Automated Query-Product Relevance Labeling using Large Language Models for E-commerce Search

Jayant Sachdev[†]
jayant.sachdev@walmart.com
Walmart Global Tech
Sunnyvale, CA, USA

Sean D Rosario[*†]
sean.drosario@walmart.com
Walmart Global Tech
Sunnyvale, CA, USA

Abhijeet Phatak[†]
abhijeet.phatak@walmart.com
Walmart Global Tech
Sunnyvale, CA, USA

He Wen
vicky.wen@walmart.com
Walmart Global Tech
Sunnyvale, CA, USA

Swati Kirti
swati.kirti@walmart.com
Walmart Global Tech
Sunnyvale, CA, USA

Chittaranjan Tripathy
ctripathy@walmart.com
Walmart Global Tech
Sunnyvale, CA, USA

ABSTRACT

Accurate query-product relevance labeling is indispensable to generate ground truth dataset for search ranking in e-commerce. Traditional approaches for annotating query-product pairs rely on human-based labeling services, which is expensive, time-consuming and prone to errors. In this work, we explore the application of Large Language Models (LLMs) to automate query-product relevance labeling for large-scale e-commerce search. We use several publicly available and proprietary LLMs for this task, and conducted experiments on two open-source datasets and an in-house e-commerce search dataset. Using prompt engineering techniques such as Chain-of-Thought (CoT) prompting, In-context Learning (ICL), and Retrieval Augmented Generation (RAG) with Maximum Marginal Relevance (MMR), we show that LLM's performance has the potential to approach human-level accuracy on this task in a fraction of the time and cost required by human-labelers, thereby suggesting that our approach is more efficient than the conventional methods. We have generated query-product relevance labels using LLMs at scale, and are using them for evaluating improvements to our search algorithms. Our work demonstrates the potential of LLMs to improve query-product relevance thus enhancing e-commerce search user experience. More importantly, this scalable alternative to human-annotation has significant implications for information retrieval domains including search and recommendation systems, where relevance scoring is crucial for optimizing the ranking of products and content to improve customer engagement and other conversion metrics.

CCS CONCEPTS

• **Computing methodologies** → *Information extraction*; **Natural language generation**; Language resources; • **Information systems** → **Relevance assessment**; Search engine indexing; **Novelty in information retrieval**.

KEYWORDS

Large Language Models, Search Relevance, Information Retrieval, Data Annotation, Prompt Engineering, Retrieval Augmented Generation, Maximum Marginal Relevance.

---
[*]Corresponding author
[†]These authors contributed equally to this research.

1 INTRODUCTION

When a customer performs a search on an e-commerce platform like Walmart, it is essential that the search results show the exact products or relevant products they are looking for, saving the customer time and effort while providing a positive shopping experience. The product search experience on e-commerce platforms is powered by a collection of machine learning models and algorithms across the stages of pre-retrieval, retrieval, and post-retrieval ranking and filtering [20]. Many of these models rely on accurate query-product (Q-P) relevance label data for training and testing. Specifically, these labels indicate how relevant a given product is to a customer search query. For example, the product "Ergonomic PU leather high back office chair with flip-up armrest" is highly relevant to the search query "leather chair", while the product "hard floor beveled edge chair mat" is not relevant to the same query.

We have worked with an external data labeling service which employs human labelers. The labelers were given Q-P pairs with detailed instructions and examples to guide labelers. They were not given any information on customer engagement data for Q-P pairs. Typically, three to five independent assessments are gathered per Q-P pair. Despite the guidelines, human labelers do not always reach consensus on an annotation, hence labeled data is often noisy. Furthermore, external human labeling is expensive and time-consuming, and hence only Q-P pairs corresponding to a small fraction of all queries can be labeled. Despite these challenges, external human labelers are considered as the most reliable method of acquiring data annotations, and is widely used across e-commerce and internet industries. Previously, Q-P relevance labels were obtained from clickstream data and human annotation as shown in Figure 1(a). Higher engagement of a product given a search query would be considered a positive signal for relevance. However, cold-start products (such as newly introduced products and tail products that are sold infrequently) may lack sufficient impressions, click-through-rate (CTR), or add-to-cart (ATC) rate information due to their limited exposure to the customers. Furthermore, some products might get a lot of impressions and clicks even if they are not very relevant to the search query. For example, the product "fresh lime" gets a relatively high number of impressions and clicks for the query "lemon", but it is not a very relevant product. Identifying the strong need for an automated framework

(a) Previous approaches of acquiring Q-P relevance

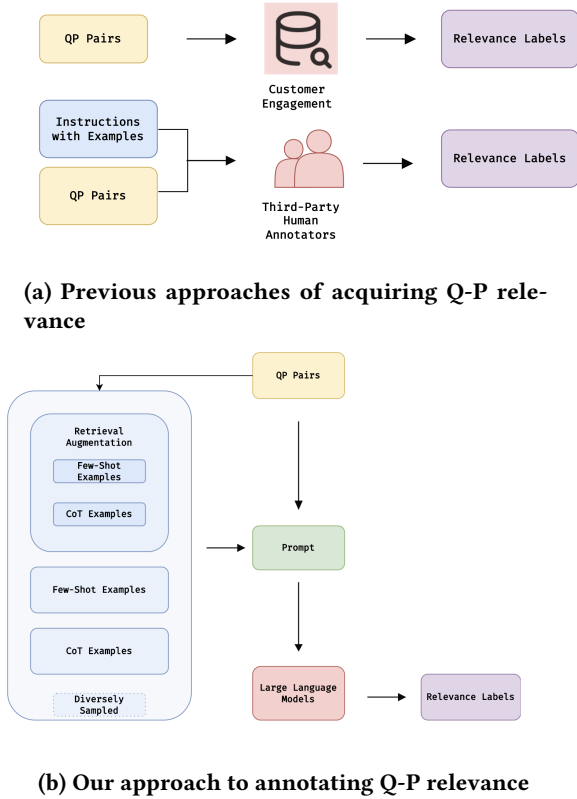**(b) Our approach to annotating Q-P relevance**

Figure 1: Comparison of pipeline architectures for Q-P relevance annotation

for Q-P relevance labeling, in this work, we demonstrate that Large Language Models (LLMs) can be used successfully to obtain accurate relevance labels in a fully automated manner and at scale. A schematic of our approach is shown in Figure 1(b), which we will detail in the subsequent sections. We have experimented with several LLMs for this task. We have explored different e-commerce search datasets, as well as ablation studies on the effectiveness of prompt engineering techniques including Chain-of-Thought (CoT) prompting, In-context Learning (ICL), and Retrieval Augmented Generation (RAG) with Maximum Marginal Relevance (MMR). Figure 2 shows Retrieval-Augmented Generation (RAG) architecture, designed and used in our work, which contains a retrieval component that retrieves relevant labeled query-product pairs for a given query-product pair. These relevant query-product pairs, providing the contextual information, are then used to create prompts which are provided as input to the LLMs.

