

# E-Commerce Product Categorization with LLM-based Dual-Expert Classification Paradigm

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## Abstract

Accurate product categorization in e-commerce is critical for delivering a satisfactory online shopping experience to customers. With the vast number of products available and the numerous potential categories, it becomes crucial to develop a classification system capable of assigning products to their correct categories with high accuracy. We present a novel dual-expert classification system that utilizes the power of large language models (LLMs). This framework integrates domain-specific knowledge and pre-trained LLM’s general knowledge through effective model fine-tuning and prompting techniques. First, the fine-tuned domain-specific expert recommends top K candidate categories for a given input product. Then, the more general LLM-based expert, through prompting techniques, analyzes the nuanced differences between candidate categories and selects the most suitable target category. Experiments on e-commerce datasets demonstrate the effectiveness of our LLM-based Dual-Expert classification system.

## Keywords

Large Language Model, Categorization, Classification, E-Commerce, Dual-Expert, Generative Artificial Intelligence, GenAI, LLM

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## 1 Introduction

Accurate product categorization on e-commerce sites is the foundation of a structured catalog system to better meet customer needs. An automatic categorization system helps sellers/buyers quickly and wisely target the right categories, which in return enhances

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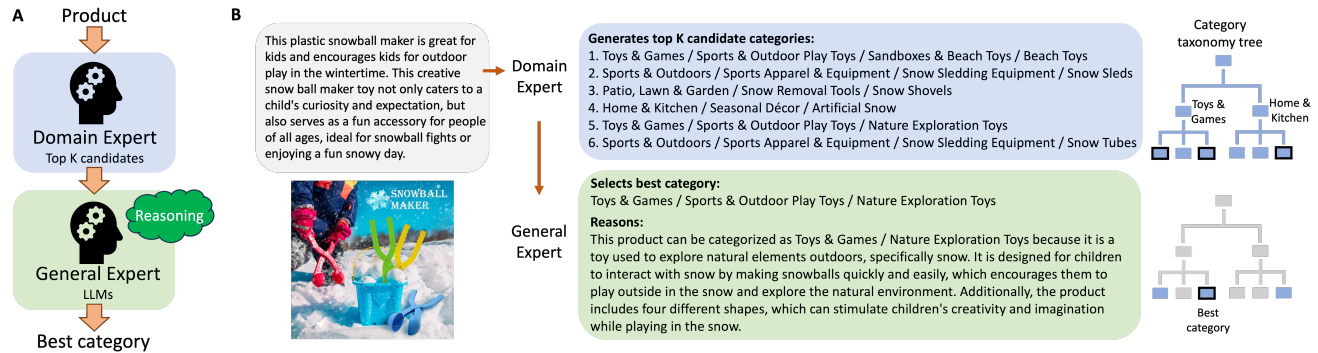
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the efficiency of downstream personalized tasks like advertisement and item recommendations. The core of a categorization system is the classification model, which relies on two types of information: informative product description and well-defined category taxonomy with over thousands of labels. However, e-commerce product categorization differs from classical classification problems. This is due to the vast volume of products with noisy and incomplete signals in both product description and categorical labels. Besides, subjective customer opinions about multi-functional products add the complexity, as these opinions can influence product descriptions and optimal category assignment. It is non-trivial to train machine learning models to discern consistent categorical patterns that meet customer expectations for a large population of catalog.

We approach product categorization as a text classification problem, since most product items in e-commerce platform are represented through structured or unstructured textual features. Recently, pre-trained models (PTMs) have shown substantial benefits in capturing universal language representations and strong reasoning capability with RLHF [9, 26]. Two prominent PTM frameworks are: 1) discriminative models with the encoder structure, like BERT (Bidirectional Encoder Representations from Transformers) [3–5], and 2) generative models with the decoder structure, like OpenAI’s GPT series (Generative Pre-trained Transformer) [1, 12, 14, 15]. Though some efforts have unified discriminative and generative tasks within a single framework, discriminative language models are generally preferred for sentence understanding, while generative language models are more commonly used for text generation and reasoning. With the increasing parameter sizes and extensive pre-training on vast datasets and various learning tasks, these language models have consistently attained state-of-the-art (SOTA) performance across numerous NLP benchmarks. Given the overlap between pretrained knowledge and e-commerce catalog, we believe that PTMs possess the domain knowledge that is necessary to differentiate the nuances between categories.

