ChatGPT

Supervised Fine-Tuning (SFT): Overview

- **Definition:** SFT takes a pre-trained model (e.g. a large language model) and further trains it on a task-specific labeled dataset [1]. In other words, we "tune" a general model to perform a specialized task.
- **Process:** During SFT the model is trained on input–output examples for the target task. Practically this means using a labeled dataset to adjust the model's weights. The training is typically done in phases – **training** on the task data, **validation** to tune hyperparameters, and **testing** on held-out examples [2]. This lets the model learn the nuances of the new domain or application [3].
- **Why use SFT:** It leverages the broad knowledge of a pre-trained model while customizing it for the specific task. Fine-tuning a smaller domain dataset is far faster and cheaper than training from scratch. SFT produces models that are more accurate on the target task (by focusing on relevant features) and helps avoid overfitting [4] [1]. In practice, SFT boosts task-specific performance and efficiency compared to using an untuned general model [4].

SFT Applications in Samsung's E-Commerce Platform

Fine-tuning can be applied to Samsung's e-commerce system to improve key tasks. For each task, we use Samsung-specific data (search logs, product info, customer Q&A) to fine-tune models for better understanding and ranking.

1. Search Query Understanding & Ranking

- **Fine-tune on query–product pairs:** Use historical search logs (queries paired with clicked or purchased product IDs) as labeled data. For example, train a dual-encoder or re-ranking model on (query, relevant product) pairs so that the model learns to score true matches higher. A sentence-transformer (e.g. DistilBERT) fine-tuned with contrastive/ranking loss on query–product data will embed queries and products in a common space [5]. At inference, the model computes a similarity score (e.g. cosine) between the query embedding and each product's embedding to rank the products [6].
- **Empirical examples:** In one e-commerce study, an LLM was fine-tuned on ~419,000 Taobao query–rewrite pairs (plus related tasks) to better rewrite and interpret long-tail queries [7]. This multi-instruction SFT significantly improved relevance and metrics for rare queries [8]. Similarly, Marqo's case study fine-tuned an embedding model (e5-base-v2) on 100k product records (out of 10M) for 14 epochs. The fine-tuned model showed clear gains in relevance: many query groups improved their NDCG scores after SFT [9]. This shows that tailoring the model to Samsung's catalog can boost ranking quality.
- **Re-ranking LLMs:** Modern search often uses a multi-stage pipeline (fast retrieval + powerful re-ranker). We can fine-tune an LLM as a re-ranker: given a query and candidate products, the LLM scores or re-orders them. Recent work shows listwise/pairwise fine-tuning of LLMs yields strong ranking gains [10]. In practice, Samsung could fine-tune such a model on its own query–ranking data.
- **Handling synonyms and ambiguity:** Out-of-the-box search often fails on vague or synonym-rich queries [11]. SFT can help here by exposing the model to those cases. For example, if users search "TV remote" but Samsung's product is labeled "SmartRemote", fine-tuning on log data teaches the model that these are equivalent. In general, fine-tuning injects Samsung-specific

vocabulary, synonyms and user intent into the model, improving recall and ranking for ambiguous queries.

2. Answering Product-Related Queries

- **Fine-tune on Q&A pairs:** Samsung's customers ask many product questions (e.g. specs, features). We can train a Q&A bot by fine-tuning an LLM on existing Q&A data. This includes FAQs, customer Q&As, manuals, and review content. For instance, Amazon's product QA dataset contains ~1.4 million question–answer pairs across many categories [12]. Training (or augmenting) on such data teaches the model to generate accurate, product-specific answers. Bitext's new "Retail Ecommerce QA Pairs" dataset (44.8K examples covering 46 intents) is explicitly designed for LLM fine-tuning in retail [13]. We could similarly collect Samsung's own Q&A data for fine-tuning.
- **Retrieval + LLM (RAG):** Another approach is Retrieval-Augmented Generation: retrieve relevant product info (spec sheets, reviews) and use a fine-tuned LLM to generate the answer. Recent e-commerce QA frameworks use RAG and LLMs tuned on product data [14]. In practice, we'd fine-tune the model on Samsung's product documents so it can accurately "cite" specs (battery life, dimensions) and opinions (review highlights) when answering.
- **Benefits:** A fine-tuned QA model will use Samsung's terminology and up-to-date info. For example, after fine-tuning, asking "Does model X support wireless charging?" will return the correct answer based on Samsung's data. Without SFT, a generic LLM might hallucinate or be unaware of the latest specs. By training on real product Q&A, the model learns to answer in Samsung's context, improving precision and trust in the answers.

3. Mapping Vague Queries to SKUs

- **Intent and category classification:** Vague queries often imply a product type or category. We can use SFT to train a model to **classify** queries into product categories or directly to SKUs. For example, if a user searches "birthday present for photographer", a fine-tuned classifier might predict the "Camera" category (and suggest popular camera models). One study highlights this idea: e-commerce models include a Query-to-Product-Type (Q2PT) classifier that maps queries to product types [15]. In the example "harry potter mug", the correct type is **mugs**, not books [15]. Fine-tuning on labeled query–category data lets the model learn these distinctions.
- **Direct query-to-SKU ranking:** Another approach is to treat each product (SKU) as a class or target in training. We can fine-tune a model on (query, correct-SKU) examples, similar to multi-label classification or retrieval. In effect, the model learns which SKUs match each query. During inference, the model scores products against the query (as in task 1) and outputs the top SKU(s). This is like embedding-based retrieval: the query is mapped to close product embeddings [6], surfacing the intended SKU.
- **Resolving ambiguity with training:** SFT can also teach the model how to handle synonyms or context. For instance, if "pants" means "trousers" in one locale but "underwear" in another, fine-tuning on Samsung's regional data will capture that. As noted in Q2PT research, fine-tuning can incorporate locale-specific intent (e.g. "pants" in UK vs US) [15]. Also, by including many examples of vague queries and their intended SKUs, the model learns to **expand or reinterpret** them. For example, training on pairs like ("cozy shoes", [winter boots SKUs]) or ("smartphone 2.0", [latest Galaxy model]) will help the model map such fuzzy inputs to the right products. (This addresses the "vocabulary mismatch" noted in search – where naive keyword matching drops recall [11].)

In summary, supervised fine-tuning adapts general AI models to Samsung's specific e-commerce data and goals. By training on Samsung's search logs, product catalogs, and Q&A data, SFT improves how the system understands queries, ranks products, and finds the right SKUs. The net effect is more accurate search results and answers, tailored to Samsung's products and customers.

Sources: We draw on recent ML literature and case studies for these points [1] [7] [9] [13] [12] [5] [10] [15] [11]. Each cited work demonstrates SFT or related techniques improving e-commerce search and QA systems.

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