2 BACKGROUND

This work is an application of data-centric Artificial Intelligence (AI), which is systematic engineering of the data used to build an AI system, including but not limited to automated data labeling, collection, augmentation, and cleaning [29]. One approach to automated data labeling is called *programmatic labeling* which includes using human-defined labeling functions (LFs) that capture labeling

logic to auto-generate large training sets [21]. Programmatic labeling significantly increases efficiency over manual labeling through automating the labeling process. However, labeling decisions still require human domain expertise on what heuristics should be applied [9].

2.1 Large Language Models

Large Language Models can generate human-like text and demonstrate state-of-the-art logical reasoning ability across a broad range of reasoning tasks and benchmarks [7]. With advancements in the field, open-source models have also proven to be an effective alternative to GPT models in multiple reasoning tasks [12, 13, 18, 25]. Prior work has shown that LLMs can be used to label data at par with human labeling on a variety of NLP tasks, with up to 96% saving in costs [26]. LLMs are proven to be a viable substitute to crowd-sourced annotators and can match or surpass crowd-sourced annotators [10]. Recent work has also explored the idea of using LLMs to annotate shopping relevance [8, 24].

2.2 Mathematical Formulation

Let (Q, P) denote the set of all possible Q-P pairs. We define the task of relevance labeling as a classification problem with the candidate classes set $\mathcal{Y} = \{y_1, y_2, \ldots, y_n\}$. We want to find a map $\Phi_h : (Q, P) \to \mathbb{R}^{\mathcal{Y}}$ that is able to ideally score the relevance for the Q-P pairs against the candidate classes. We assume Q and P are infinite sets [1]. Given an input query $q \in Q$ and product $p \in P$, we want to maximize the probability

$$P(y_{pred} = y_{true}|q, p),$$

where

$$y_{pred} = \underset{y_i \in \mathcal{Y}}{\operatorname{argmax}} \, \Phi_h(q, p).$$

Φ_h can be expressed as a function of the choice of the LLM and associated sampling parameters ($\mathcal{L}$) along with the baseline input prompt or context ($\mathcal{P}$) to the LLM. With advanced prompting techniques, we modify the context to include additional instructions I and set of k few shot examples or demonstrations that are added to the input context provided to the LLM. This can be represented as $\mathcal{P}_{I,k}$, and we can express

$$\Phi_h = \Psi(\mathcal{L}, \mathcal{P}_{I,k}),$$

where $\Psi(\cdot, \cdot)$ is a function of $\mathcal{L}$ and $\mathcal{P}_{I,k}$. In case of Chain-of-Thought (CoT) prompting, we include additional instructions to step by step reason through the generation process that is I_{CoT}. With crowd-sourced data annotation, we first need to provide the annotators with a thorough description of the labeling task, with meanings of each category and specific examples with explanations. Therefore, using the same approach, we guide LLMs to annotate data by providing the task description and some labeled examples. We observe that prompting the LLM to explain the reasoning behind the provided annotation can improve the labeling accuracy. We use RAG to retrieve most similar and hence most relevant demonstrations or examples that are represented as k_{RAG}. Since we use the retriever to provide additional context simply by concatenating the context with these examples. RAG exhibits significant potential in enhancing the quality of prompts by providing external knowledge as a preliminary step before generating the response, thereby ensuring contextual precision and a higher degree of detail. We use
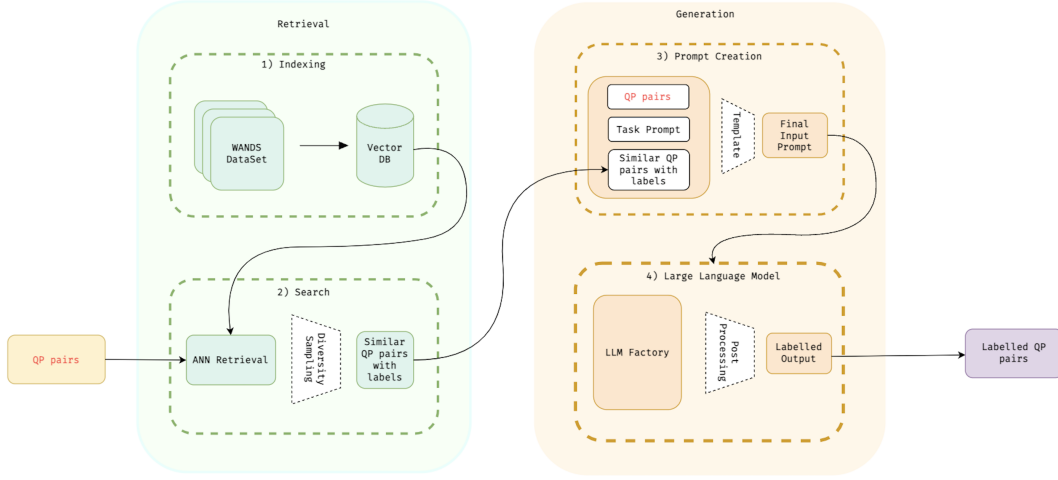
Figure 2: System Architecture for Automated Q-P relevance with LLM and RAG

Maximum Marginal Relevance (MMR) [3] retrieval to iteratively find documents that are dissimilar to previous results. MMR has been shown to improve retrievals in LLMs [28]. Consider the set D consisting of all candidate documents and R consisting of the previously chosen (retrieved) documents, and q representing a query. We also consider two similarity functions – Sim_1 that compares a document with the query, and Sim_2 that assesses the similarity between two documents. Let d_i and d_j denote individual documents in D and R. Then MMR is given by the following formula:

$$\text{MMR} = \arg \max_{d_i \in D \backslash R} [\lambda_{MMR} \cdot Sim_1(d_i, q) - (1 - \lambda_{MMR}) \cdot \max_{d_j \in R} Sim_2(d_i, d_j)],$$

where the first term and the second term respectively represent relevance and diversity. The adjustable parameter λ_{MMR} balances the importance of relevance and diversity. $\lambda_{MMR} \to 1$ prioritizes relevance whereas $\lambda_{MMR} \to 0$ prioritizes diversity. Finally, we select the optimal map $\hat{\Phi}_h$ through experiments on ground truth data and ablation studies.

3 METHODS

3.1 Prompt Engineering

Prompt engineering is the systematic design and optimization of input prompts to guide the LLM responses, ensuring accuracy, relevance, and coherence in the generated output [4].

3.1.1 In-Context Learning (Few-Shot Prompting). In-context learning refers to a setting in which the model is given a few demonstrations of the task at inference time, but no weight and gradient updates are allowed [2, 6]. The major advantage of this technique is reduced reliance on task-specific data and does not require fine-tuning on domain specific datasets.

3.1.2 Chain-of-Thought (CoT) Prompting. CoT prompting can enhance reasoning in language models by decomposing problems into intermediate steps [27]. It provides an interpretable insight into the model's behavior, revealing how it might have reached

a certain answer and helping identify where the reasoning may have gone wrong. Using CoT, we provided the reasoning as to why certain label was selected for each of the examples used in few-shot prompting. There are multiple ways to invoke a CoT response. In our experiments we use the words `'Let's think step by step'` in the few-shot examples to invoke CoT responses [14].