In this study, we introduce an innovative dual-expert framework that integrates both discriminative and generative large language models (LLMs) in a cascading approach to achieve precise product categorization. Initially, the discriminative language model is fine-tuned with domain data, acting as a domain expert to recommend the top K candidate classes for each product. Subsequently, an off-the-shelf LLM selects the optimal target from the top K suggestions based on certain criteria via prompting. The LLM in our framework



**Figure 1: LLM-based Dual-Expert E-commerce Categorization Framework.** (A) The system comprises two key components that operate sequentially: a Domain Expert that identifies the top K categories, followed by a General Expert that decides the optimal category from the top candidates by applying reasoning capabilities. We inject the domain knowledge to each expert through model fine-tuning (domain expert) and prompting (LLM-based general expert). (B) An example product processed by Dual-Expert.

serves as the general expert due to its capability acquired through pre-training on a large corpus of general data and well alignment with human instructions. The major contribution of this study can be summarized in 3 folds:

- 1) We propose a novel LLM-based dual-expert categorization system, which is designed to achieve accurate product classification in e-commerce and output reasons for hard cases.
- 2) We introduce the key components of domain-specific and general experts, and describe the strategies to inject domain knowledge into the model’s decision-making process.
- 3) We compare the performance of this dual-expert framework against the popular text classification models as well as the SOTA model in two e-commerce catalog datasets, proved its superiority on e-commerce categorization.

## 2 E-commerce Product Categorization

In e-commerce, product categorization involves assigning one or more optimal categories from thousands of labels based on product features. This task is challenging due to noisy and incomplete catalog data. E-commerce sites generally define a taxonomy (a hierarchical structure) as the target label space for categorization. As this taxonomy becomes more granular, categories can become very similar, with only subtle differences distinguishing them.

**Output Label Space.** Online e-commerce sites pre-define the semantic structure of item categories (known as taxonomy) according to business purpose. This taxonomy serves as the target label space for categorization, and is constructed as hierarchical trees. As the taxonomy tree becomes fine and granular, the categories may appear similar to each other, with only subtle differences separating them. Extreme multi-label text classification aims to identify relevant labels from an extremely large set of labels, making it a challenging task [2, 23]. Catalog data inherently suffers from label imbalance, which is widely known as the long tail issue. Classification models may struggle to learn patterns for the underrepresented, smaller categories in the skewed distribution.

**Catalog Noise and Incompleteness.** The training data for our ML-based categorization model is mainly derived from samples of

catalog data, which often includes noisy labels and incomplete information. A key challenge for e-commerce categorization systems is to extract meaningful signals about customer preferences from this low-quality data. We classify the quality of the model training data into two types:

- **Noisy Signals.** Product features and labels often contain noise, leading to unstable learning. This noise can be soft (exaggerated properties) or hard (misleading/irrelevant descriptions) and is common in popular categories. Meanwhile, label assignments can be noisy due to outdated categorization systems, internal biased corrections, and incorrect label suggestions from sellers. These are the major sources of label noise.
- **Incomplete Information.** Incomplete information often arises from the subjective opinions of sellers and customers. For instance, sellers in an automobile store might omit keywords and only provide brand and series numbers, resulting in very brief item descriptions. This limited information confuses general buyers. Additionally, catalog labels are incomplete because selling items may be multi-functional, yet sellers typically provide only a single label which may not align with how different buyers perceive or intend to use the product. In this scenario, our task is to find the most favored category, even when multiple options are acceptable.

