rank each item into one of the taxonomy categories:

User Query: {query}

Item 1 Description: Title: {Title 1} Description: {Item Description 1}

Item 2 Description: Title: {Title 2} Description: {Item Description 2}

User Query: {query}

Categories:

3. Overall Best: The item meets the following criteria: The item is overall best in its category on various parameters – excellence in quality, user experience, value for money, innovation, aesthetics, environmental impact, market position, safety, versatility, processing speed, has been rated highly, etc..

2. Almost Best: The item scores high on most or majority of the parameters except for a few. Most users would consider this as item as the best..

1. Relevant But Not Best: The item is suitable in certain contexts but not the best option..

0. Not Relevant: The item is generally not recommended as it is not relevant to the user's query..

Please rank each item into one of the four types. First, return two numbers separated by ' ' where each number ranges between between 3 (Overall Best) and 0 (Not Relevant). And then briefly explain why the category of best is suitable.

Table 14: Pairwise Prompt Used For Best Annotations – Provides one additional item as context

Based on the following descriptions of two items, their reviews, and a user's shopping query, you need to rank each item into one of the taxonomy categories:

User Query: {query}

The best item would possibly possess many of such attributes: {Predicted Attributes}

Item 1 Description: Title: {title} Description: {Item Description}

User Query: {query}

Categories:

3. Overall Best: The item meets the following criteria: The item is overall best in its category on various parameters – excellence in quality, user experience, value for money, innovation, aesthetics, environmental impact, market position, safety, versatility, processing speed, has been rated highly, etc..

2. Almost Best: The item scores high on most or majority of the parameters except for a few. Most users would consider this as item as the best..

1. Relevant But Not Best: The item is suitable in certain contexts but not the best option..

0. Not Relevant: The item is generally not recommended as it is not relevant to the user's query..

Please rank each item into one of the four types. First, return two numbers separated by ' ' where each number ranges between between 3 (Overall Best) and 0 (Not Relevant). And then briefly explain why the category of best is suitable.

Table 15: Deliberated Pointwise Prompt Used For Best Annotations – Predicted attributes are provided as context

Based on the item description and some of its reviews, your internal knowledge about all the features of such types of items, and a user's given shopping query, you should classify the item into one of the taxonomy categories and provide a confidence score for your prediction:

User Query: {query}

The best item would possibly possess many of such attributes: {Predicted Attributes}

Item Description: Title: {title} Description: {description}

User Query: {query}

Categories:

3. Overall Best: The item meets the following criteria: The item is overall best in its category on various parameters – excellence in quality, user experience, value for money, innovation, aesthetics, environmental impact, market position, safety, versatility, processing speed, user rating, etc..

2. Almost Best: The item scores high on most or majority of the parameters except for a few. Most users would consider this as item as the best..

1. Relevant But Not Best: The item is suitable in certain contexts but not the best option..

0. Not Relevant: The item is generally not recommended as it is not relevant to the user's query..

You should return a number between between 3 (Overall Best) and 0 (Not Relevant) followed by the confidence of your prediction between 1 to 9 and an explanation on the next line justifying why that category of best is suitable. Your output should look something like this: 2 8 some explanation or 3 4 some explanation. If you are fully confident, then your confidence should have high values like 7, 8 upto 9. If you are not sure, then you should assign low confidence values like 1, 2 or 3. If you are partially confident, then assign other values.

Table 16: Deliberated Pointwise Prompt Used For Ranking for generating labels and confidence scores.

Based on the following descriptions of multiple items and a user's shopping query, you need to rank the items using the below taxonomy:

User Query: {query}

Item 1 Description: Title: {Title 1} Description: {Item Description 1}

Item 2 Description: Title: {Title 2} Description: {Item Description 2}

...

...

Item N-1 Description: Title: {Title N-1} Description: {Item Description N-1}

Item N Description: Title: {Title N} Description: {Item Description N}

User Query: {query}

Classification Categories:

3. Overall Best: The item meets the following criteria: The item is overall best in its category on various parameters – excellence in quality, user experience, value for money, innovation, aesthetics, environmental impact, market position, safety, versatility, processing speed, has been rated highly, etc..

2. Almost Best: The item scores high on most or majority of the parameters except for a few. Most users would consider this as item as the best..

1. Relevant But Not Best: The item is suitable in certain contexts but not the best option..

0. Not Relevant: The item is generally not recommended as it is not relevant to the user's query..

The 'Overall Best' item(s) should be ranked higher, followed by the 'Almost Best' item(s), the 'Relevant But not the best' and then the 'not relevant' ones. You should return the item ids separated by ' ' something like 8 3 9 1 2... You should start your answer with only the rankings and not a description. Ensure that each item id is present in the list. Ensure that the number of rankings is equal to the number of items shown i.e. exactly K .

Table 17: Listwise Prompt Used For Ranking