3.1.3 Retrieval Augmented Generation (RAG). RAG technique utilizes input to identify relevant information for the task at hand, which is then used to offer additional context in the formation of input prompt to the LLMs. The RAG architecture contains two main components: a retriever that identifies relevant information (documents) in response to input query, and a generator that generates the ouput, taking into account the context of retrieved information, the initial query, and required task information. It has been noted that extensive pre-trained language models have the capacity to encapsulate factual knowledge within their parameters and can attain superior outcomes when they are fine-tuned for distinct NLP tasks. Despite this, their proficiency in accessing and manipulating knowledge precisely is still lacking, leading to less than satisfactory performance in tasks that are heavily reliant on knowledge[16]. As shown in Figure 2, given a query-product pair, using the RAG technique, we provide the relevant context information about the query-product pair to the LLMs, which proves to be beneficial in generating the correct relevance labels.

3.1.4 Maximum Marginal Relevance Retrieval (MMR). Retrieving similar Q-P pairs as few shot examples with RAG often leads to a set of examples with a high degree of overlap. Hence the amount of new information that each example adds to the prompt is limited. In order to overcome this, we added a component of diversity into the few-shot examples retrieved, as described in the previous section. MMR ensures that examples retrieved are both relevant to the question Q-P pair, while being sufficiently diverse. We experiment

with different values of λ_{MMR} to find the optimal balance between similarity and diversity.

3.2 Details of our Prompt

Our prompt consists of three parts. First, we have a context prompt which specifies the instruction I to the LLM including the classes relevance labels with explanations of each label and the expected output structure. Second, we do in-context learning by providing sample inputs (search query and product title) and the outputs (corresponding relevance labels). For CoT, we included more instructions in the instruction prompt I and provided annotated few-shot examples. Lastly, we provide the Q-P actual pairs we want labeled by the LLM (see Figure 2 for a schematic).

3.3 Datasets

We perform experiments on two publicly available datasets and also on our proprietary dataset to validate the effectiveness of our methods.

ESCI Dataset: ESCI dataset [22] is an e-commerce dataset that has Q-P pairs that are human-annotated with corresponding relevance labels. We assume that the annotations provided are accurate, and serve as ground truth labels. There are 4 classes for relevance labels: `Exact`, `Substitute`, `Complement`, and `Irrelevant`. We sampled 5000 Q-P pairs from the test split of the ESCI dataset, with an even split across the four class labels to create a test set for experimentation and evaluation purposes.

WANDS Dataset: WANDS [5] is another e-commerce dataset that contains Q-P pairs that are human-annotated with the corresponding relevance labels. We assume that the annotations provided are accurate, and serve as ground truth labels. There are 3 classes for relevance labels: `Exact`, `Partial`, and `Irrelevant`. Since there is no train/test split in the data, we sampled 5000 Q-P pairs evenly across the three class labels to create a test set for experimentation and evaluation purposes.

Walmart Mexico Search Dataset: Our primary data source is Walmart Mexico search session data, which contains customer search queries and product impressions. This data is proprietary and acquired from Walmart's internal databases. We sampled 100 queries uniformly across search traffic segments. For each of the 100 sampled queries, we sample 10 products retrieved before re-ranking. Thus, we have 1000 distinct query product pairs in our ground truth data, mostly in Spanish. Domain experts have manually annotated relevance across the 1000 Q-P pairs. The ground truth data has 5 relevance classes: `Excellent`, `Good`, `Okay`, `Bad`, and `Embarrassing`. The data is heavily skewed towards `Excellent` because the products per query are sampled from search retrieval data, which is likely to be more relevant than not. Hence, for this dataset, weighted F1 score is a more reliable metrics than average F1 score.

3.4 Experimental Setup

Across all three datasets, we experimented with 8 Few-Shot examples and 16 Few-Shot examples for in-context learning. These examples could be randomly sampled from the training set (referred to as FS in the tables and figures), or retrieved based on embedding distance from the test question (referred to as FS_RAG in the tables and figures), and diversity could be introduced to the RAG examples (referred to as FS_RAG_MMR in tables and figures). For experiments with Walmart Mexico data, we sampled some Q-P pairs outside the test set from historical search relevance data to be used as Few-Shot (FS) examples. Explanations for few shot example were also manually annotated for CoT examples. Third-party human annotations serve as the baseline for experiments on this data. For the ESCI dataset, FS examples were randomly sampled from the train split of the ESCI dataset. For the prompt, we made use of descriptions of relevance labels as defined in the [5, 22] for the experiments on WANDS and ESCI respectively. We used an 80GB GPU for running inference of open source LLMs: LLM1 is an 8 billion parameter LLM [18], and LLM2 is a 70 billion parameter version of the same model. LLM3 is another open-source model with 7 billion parameters [12], and LLM4 [13] is a Mixture-of-Experts model based on 8 models of LLM3. We used vLLM [15] that uses PagedAttention to speed up the inference to make our approach more scalable and resource friendly. We used Activation-aware Weight Quantized (AWQ) models [17] that could not be fit in a single 80GB GPU like LLM2 and LLM4. LLM5 [23] is not open-sourced, so we used a paid API provided to perform the LLM calls. To implement RAG as shown in Figure 2, we used ChromaDB [11] as our vector store for retrieving similar query-product pairs from training set. We then use this retrieved query-product pairs along with our task prompt, and input query-product pair to create an input prompt for the LLM. We used scikit-learn [19] implementations for computing evaluation metrics that are described in the subsequent section in detail.

3.5 Evaluation Metrics

We compute the following metrics across LLM predictions on the aforementioned datasets.

Accuracy: $\text{Accuracy}(y, \hat{y}) = \frac{1}{n_{\text{samples}}} \sum_{i=1}^{n_{\text{samples}}} \mathbf{1}(\hat{y}_i = y_i)$,where $\hat{y}_i$ is the predicted value of the i-th sample and y_i is the corresponding true value, then the fraction of correct predictions over all $n_{samples}$ gives us the accuracy score. $\mathbf{1}(x)$ is the indicator function.

Average F_1 Score: $F_1 = 2\frac{PR}{P+R}$, where P is Precision and R is Recall. This measures the prediction accuracy across all relevance classes without accounting for class imbalance. Higher Average F_1 score means better classification performance.

Weighted F_1 Score: $F_1^{\omega} = \sum_{j=1}^{n_i} \hat{w}_i F_1(i)$ To compute the weighted F_1 score the F_1 score for each class is calculated individually, and averaged using normalized support weights per label. This can result in a better measure than average F_1 score, as it accounts for class imbalance. Higher weighted F_1 score means better classification performance.