## 3 LLM Based Dual-Expert System

LLM-based multi-agent systems have emerged as a novel technology with advanced capabilities. These systems specialize LLMs into various distinct agents, each with different expertise [13, 20, 22]. Our domain-specific and general expert system has two language models cooperating with each other and each has a specialty. Specifically, we have designed two expert models that work sequentially to assign the optimal category to a given product. The whole framework is shown in Figure 1. First, a discriminative model work as the domain expert to find top K candidate categories for the selling product given its item data. Then, an off-the-shelf LLM serves as the general expert, evaluating which categories from the top K candidates are most suitable and accurate for the selling product in

question. The LLM outputs its decision and the reasoning behind its selection.

### 3.1 Domain Expert

The primary objective of the domain expert is to identify the top K most relevant leaf categories for a given product, with relevance determined by similar patterns observed in the training data. Simultaneously, the domain expert ensures a highly accurate top 1 prediction to support the online inference pipeline (Supplementary A.1). The backbone of the domain expert is XLM-R [3], a Transformer model that is pre-trained on monolingual data using the multilingual masked language modeling (MLM) objective.

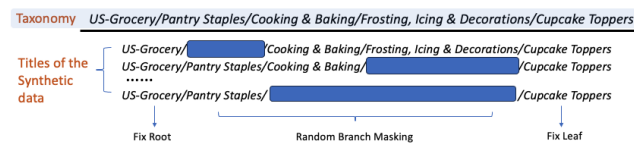
**3.1.1 Label Semantic Capture via Label Augmentation.** Discriminative models face a limitation in explicitly lacking semantic knowledge about the labels. Our in-depth study observed a high frequency of label-related keywords in the item data written by sellers, indicating that keyword matching could benefit semantic understanding in our domain tasks. Therefore, we strategically expose the label names to the model, aiding its few-shot and zero-shot learning capabilities. To enhance the training data with label names, we use the full path of labels, i.e., a path in a taxonomy tree. We randomly mask the branch along this path and replace the title or description of sampled training data with the masked path (Figure 2). These synthetic training samples are then added to the original data.

**3.1.2 Two-phase Learning.** Learning from large, noisy catalog data is difficult due to label imbalance and errors in signals. To tackle this, we split model training into two phases. In the first phase, the domain expert reviews challenging cases and uses focal loss to handle imbalance. In the second phase, the model focuses on major patterns, reinforcing the initial phase with bootstrap loss. Further details are in the following sections.

**Phase 1: Exploration of Category Relationship.** The catalog data inherently suffers from label imbalance, commonly referred to as the long tail issue. To address this, we incorporate focal loss [10] into our objectives as a dynamic learning approach to better capture challenging cases in smaller categories. The mathematics definition of focal loss for classification can be expressed as:

$$L_{FL} = - \sum_{k=1}^N \alpha_k (1 - q_k)^\gamma \log(q_k), \quad (1)$$

where  $q_k$  is the predicted probability of the true label  $k$  by model.  $\alpha_k$  is the corresponding class weight of the true label. It is predefined based on the desired label distribution, e.g., popularity score of the



**Figure 2: Example of Synthetic Data for Capturing Label Semantics.**

product in catalog.  $\gamma$  is a hyperparameter controlling the learning weight of hard examples. The higher the value of  $\gamma$ , the lower the loss for well-classified examples.

**Phase 2: Self-Exploitory.** The second phase of training employs a self-justifying learning mechanism that accounts for knowledge consistency during training [16]. It augments the usual prediction objective with a notion of perceptual consistency, which allows the model to disagree with a perceptually-inconsistent training label and effectively relabel the data while training. The assumption behind this idea is that incorrect labels are likely to be eventually highly inconsistent with other data points predicted to the same label by the model. Therefore, it acts in a manner of self label cleanup and bootstraps itself until convergence to stable knowledge. Here, we incorporate this idea into the cross-entropy training loss:

$$L_{BT\_BCE}(p, q) = - \sum_{k=1}^N \beta p_k \log(q_k) + \beta (1 - p_k) \log(1 - q_k) + \sum_{k=1}^N (1 - \beta) q_k \log(q_k), \quad (2)$$

where  $p_k, q_k$  are ground truth label and model prediction, respectively.  $N$  is the size of target labels. Parameter  $0 \leq \beta \leq 1$  balances bootstrap learning and supervised classification. It is empirically set in the range [0.8, 0.95]. Due to the large batch training steps ( $t_{batch}$ ), we can set a delta activation  $\hat{\beta}$  that adaptively turns on/off the bootstrap loss at a given global step  $T_{gate}$ :

$$\hat{\beta} = \begin{cases} 1, & \text{if } t_{batch} < T_{gate} \\ \beta, & \text{if } t_{batch} \geq T_{gate} \end{cases} \quad (3)$$

### 3.2 General Expert

After the Domain Expert produces top K candidate categories, the LLM-based General Expert then reasons about the top candidate categories via proper prompting strategies, and selects optimal category among the candidates.

(a) *Zero-shot:*  
You will try to classify a product in the catalog of an e-commerce site to a product category. Below is the data for the product: {product information}  
Can this product be categorized to any of the categories listed below?  
Category 0: ..., Category 1: ..., Category 2: ...  
If this product belongs to none of them, answer none. If the product information is not provided enough for you to make judgement, answer "cannot decide". If this product is multi-functional, answer the categories with its primary function.

(b) *Representation of the categories:*

- Leaf node only: Category 0: Shorts, ...
- Full path: Category 0: Fashion / Women / Clothing / Active / Base Layers & Compression / Shorts, ...
- Descriptive name: Category 0: Women's Base layers & Compression Shorts, ...
- Descriptive name with In-Context Learning via LLM self-generated summarization/definition:  
Category 0: Women's Base layers & Compression Shorts, Women's Base Layer Shorts are designed for various activities such as gym workouts, cycling, running. They are typically made of stretchy, breathable, and moisture-wicking materials that provide support, comfort, and flexibility. They are shorts or tights that cover the upper part of the legs ...

(c) *Enhanced reasoning via ranking:* This product can be possibly categorized to the categories listed below. Can you rank the relevant categories for this product in order of likelihood, starting with the most probable and ending with the least probable.

(d) *Enhanced reasoning via CoT and ranking:* Let's think step by step. First, find clues in the product data sources and candidate category data, then think about who the users of this product might be and in what scenarios the product will be used, finally rank the candidate categories. Your thinking process should be in the reasons section.

**Figure 3: Prompting Strategies.** (a) LLM is prompted to directly select an optimal category. (b) Categories are represented by various levels of information, including in-context learning via summarization. (c) LLM is enforced to rank in order to reason. (d) LLM is encouraged to execute CoT before ranking.

**3.2.1 Zero-shot.** Product category names often carry rich semantic meaning. For instance, hierarchical path of category "Toys and Games / Sports & Outdoor Play Toys / Sandboxes & Beach Toys / Beach Toys" self explains that "Beach Toys" is for outdoor play and is under Toys and Games department. Thus, we directly prompt the LLM-based General Expert with product item data and candidate categories' path names.

**3.2.2 In-context learning via LLM self-generated summarization.** LLMs demonstrate remarkable capabilities in in-context learning (ICL), they can learn to do a specific task by conditioning on a prompt consisting of input-output examples [1]. LLMs can generalize to previously unseen data by using few-shot examples provided in the prompt, without explicit pre-training for the specific task [21]. ICL are recently used in text classification [6, 11, 17, 25].