4 RESULTS AND DISCUSSION

4.1 Experiment Metrics

Across experiments on all three datasets, we observe LLM2 and LLM5 outperform all other models (Please refer to Fig 3, and for the numeric outputs in Table 3). Our results show that providing FS examples improves accuracy over zero-shot in most cases, and RAG FS offers further improvements in accuracy metrics in some

instances (see Table 3). However, we observe that the best accuracy is obtained when RAG is used in combination with diversification by MMR, which we believe is due to how the contextual information exploited by the different LLMs. Further, for experiments with 8 and 16 few shot examples using RAG to select examples, we tried various values of $\lambda_{MMR} \in [0.75, 0.5, 0.25, 0.0]$. Setting $\lambda_{MMR} = 1$ is the same as the FS_RAG experiments because retrieval is solely based on relevance thus inducing zero diversity. We observe that for different datasets, and different values of FS, the optimal value of λ_{MMR} up to the resolution of our grid (0.25), can be different. Overall, we observe that diversity helps in improving accuracy. We observe that increasing diversification i.e. lower values of λ_{MMR} improves accuracy metrics, as shown in Fig 4. This is because the retrieved examples may have some degree of semantic overlap, hence diversification helps add novel information within the prompt. We also include sample prompts from our experiments with WANDS data in the Appendix A1 and A2. A sample set of Q-P pairs on the ESCI data is shown in Table 1 and a sample set of Q-P pairs on the WANDS data is shown in Table 2. For some predictions that do not match the ground truth, such as Example #2 in Table 1 and Example #4 in Table 2, the prediction labels are arguably more accurate than the ground truth labels. We can potentially use this approach to improve these datasets by identifying errors in the existing human-annotated ground truth labels. For Walmart Mexico data, LLM5 with 16 FS_RAG_MMR with $\lambda_{MMR} = 0.75$ approaches human-level weighted F1 Score (see Table 3).

Table 1: Example results on ESCI data

#	Query-Product pair	Ground Truth	Prediction
1	**Q:** `womens knee high socks` **P:** `12 Pairs Women Knee High Socks 196013`	Exact	Exact
2	**Q:** `bar style dartboard` **P:** `Viper EVA V-Foam Dartboard Surround Wall Protector, Black`	Exact	Complement
3	**Q:** `fiskars axe sharpener` **P:** `Fiskars X25 Splitting Axe, 28-Inch`	Complement	Irrelevant
4	**Q:** `helium tank` **P:** `Helium Tank with 50 Balloons and White Ribbon`	Substitute	Exact

4.2 Time and Cost Analysis

External human-annotations had a turnaround time of about 2-3 weeks. Labelers often take about a week to familiarize themselves with the task requirements, and then another 2 weeks to manually label the 1000 records (Q-P pairs) they are provided. Therefore, turnaround for third party human-annotations is estimated to be about 30 mins/record. In contrast, our experiments show that LLMs do the task in a fraction of the time. Our best performing configuration for LLM5 takes a little over 3 hours to complete, so the upper bound on LLMs for this annotation task is about 8.3 seconds/record. However, with open-source models most experiments ran in under 5 minutes on a GPU machine with an inference time of about 0.3 seconds/record. These models demonstrate a significantly efficient run time for large datasets such as those from Walmart's e-commerce
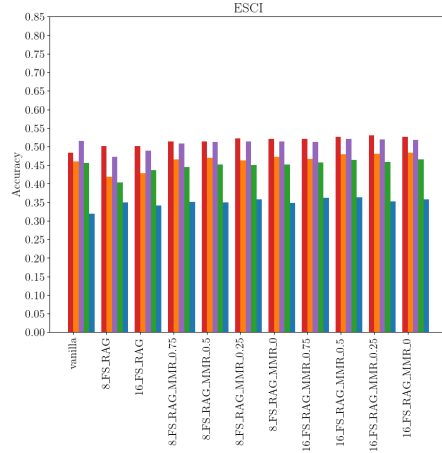
Table 2: Example results on WANDS data

#	Query-Product pair	Ground Truth	Prediction
1	**Q:** `leather chair` **P:** `31" wide top grain leather armchair`	Exact	Exact
2	**Q:** `coffee container` **P:** `gillis coffee table with storage`	Irrelevant	Irrelevant
3	**Q:** `basket planter` **P:** `classic rolled rim stone pot planter`	Partial	Partial
4	**Q:** `wine bar` **P:** `corene sixteenth century italian replica mini bar`	Partial	Exact
5	**Q:** `unique coffee tables` **P:** `solid wood block coffee table`	Partial	Exact
6	**Q:** `beaded curtains` **P:** `fade single curtain rod`	Irrelevant	Partial

ecosystem, thereby offering a viable alternative. Moreover, the opensource nature of these models confers an added advantage in terms of flexibility, allowing for more customized adjustments according to specific requirements through fine-tuning.
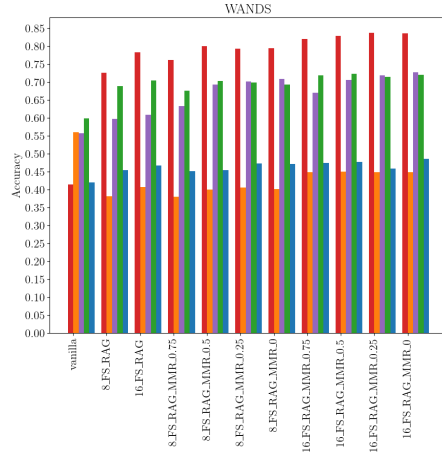
The costs of using LLMs are also significantly less than thirdparty human labelers. According to our estimates, labeling each Q-P pair is about 500 times cheaper with LLMs than human labelers, even when considering compute resources and API costs. LLMs have the potential to be even more cost-effective with techniques like batching of inputs/outputs, and conciseness of prompts. Opensource models may be a more suitable choice over proprietary LLMs in many situations since they can be fine-tuned on custom data to achieve better performance and mitigate any potential data privacy/leakage concerns.
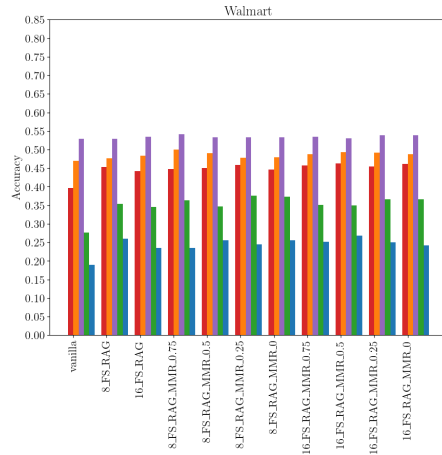
5 CONCLUSION

Our work demonstrates the potential of LLMs in providing accurate and reliable query-product relevance data at scale. By leveraging LLMs with the state-of-the-art prompt engineering techniques, we are able to achieve accuracy comparable to human-labelled query-product pairs, while significantly reducing the time and cost required. Our experiments demonstrated the novel use of MMR in RAG for query-product relevance labeling has shown good improvements and strong promise for future work. We also showed how techniques like Chain-of-Thought and Few Shot prompting can help improve the accuracy of LLMs for this task. This scalable alternative to traditional human-annotation methods has far-reaching implications for information retrieval domains such as search and recommendation. One could consider using product descriptions and other attributes that are often available in the product catalogs and taxonomies, however, they are often noisy and would increase the number of input tokens to the LLMs which would have additional computational cost. Our productionized approach within Walmart Global Tech has already yielded a large number of query-product relevance labels, which are currently being used to evaluate improvements to various search algorithms. This not only improves the efficiency of our search systems but also enables us to provide better user experiences through more relevant search

(a) Accuracy of experiments on ESCI data

(b) Accuracy of experiments on WANDS data

(c) Accuracy of experiments on Walmart data

Figure 3: Color Code: ■ **LLM1,** ■ **LLM2,** ■ **LLM3,** ■ **LLM4,** ■ **LLM5**

results. Furthermore, our method's broad applicability across various information retrieval domains makes it a valuable tool for optimizing products and content for greater user interactions and revenue generation.

REFERENCES

[1] Alireza Bagheri Garakani, Fan Yang, Wen-Yu Hua, Yetian Chen, Michinari Momma, Jingyuan Deng, Yan Gao, and Yi Sun. 2022. Improving Relevance Quality in Product Search using High-Precision Query-Product Semantic Similarity. In *Proceedings of the Fifth Workshop on e-Commerce and NLP (ECNLP 5)*, Shervin Malmasi, Oleg Rokhlenko, Nicola Ueffing, Ido Guy, Eugene Agichtein, and Surya Kallumadi (Eds.). Association for Computational Linguistics, Dublin, Ireland, 44–48. https://doi.org/10.18653/v1/2022.ecnlp-1.6

[2] Tom Brown, Benjamin Mann, Nick Ryder, Melanie Subbiah, Jared D Kaplan, Prafulla Dhariwal, Arvind Neelakantan, Pranav Shyam, Girish Sastry, Amanda Askell, et al. 2020. Language models are few-shot learners. *Advances in neural information processing systems* 33 (2020), 1877–1901.

[3] Jaime Carbonell and Jade Goldstein. 1998. The use of MMR, diversity-based reranking for reordering documents and producing summaries. In *Proceedings of the 21st annual international ACM SIGIR conference on Research and development in information retrieval.* 335–336.

[4] Banghao Chen, Zhaofeng Zhang, Nicolas Langrené, and Shengxin Zhu. 2023. Unleashing the potential of prompt engineering in Large Language Models: a comprehensive review. arXiv:2310.14735 [cs.CL]

[5] Yan Chen, Shujian Liu, Zheng Liu, Weiyi Sun, Linas Baltrunas, and Benjamin Schroeder. 2022. WANDS: Dataset for Product Search Relevance Assessment. In *Proceedings of the 44th European Conference on Information Retrieval.* 12 pages.

[6] Qingxiu Dong, Lei Li, Damai Dai, Ce Zheng, Zhiyong Wu, Baobao Chang, Xu Sun, Jingjing Xu, Lei Li, and Zhifang Sui. 2023. A Survey on In-context Learning. arXiv:2301.00234 [cs.CL]

[7] OpenAI: Achiam et al. 2023. GPT-4 Technical Report. https://api.semanticscholar.org/CorpusID:257532815

[8] Guglielmo Faggioli, Laura Dietz, Charles LA Clarke, Gianluca Demartini, Matthias Hagen, Claudia Hauff, Noriko Kando, Evangelos Kanoulas, Martin Potthast, Benno Stein, et al. 2023. Perspectives on large language models for relevance judgment. In *Proceedings of the 2023 ACM SIGIR International Conference on Theory of Information Retrieval.* 39–50.

[9] Naiqing Guan, Kaiwen Chen, and Nick Koudas. 2023. Can Large Language Models Design Accurate Label Functions? arXiv:2311.00739 [cs.CL]

[10] Xingwei He, Zhenghao Lin, Yeyun Gong, A-Long Jin, Hang Zhang, Chen Lin, Jian Jiao, Siu Ming Yiu, Nan Duan, and Weizhu Chen. 2023. AnnoLLM: Making Large Language Models to Be Better Crowdsourced Annotators. arXiv:2303.16854 [cs.CL]

[11] Jeff Huber. 2024. *Chroma DB.* https://pypi.org/project/chromadb/

[12] Albert Q Jiang, Alexandre Sablayrolles, Arthur Mensch, Chris Bamford, Devendra Singh Chaplot, Diego de las Casas, Florian Bressand, Gianna Lengyel, Guillaume Lample, Lucile Saulnier, et al. 2023. Mistral 7B. *arXiv preprint arXiv:2310.06825* (2023).

[13] Albert Q. Jiang, Alexandre Sablayrolles, Antoine Roux, Arthur Mensch, Blanche Savary, Chris Bamford, Devendra Singh Chaplot, Diego de las Casas, Emma Bou Hanna, Florian Bressand, Gianna Lengyel, Guillaume Bour, Guillaume Lample, Lélio Renard Lavaud, Lucile Saulnier, Marie-Anne Lachaux, Pierre Stock, Sandeep Subramanian, Sophia Yang, Szymon Antoniak, Teven Le Scao, Théophile Gervet, Thibaut Lavril, Thomas Wang, Timothée Lacroix, and William El Sayed. 2024. Mixtral of Experts. arXiv:2401.04088 [cs.LG] https://arxiv.org/abs/2401.04088

[14] Takeshi Kojima, Shixiang Shane Gu, Machel Reid, Yutaka Matsuo, and Yusuke Iwasawa. 2023. Large Language Models are Zero-Shot Reasoners. arXiv:2205.11916 [cs.CL]

[15] Woosuk Kwon, Zhuohan Li, Siyuan Zhuang, Ying Sheng, Lianmin Zheng, Cody Hao Yu, Joseph E. Gonzalez, Hao Zhang, and Ion Stoica. 2023. Efficient Memory Management for Large Language Model Serving with PagedAttention. In *Proceedings of the ACM SIGOPS 29th Symposium on Operating Systems Principles.*

[16] Patrick Lewis, Ethan Perez, Aleksandra Piktus, Fabio Petroni, Vladimir Karpukhin, Naman Goyal, Heinrich Küttler, Mike Lewis, Wen-tau Yih, Tim Rocktäschel, et al. 2020. Retrieval-augmented generation for knowledge-intensive nlp tasks. *Advances in Neural Information Processing Systems* 33 (2020), 9459–9474.

[17] Ji Lin, Jiaming Tang, Haotian Tang, Shang Yang, Xingyu Dang, and Song Han. 2023. Awq: Activationaware weight quantization for llm compression and acceleration. *arXiv preprint arXiv:2306.00978* (2023).