In e-commerce product categorization task, there are a vast number of different categories in the taxonomy tree, each with numerous products associated with it. In the traditional approach of few-shot in-context learning, we need to select example products for each candidate category in the prompt. However, the selected products may contain information irrelevant to the candidate category, and may not adequately represent the candidate category.

To address these issues, we propose a novel in-context learning approach. Rather than providing a few products and their associated categories as few-shot examples in the prompts, we provide clear definitions of the candidate categories to the LLM-based General Expert, where the category definitions are self-generated by LLMs. The self-generation process is as follows. For each category, we curated a collection of data points that have been previously labeled as belonging to that particular category, then LLMs were instructed to summarize from the pool of data and generate a clear definition for the category based on the provided data. To ensure diversity in the summarizing samples, we include multi-source data from both popular selling products and catalog representatives of each category via unsupervised learning. Consequently, a summarized definition of each category was self-generated by LLMs. We then feed these LLM-generated category definitions to the LLM-based General Expert, aiding in more accurate category selection (Figure 3b, Figure 6).

**3.2.3 Enhanced reasoning.** To boost LLM's decision-making capabilities, we employed prompts that are designed to enhance the reasoning processes within LLMs. We instructed LLMs to identify the categories that match the main functionality or intended usage of the product (Figure 3a). A product category consists of a root level node (typically a Department) and intermediate nodes, followed by a fine-grained leaf node. We experiment with prompts containing various levels of information from the categories (Figure 3b).

Think step-by-step enables LLMs to generate task reasoning processes [8]. Chain-of-thought (CoT) prompting significantly enhances reasoning abilities of LLMs through chained reasoning steps [18, 19]. CoT prompting, which involves the presentation of intermediate reasoning steps, has proven effective in zero-shot [8] and in-context learning [19] settings. To enhance LLM's reasoning capability on product classification task, we instructed LLMs to rank the relevant candidate categories from the most likely to the least likely for a given product (Figure 3c). Furthermore, LLM is encouraged to find clues in the product item data, think of a potential

**Table 1: Model Performance on RetailProducts2023 Dataset.**

	Precision*	Recall*	F1 score*	F1 score (macro)
fastText	0.857	0.837	0.836	0.716
BERT	0.901	0.890	0.891	0.779
XML-R	0.902	0.910	0.899	0.782
Domain Expert alone	0.925	0.929	0.921	0.825
Dual-Expert	<b>0.972</b>	<b>0.969</b>	<b>0.968</b>	<b>0.925</b>

\*Weighted average.

**Table 2: Classification Accuracy on E-commerceCatalog Dataset.**

	Locale 1	Locale 2	Locale 3
DHPC [24] (baseline)	+0%	+0%	+0%
Domain Expert alone	+1.01%	+1.33%	+1.57%
Domain Expert w/ XML-R Selector	+1.12%	+1.05%	+1.31%
Dual-Expert	<b>+3.81%</b>	<b>+4.01%</b>	<b>+3.14%</b>

user and a use case for the product, then finally proceed to perform the ranking task (Figure 3d).

## 4 Experiments

### 4.1 Dataset

We evaluate our Dual-Expert framework on two benchmark datasets.

**RetailProducts2023.** This dataset contains 95,526 products that potentially belong to 2,214 categories from an E-commerce site. The dataset contains categories that have limited number of data entries. We leverage Mixtral from mistral.ai, a high-quality sparse mixture of experts model (SMoE) as the General Expert. Unless otherwise stated, we perform experiments with a temperature of 0.

**E-commerceCatalog.** For curating this data, we select the e-commerce catalog data of 3 locales in different languages to assess the robustness of our dual-expert approaches. In each locale, we collect an evaluation dataset of 10K products. This dataset was curated through multiple iterations of human review to provide a fair evaluation of all models compared. The Domain Expert is fine-tuned on millions of sampled catalog data per locale and we pick  $K = 10$  as the number of suggested candidate categories for the LLM-based General Expert. The SOTA model Deep Hierarchical Product Classifier (DHPC) [24] is used as the baseline for comparison.