[18] AI @ Meta Llama Team. 2024. The Llama 3 Herd of Models. arXiv:2407.21783 [cs.AI] https://arxiv.org/abs/2407.21783

[19] F. Pedregosa, G. Varoquaux, A. Gramfort, V. Michel, B. Thirion, O. Grisel, M. Blondel, P. Prettenhofer, R. Weiss, V. Dubourg, J. Vanderplas, A. Passos, D. Cournapeau, M. Brucher, M. Perrot, and E. Duchesnay. 2011. Scikit-learn: Machine

Learning in Python. *Journal of Machine Learning Research* 12 (2011), 2825–2830.

[20] Yiming Qiu, Chenyu Zhao, Han Zhang, Jingwei Zhuo, Tianhao Li, Xiaowei Zhang, Songlin Wang, Sulong Xu, Bo Long, and Wen-Yun Yang. 2022. Pre-training Tasks for User Intent Detection and Embedding Retrieval in E-commerce Search. In *Proceedings of the 31st ACM International Conference on Information & Knowledge Management* (Atlanta, GA, USA) *(CIKM '22).* Association for Computing Machinery, New York, NY, USA, 4424–4428. https://doi.org/10.1145/3511808.3557670

[21] Alexander J. Ratner, Stephen H. Bach, Henry R. Ehrenberg, Jason Alan Fries, Sen Wu, and Christopher Ré. 2017. Snorkel: Rapid Training Data Creation with Weak Supervision. *Proceedings of the VLDB Endowment. International Conference on Very Large Data Bases* 11 3 (2017), 269–282. https://api.semanticscholar.org/CorpusID:6730236

[22] Chandan K. Reddy, Lluís Màrquez, Fran Valero, Nikhil Rao, Hugo Zaragoza, Sambaran Bandyopadhyay, Arnab Biswas, Anlu Xing, and Karthik Subbian. 2022. Shopping Queries Dataset: A Large-Scale ESCI Benchmark for Improving Product Search. (2022). arXiv:2206.06588

[23] Machel Reid, Nikolay Savinov, Denis Teplyashin, Dmitry Lepikhin, Timothy Lillicrap, Jean-baptiste Alayrac, Radu Soricut, Angeliki Lazaridou, Orhan Firat, Julian Schrittwieser, et al. 2024. Gemini 1.5: Unlocking multimodal understanding across millions of tokens of context. *arXiv preprint arXiv:2403.05530* (2024).

[24] Beatriz Soviero, Daniel Kuhn, Alexandre Salle, and Viviane Pereira Moreira. 2024. ChatGPT Goes Shopping: LLMs Can Predict Relevance in eCommerce Search. In *European Conference on Information Retrieval.* Springer, 3–11.

[25] Tyler Vergho, Jean-Francois Godbout, Reihaneh Rabbany, and Kellin Pelrine. 2024. Comparing GPT-4 and Open-Source Language Models in Misinformation Mitigation. arXiv:2401.06920 [cs.CL]

[26] Shuohang Wang, Yang Liu, Yichong Xu, Chenguang Zhu, and Michael Zeng. 2021. Want To Reduce Labeling Cost? GPT-3 Can Help. In *Findings of the Association for Computational Linguistics: EMNLP 2021*, Marie-Francine Moens, Xuanjing Huang, Lucia Specia, and Scott Wen-tau Yih (Eds.). Association for Computational Linguistics, Punta Cana, Dominican Republic, 4195–4205. https://doi.org/10.18653/v1/2021.findings-emnlp.354

[27] Jason Wei, Xuezhi Wang, Dale Schuurmans, Maarten Bosma, Brian Ichter, Fei Xia, Ed Chi, Quoc Le, and Denny Zhou. 2023. Chain-of-Thought Prompting Elicits Reasoning in Large Language Models. arXiv:2201.11903 [cs.CL]

[28] Xi Ye, Srinivasan Iyer, Asli Celikyilmaz, Ves Stoyanov, Greg Durrett, and Ramakanth Pasunuru. 2022. Complementary explanations for effective in-context learning. *arXiv preprint arXiv:2211.13892* (2022).

[29] Daochen Zha, Zaid Pervaiz Bhat, Kwei-Herng Lai, Fan Yang, Zhimeng Jiang, Shaochen Zhong, and Xia Hu. 2023. Data-centric Artificial Intelligence: A Survey. arXiv:2303.10158 [cs.LG]

A APPENDIX

A.1 Sample prompt : WANDS Dataset - 8 FS with RAG

```
You are a search engine in an eCommerce website. For a given customer query and a product title, p
Exact : this label represents the surfaced product fully matches the search query.
Partial : this label represents the surfaced product that does not fully match the search query. It
Irrelevant : this label indicates the product is not relevant to the query.
The response should be in a python dictionary format {"rating":label}, where label which is either

#### Here are some examples:

query: wood coffee table set by storage, product title: coffee table
{'rating': 'Partial'}

query: wood coffee table set by storage, product title: coffee table with storage
{'rating': 'Partial'}

query: wood coffee table set by storage, product title: onshuntay coffee table
{'rating': 'Partial'}

query: wood coffee table set by storage, product title: wooden coffee table
{'rating': 'Partial'}

query: wood coffee table set by storage, product title: wood coffee table
{'rating': 'Partial'}

query: wood coffee table set by storage, product title: ahern coffee table
{'rating': 'Partial'}

query: wood coffee table set by storage, product title: fromm wood table
{'rating': 'Partial'}

query: wood coffee table set by storage, product title: bahareh coffee table
{'rating': 'Partial'}

Now rate the relevance of this pair:
query: wood coffee table set by storage, product title: mikell 2 piece coffee table set
```

In the prompt above, there are some examples from RAG that have a high degree of overlap like the product titles "wooden coffee table" and "wood coffee table". This issue is overcome by MMR-based diversity, as seen in the next prompt