### 4.2 Results

#### 4.2.1 Dual-Expert model achieves better classification performance compared to the baseline.

The results indicate that Dual-Expert model achieves higher classification performance consistently across RetailProducts2023 and E-commerceCatalog datasets compared to baseline models (Tables 1 and 2). On the RetailProducts2023 dataset, many categories have limited number of data points, consequently, vanilla XML-R models exhibit poor performance on these minority classes, as evidenced by the significantly lower macro F1 score of 0.782, when compared to our Dual-Expert model (0.925). Similarly, fastText [7] and BERT models exhibit relatively poor performance (Table 1). The Domain Expert model, which is a specialized version of XML-R, has improved classification performance, although it requires relatively large amount of training data to accurately learn and distinguish between different

**Table 3: Ablation Study: Impact of Domain Expert Training Strategies, i.e. Label Augmentation(LA), Phase 1&2 training.**

Training Method	Domain Expert Acc	Dual-Expert Acc
Domain Expert w/o LA	-0.7%	-1.5%
Domain Expert w/o Phase1	-0.2%	-0.5%
Domain Expert w/o Phase2	-1.4%	-0.25%

**Table 4: Comparison of LLM prompting strategies on Dual-Expert's Classification Accuracy. Baseline is DHPC [24].**

Prompt Strategy	Locale 1	Locale 2	Locale 3
with ambiguous category definition	+0.85%	+0.53%	-0.68%
descriptive category name	+1.23%	+0.80%	+2.06%
descriptive category name with ICL summarization*	<b>+3.81%</b>	<b>+4.01%</b>	<b>+3.14%</b>
enhanced reasoning via rank	<b>+3.85%</b>	<b>+3.55%</b>	<b>+2.26%</b>
enhanced reasoning via CoT and rank	+3.32%	<b>+3.59%</b>	<b>+2.86%</b>

\*Selected prompt strategy in Dual-Expert

categories. The Dual-Expert model demonstrates generalization capabilities on minority classes, showcasing its remarkable zero-shot and few-shot capabilities (Table 1). This is powered by the extensive knowledge gained during pretraining and alignment stages of the LLMs.

On E-commerceCatalog dataset, Dual-Expert model demonstrates significant accuracy improvement in 3 locales compared to the baseline SOTA model DHPC and Domain-specific Expert alone (Table 2). These results demonstrate that collaboration between the two experts, where the Domain Expert provides relevant categories and the LLM-based General Expert applies its reasoning capability to distinguish among categories and select the optimal one, leads to increased classification performance. Of note, we trained a XLM-R based binary classification model that makes binary predictions for (product, category) pairs. We used this model as a selector, substituting the General Expert. The overall accuracy was comparable or inferior to Domain Expert, suggesting these models likely learned the same noise in the training data (Table 2).

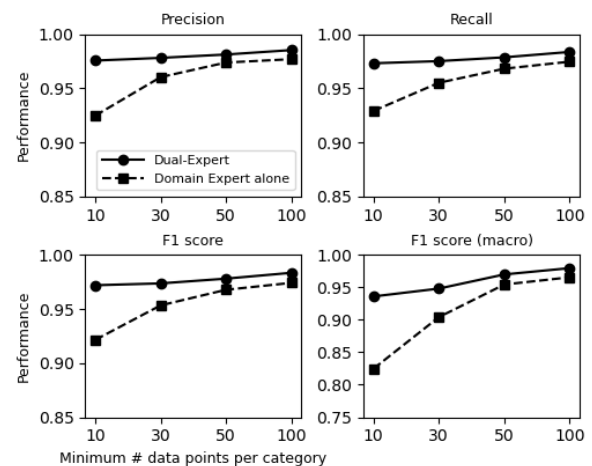
Dual-Expert achieves higher classification accuracy partially due to its ability to address noisy mislabeled data in the training set. Consider the product shown in Figure 1, there are snowball clipper that are incorrectly labeled as beach toys in training data, a BERT-based discriminative model would learn this inaccurate classification during fine-tuning. In contrast, LLMs have the extensive general knowledge to recognize that such product is not a beach toy, but rather a snow exploration toy. Consequently, this approach effectively mitigates the issue of incorrect labeling in training data.