A.2 Sample prompt : WANDS Dataset - 8 FS RAG MMR $\lambda_{MMR} = 0$

```
You are a search engine in an eCommerce website. For a given customer query and a product title, please annotate each product title in the list as one of these
options: 'Exact', 'Partial', 'Irrelevant'
Exact : this label represents the surfaced product fully
matches the search query.
Partial : this label represents the surfaced product that
does not fully match the search query. It only
matches the target entity of the query, but does not
satisfy the modifiers for the query.
Irrelevant : this label indicates the product is not relevant to the query.
The response should be in a python dictionary format {"rating":label},
where label which is either 'Exact', 'Partial', or 'Irrelevant'.


#### Here are some examples:

query: wood coffee table set by storage, product title: coffee table
{'rating': 'Partial'}

query: wood coffee table set by storage, product title: gabrielle end table storage
{'rating': 'Partial'}

query: wood coffee table set by storage, product title: mylor solid wood coffee table
{'rating': 'Partial'}

query: wood coffee table set by storage, product title: oday solid wood coffee table with
storage
{'rating': 'Partial'}

query: wood coffee table set by storage, product title: radford coffee table with storage
{'rating': 'Partial'}

query: wood coffee table set by storage, product title: berg solid coffee table with storage
{'rating': 'Partial'}

query: wood coffee table set by storage, product title: aule solid wood end table with storage
{'rating': 'Partial'}

query: wood coffee table set by storage, product title: hedda coffee table
{'rating': 'Partial'}

Now rate the relevance of this pair:
query: wood coffee table set by storage, product title: mikell 2 piece coffee table set
```
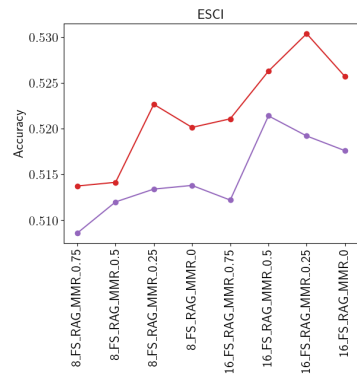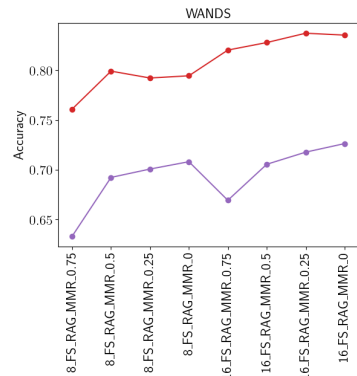
A.3 Experimental results

Model	ESCI			WANDS			Walmart		
	Acc.	F_1	F_1^ω	Acc.	F_1	F_1^ω	Acc.	F_1	F_1^ω
3rd-party labelers	-	-	-	-	-	-	0.648	0.615	0.452
LLM1 + VANILLA	0.460	0.340	0.434	0.560	0.522	0.567	0.469	0.208	0.442
LLM1 + 8_FS	0.463	0.335	0.430	0.468	0.463	0.480	0.494	0.204	0.447
LLM1 + 16_FS	0.466	0.343	0.427	0.443	0.444	0.449	0.479	0.196	0.442
LLM1 + 8_FS_RAG	0.419	0.342	0.423	0.381	0.376	0.353	0.476	0.208	0.445
LLM1 + 16_FS_RAG	0.428	0.348	0.423	0.407	0.406	0.380	0.484	0.199	0.442
LLM1 + 8_FS_COT	0.470	0.346	0.444	0.461	0.455	0.476	0.471	0.175	0.420
LLM1 + 16_FS_COT	0.460	0.330	0.424	0.439	0.441	0.450	0.487	0.197	0.439
LLM1 + 8_FS_RAG_COT	0.428	0.348	0.433	0.378	0.368	0.356	0.485	0.217	0.453
LLM1 + 16_FS_RAG_COT	0.429	0.345	0.426	0.436	0.430	0.420	0.457	0.190	0.426
LLM1 + 8_FS_RAG_MMR_0.75	0.466	0.363	0.455	0.381	0.379	0.363	0.500	0.297	0.458
LLM1 + 8_FS_RAG_MMR_0.5	0.469	0.363	0.448	0.400	0.398	0.398	0.490	0.278	0.447
LLM1 + 8_FS_RAG_MMR_0.25	0.463	0.351	0.443	0.406	0.408	0.403	0.478	0.268	0.437
LLM1 + 8_FS_RAG_MMR_0	0.473	0.358	0.450	0.402	0.402	0.399	0.479	0.280	0.443
LLM1 + 16_FS_RAG_MMR_0.75	0.467	0.374	0.453	0.449	0.449	0.438	0.488	0.274	0.454
LLM1 + 16_FS_RAG_MMR_0.5	0.479	0.365	0.459	0.450	0.451	0.445	0.493	0.291	0.454
LLM1 + 16_FS_RAG_MMR_0.25	0.481	0.371	0.456	0.449	0.452	0.439	0.492	0.260	0.446
LLM1 + 16_FS_RAG_MMR_0	0.484	0.368	0.457	0.449	0.452	0.438	0.488	0.283	**0.455**
LLM2 + VANILLA	0.515	0.367	0.469	0.557	0.531	0.568	0.529	0.159	0.409
LLM2 + 8_FS	0.522	0.410	0.499	0.542	0.515	0.555	0.508	0.175	0.427
LLM2 + 16_FS	0.520	0.395	0.494	0.521	0.504	0.538	0.507	0.174	0.424
LLM2 + 8_FS_RAG	0.472	0.388	0.464	0.597	0.571	0.611	0.529	0.164	0.415
LLM2 + 16_FS_RAG	0.489	0.387	0.477	0.609	0.582	0.627	0.535	0.170	0.419
LLM2 + 8_FS_COT	0.522	0.401	0.504	0.508	0.496	0.519	0.509	0.170	0.423
LLM2 + 16_FS_COT	0.517	0.403	0.497	0.511	0.501	0.524	0.501	0.174	0.418
LLM2 + 8_FS_RAG_COT	0.460	0.366	0.452	0.599	0.572	0.613	0.526	0.151	0.403
LLM2 + 16_FS_RAG_COT	0.476	0.387	0.464	0.625	0.598	0.639	0.533	0.164	0.413
LLM2 + 8_FS_RAG_MMR_0.75	0.509	0.408	0.498	0.633	0.604	0.648	0.541	0.227	0.422
LLM2 + 8_FS_RAG_MMR_0.5	0.512	0.409	0.499	0.692	0.654	0.704	0.533	0.215	0.415
LLM2 + 8_FS_RAG_MMR_0.25	0.513	0.399	0.499	0.701	0.660	0.711	0.533	0.215	0.409
LLM2 + 8_FS_RAG_MMR_0	0.514	0.408	0.499	0.708	0.666	0.718	0.534	0.212	0.414
LLM2 + 16_FS_RAG_MMR_0.75	0.512	0.411	0.498	0.669	0.639	0.686	0.535	0.227	0.415
LLM2 + 16_FS_RAG_MMR_0.5	0.521	0.410	0.507	0.706	0.664	0.719	0.531	0.213	0.408
LLM2 + 16_FS_RAG_MMR_0.25	0.519	0.407	0.502	0.718	0.678	0.730	0.539	0.215	0.422
LLM2 + 16_FS_RAG_MMR_0	0.518	0.406	0.502	0.726	0.687	0.738	0.539	0.225	0.419
LLM3 + VANILLA	0.456	0.394	0.469	0.599	0.535	0.601	0.276	0.171	0.259
LLM3 + 8_FS	0.426	0.374	0.445	0.637	0.561	0.636	0.225	0.140	0.195
LLM3 + 16_FS	0.436	0.377	0.456	0.658	0.567	0.652	0.224	0.126	0.208
LLM3 + 8_FS_RAG	0.404	0.360	0.411	0.688	0.571	0.673	0.354	0.200	0.361
LLM3 + 16_FS_RAG	0.437	0.386	0.437	0.705	0.573	0.683	0.345	0.193	0.353
LLM3 + 8_FS_COT	0.428	0.372	0.447	0.651	0.541	0.636	0.233	0.132	0.186
LLM3 + 16_FS_COT	0.433	0.371	0.450	0.664	0.530	0.640	0.220	0.121	0.182
LLM3 + 8_FS_RAG_COT	0.408	0.356	0.406	0.680	0.511	0.639	0.379	0.190	0.384
LLM3 + 16_FS_RAG_COT	0.424	0.358	0.411	0.692	0.512	0.650	0.379	0.191	0.387
LLM3 + 8_FS_RAG_MMR_0.75	0.445	0.390	0.448	0.675	0.543	0.654	0.364	0.241	0.371
LLM3 + 8_FS_RAG_MMR_0.5	0.452	0.393	0.456	0.703	0.580	0.679	0.347	0.234	0.353
LLM3 + 8_FS_RAG_MMR_0.25	0.451	0.394	0.455	0.698	0.569	0.674	0.376	0.260	0.381
LLM3 + 8_FS_RAG_MMR_0	0.452	0.394	0.457	0.693	0.565	0.670	0.373	0.255	0.382
LLM3 + 16_FS_RAG_MMR_0.75	0.457	0.398	0.451	0.719	0.580	0.693	0.351	0.222	0.354
LLM3 + 16_FS_RAG_MMR_0.5	0.464	0.400	0.461	0.722	0.598	0.697	0.350	0.264	0.359
LLM3 + 16_FS_RAG_MMR_0.25	0.459	0.407	0.457	0.714	0.585	0.688	0.367	0.257	0.376
LLM3 + 16_FS_RAG_MMR_0	0.465	0.406	0.462	0.720	0.591	0.695	0.367	0.255	0.373
LLM4 + VANILLA	0.319	0.259	0.329	0.420	0.367	0.443	0.189	0.123	0.245
LLM4 + 8_FS	0.318	0.256	0.333	0.392	0.362	0.420	0.229	0.129	0.273
LLM4 + 16_FS	0.339	0.272	0.352	0.396	0.371	0.425	0.196	0.117	0.244
LLM4 + 8_FS_RAG	0.349	0.290	0.361	0.454	0.402	0.483	0.259	0.172	0.314
LLM4 + 16_FS_RAG	0.342	0.277	0.351	0.468	0.420	0.495	0.236	0.145	0.288
LLM4 + 8_FS_COT	0.321	0.264	0.339	0.356	0.332	0.388	0.227	0.122	0.268
LLM4 + 16_FS_COT	0.315	0.253	0.329	0.369	0.339	0.402	0.192	0.117	0.236
LLM4 + 8_FS_RAG_COT	0.331	0.270	0.342	0.437	0.388	0.467	0.250	0.152	0.301
LLM4 + 16_FS_RAG_COT	0.353	0.283	0.362	0.461	0.410	0.491	0.244	0.140	0.289
LLM4 + 8_FS_RAG_MMR_0.75	0.350	0.282	0.362	0.452	0.402	0.479	0.235	0.146	0.286
LLM4 + 8_FS_RAG_MMR_0.5	0.349	0.275	0.359	0.454	0.402	0.482	0.255	0.160	0.307
LLM4 + 8_FS_RAG_MMR_0.25	0.358	0.288	0.368	0.473	0.421	0.500	0.245	0.146	0.302
LLM4 + 8_FS_RAG_MMR_0	0.348	0.289	0.355	0.472	0.420	0.498	0.256	0.150	0.315
LLM4 + 16_FS_RAG_MMR_0.75	0.362	0.292	0.369	0.475	0.432	0.501	0.251	0.149	0.303
LLM4 + 16_FS_RAG_MMR_0.5	0.363	0.282	0.369	0.477	0.435	0.505	0.268	0.159	0.323
LLM4 + 16_FS_RAG_MMR_0.25	0.353	0.280	0.361	0.459	0.414	0.489	0.250	0.158	0.303
LLM4 + 16_FS_RAG_MMR_0	0.358	0.287	0.366	0.485	0.439	0.511	0.243	0.151	0.293
LLM5 + VANILLA	0.483	0.417	0.489	0.415	0.368	0.383	0.397	0.231	0.437
LLM5 + 8_FS	0.514	0.454	0.519	0.635	0.612	0.643	0.359	0.203	0.394
LLM5 + 16_FS	0.516	0.447	0.524	0.656	0.633	0.663	0.344	0.199	0.386
LLM5 + 8_FS_RAG	0.501	0.442	0.507	0.726	0.683	0.728	0.453	0.236	0.481
LLM5 + 16_FS_RAG	0.501	0.446	0.507	0.783	0.741	0.783	0.443	0.237	0.474
LLM5 + 8_FS_COT	0.490	0.431	0.499	0.647	0.617	0.653	0.362	0.207	0.395
LLM5 + 16_FS_COT	0.483	0.439	0.492	0.663	0.637	0.668	0.322	0.176	0.360
LLM5 + 8_FS_RAG_COT	0.477	0.435	0.483	0.730	0.691	0.732	0.438	0.235	0.466
LLM5 + 16_FS_RAG_COT	0.458	0.428	0.463	0.715	0.683	0.719	0.399	0.227	0.438
LLM5 + 8_FS_RAG_MMR_0.75	0.514	0.457	0.518	0.761	0.720	0.762	0.448	0.240	0.475
LLM5 + 8_FS_RAG_MMR_0.5	0.514	0.464	0.518	0.799	0.761	0.799	0.451	0.244	0.481
LLM5 + 8_FS_RAG_MMR_0.25	0.523	0.453	0.526	0.792	0.753	0.792	0.458	0.247	0.488
LLM5 + 8_FS_RAG_MMR_0	0.520	0.454	0.524	0.795	0.750	0.794	0.446	0.242	0.476
LLM5 + 16_FS_RAG_MMR_0.75	0.521	0.464	0.526	0.820	0.786	0.821	0.457	0.244	0.487
LLM5 + 16_FS_RAG_MMR_0.5	0.526	0.463	0.530	0.828	0.790	0.828	0.462	0.252	0.492
LLM5 + 16_FS_RAG_MMR_0.25	0.530	0.467	0.533	0.837	0.800	0.837	0.454	0.243	0.483
LLM5 + 16_FS_RAG_MMR_0	0.526	0.456	0.529	0.835	0.796	0.834	0.461	0.247	**0.489**

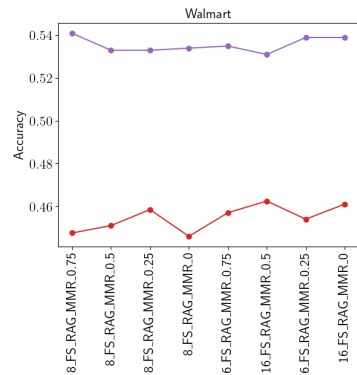**Table 3: Experimental results**

A.4 Plots for MMR Experiments

(a) ESCI MMR experiments

(b) WANDS MMR experiments

(c) Walmart MMR experiments

Figure 4: Color Code: ■ LLM2, ■ LLM5