**4.2.2 Impact of domain expert training strategy.** We conduct ablation study to assess the impact of removing the proposed components of domain expert's training strategies. As shown in table 3, removing any of these strategies causes performance drop. The bootstrap learning in phase 2 has the most significant impact on the accuracy of domain-expert's top1 prediction, as it stabilizes the later stages of model training and prevent over-fitting. For the entire dual-expert system, label augmentation and phase 1 training play a more crucial role than phase 2 since they enhance model's learning from the few-shot knowledge and improves topK retrieval performance of the domain expert.

**4.2.3 Clear category definitions through LLM self-generated summarization enhance Dual-Expert's decision-making capabilities.** Table 4 summarizes Dual-Expert's performance when using prompts that provide clear category definitions and enhance its reasoning capabilities. We observed that the prompts employing short phrases to represent categories achieved relatively low classification accuracy (Table 4, with ambiguous category definition). This is expected, as short phrases encode limited category information. For example, 'accessory' as a category name is ambiguous, therefore LLM misunderstands the category and makes errors.

To make the category definitions more clear, we propose a novel in-context learning approach via LLM self-generated summarization. For each category, we first instructed LLMs to summarize from the pool of data and generate a clear definition for the category based on the provided data. Then, instead of providing products and their associated categories as few-shot examples directly in the prompts, we provide the LLM with self-generated category summary, and instruct the LLM to select the most appropriate category among the candidates. As a result, the Dual-Expert model achieves the highest classification accuracy improvement of 3.8%, 4.0%, 3.1% for the 3 locales, respectively (Table 4, descriptive category name with ICL summarization). The findings suggest that LLMs excel at summarizing the core characteristics of a particular category. By leveraging the summarizations of categories generated by LLMs themselves, the models are equipped with more precise and well-defined descriptions of the categories, enabling them to make more accurate classification predictions (Figure 6).

**4.2.4 Classification accuracy of the LLM-based Dual-Expert improves via enhanced reasoning.** Our baseline prompting strategy involves instructing the LLM to directly choose optimal category from candidate classes (Table 4, zero-shot). LLM often states that "category A is correct" and that "categories B, C, and D are incorrect" without further explanations and reasoning. LLMs likely did not engage in extensive reasoning, classification accuracy was relatively low. When prompted to rank all relevant candidate categories in descending order, from the most likely to the least likely, LLM enhanced its reasoning capabilities. As a result, we

**Figure 4: Framework feasibility on RetailProducts2023.**

observe classification accuracy improvement by 3.85%, 3.55% and 2.26% in the 3 locales, respectively (Table 4).

### 4.3 Discussion

**4.3.1 Inference cost.** Inference cost is crucial for the practical application of this work to large-scale e-commerce product categorization. Consider the online/offline traffic of practical categorization system, we utilized the thresholding within the domain expert to regulate the traffic flowing into the general expert. In our practice, this approach reduces total traffic by 80% while maintaining overall accuracy improvements, as the 20% of data that passed through the entire workflow are typically cases the Domain Expert alone struggles to classify correctly (Figure 5). Furthermore, the Dual-Expert system (Table 1), in return, can act as a reliable auditor for determining the appropriate threshold for the Domain Expert model, further dynamically optimizing the trade-off between performance and computational cost.

**4.3.2 Probing framework feasibility.** From our experiments, we found that for classification tasks with fine-grained categories and limited number of data points per category, LLMs demonstrate robust zero-shot and few-shot capabilities. As shown in Figure 4, when minimum number of data points per category is small, Dual-Expert outperforms the Domain Expert with larger margin. E-commerce categorization task falls under this regime, since catalog data inherently exhibits long tail distribution, and the categories are fine-grained with subtle differences, such example categories are shown in Figure 6. As the categories become larger with sufficient amount of training data per category, and categories are well-separated with no conceptual overlap or nuanced difference, discriminative classification models tend to provide on-par classification performance compared to the LLM-based Dual-Expert (Figure 4).

## 5 Conclusion

In this study, we propose a Dual-Expert classification workflow, which leverages the pre-trained LLMs for accurate e-commerce product categorization. It comprises two experts: a domain-specific expert, trained on a large e-commerce domain data, identifies relevant candidate classes; and a general expert, powered by a LLM with In-Context Learning, that handles nuanced reasoning and decision-making. This dual-expert architecture leverages the complementary strengths of each expert, blending specialized domain knowledge with general reasoning capabilities from pre-training, to achieve high classification accuracy in e-commerce categorization.

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## A Supplementary

### A.1 Interaction between two experts to reduce latency of the Dual-Expert system.

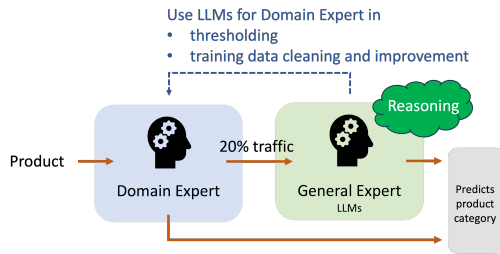


Figure 5: Modified framework that utilizes both Dual-Expert and Domain Expert alone for large scale applicability.

### A.2 Example that showcases the effectiveness of in-context learning via LLM self-generated summarization/definition

LLM self-generated summarization/definition of the categories helps clarify the category definitions to the LLM, which in turn improves LLM's product categorization capability (Figure 6).



Black Glitter Level 16 Unlocked Game Birthday Cake Topper  
- Boy's 16th Birthday Cake Decorations. The cake toppers are approx 5.9" wide and 5.6" high. This unique decoration is the perfect centerpiece for a truly epic birthday bash. The bottom of the cake topper is made of wooden sticks, please pay attention to your child to avoid accidents.

Candidate categories produced by Domain Expert that have nuanced difference:

- Grocery / Pantry Staples / Cooking & Baking Grocery Supplies / Frosting, Icing & Decorations / Cake Toppers (denoted as cake toppers 1)
- Toys & Games / Kids' Party Supplies / Kids' Party Decorations / Cake & Cupcake Toppers / Cake Toppers (denoted as cake toppers 2)
- ...

LLM self-generated summarization/definition:

- Cake toppers 1: Cake toppers are **edible** decorative elements used to decorate cakes. They are typically made from sweet ingredients like sugar, chocolate, or marzipan. These decorative pieces are placed directly on top of the cake.
- Cake toppers 2: Cake toppers are **non-edible** decorative elements used to embellish cakes. They are typically made of materials like plastic or cardboard and fashioned into various figures or shapes. These decorative pieces are usually made of plastic or made of cardboard attached to toothpicks.

Optimal category selected by the LLM-based General Expert:

Cake toppers 2.

Reasoning:

Based on the product information, this product is made of glittery card-stock with wooden stick to insert into the cake. The dimensions of 5.9" wide and 5.6" high are suitable for most cake sizes. All these details indicate that this product is meant to decorate cakes. This product is a **non-edible** cake topper made of glittery card-stock and wooden sticks. Therefore, it belongs to the category of **non-edible** decorative cake toppers.

**Figure 6: An example product that showcases the effectiveness of LLM self-generated summarization/definition.** Two candidate categories are similar with subtle differences. LLM self-generated summarization identifies the key features that separate them: one is edible cake topper, the other is non-edible.