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Large Language Models for the Generation of reviews for products in e-commerce

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Abstract

*Large Language Models (LLMs) have demonstrated exceptional versatility across diverse domains, yet their application in e-commerce remains underexplored due to a lack of domain-specific datasets. To address this gap, we introduce **eC-Tab2Text**, a novel dataset designed to capture the intricacies of e-commerce, including detailed product attributes and user-specific queries. Leveraging eC-Tab2Text, we focus on text generation from product tables, enabling LLMs to produce high-quality, attribute-specific product reviews from structured tabular data. Fine-tuned models were rigorously evaluated using standard Table2Text metrics, alongside correctness, faithfulness, and fluency assessments. Our results demonstrate substantial improvements in generating contextually accurate reviews, highlighting the transformative potential of tailored datasets and fine-tuning methodologies in optimizing e-commerce workflows. This work highlights the potential of LLMs in e-commerce workflows and the essential role of domain-specific datasets in tailoring them to industry-specific challenges*[1].

[1]We make our dataset, code, model outputs, and other resources available at the anonymous link.

Contents

Chapter 1

Context and Motivation

1.1 Introduction

Tabular data, including product descriptions and features, is a major component of e-commerce, although natural language is used for most user interactions, such as Q&A and helper agents. The need for models that can efficiently interpret tabular data and engage consumers through logical, context-aware communication is thus urgent.

In order to meet this need, table-to-text creation is essential, particularly in e-commerce, where it makes it possible to provide user-specific summaries, customized descriptions, and product reviews. The ability to convert structured patient records into succinct summaries for physicians [He et al., 2023] and turn tabular financial data into analytical reports [Varshney, 2024] are two examples of industries that possess this capability in addition to e-commerce. Despite its benefits, creating text that is both comprehensible and appropriate for the context from structured data is still quite difficult, especially when coordinating input data and goal outputs with user-specific needs.

User or query-centric scenarios, which require high-quality datasets that capture domain-specific perspectives, exacerbate these difficulties. The depth needed for specialized applications such as product reviews is typically absent in existing table-to-text datasets, which tend to concentrate on general-purpose summaries [Macková and Pilát, 2024b]. The utility of datasets such as QTSUMM [Zhao et al., 2023b] for attribute-specific product reviews is limited because they provide tabular summaries that are unrelated to the product domain. Product-specific text production, on the other hand, needs to take into account a variety of characteristics (such as battery life and display quality) and adjust to different user intents, including offering technical details or condensed pros and drawbacks.

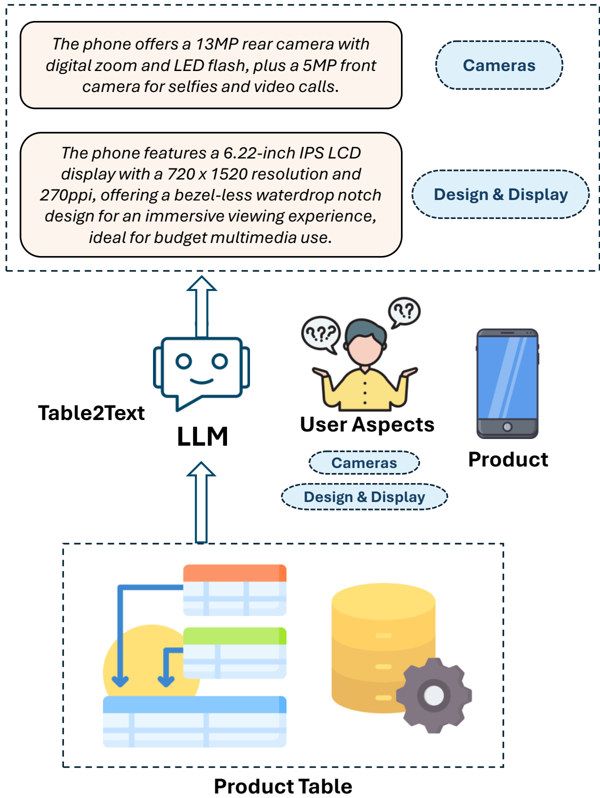


Figure 1.1: Product Table2Text

The challenges of generating text from tables have been present in several studies. Fine-tuned models like LLama2-chat [Jiang et al., 2023] and StructLM [Gao et al., 2024] have improved performance on table-based datasets by using training data tailored to specific domains. Meanwhile, general-purpose LLMs like GPT-4 and BERT have shown impressive capabilities in generating text [OpenAI et al., 2024, Devlin et al., 2019]. However, creating attribute-specific text for complex e-commerce tasks requires customized datasets, as current methods struggle with the unique demands of product-related domains.

Some progress has been made with datasets designed for table-to-text tasks, like ROTOWIRE [Wiseman et al., 2017], TabFact [Chen et al., 2020b], and WikiTableT [Chen et al., 2021]. For example, ROTOWIRE generates sports summaries, TabFact supports fact-checking, and WikiTableT focuses on creating descriptions from Wikipedia tables. But these datasets don't provide the depth needed for generating product-specific text. Other datasets, such as ToTTo [Parikh et al., 2020] and LogicNLG [Chen et al., 2020a], focus on logical deductions and advanced sentence generation but they still not significant for product-related tasks. The growing need for domain-specific datasets tailored to product reviews and attribute-based summaries has been underscored by recent research [He and Abisado, 2023].

This paper introduces a table-to-text dataset for the products domain and explores whether fine-tuned LLMs can bridge the gap between general-purpose capabilities and domain-specific needs in e-commerce. By leveraging tailored datasets and fine-tuning techniques, this work seeks to empower e-commerce platforms to generate more precise and engaging product reviews, enhancing customer satisfaction and business outcomes.

1.2 Problem Description

LLMs have shown impressive abilities in industries like healthcare [He and Abisado, 2023], finance [Varshney, 2024], and e-commerce [Peng et al., 2024], handling all sorts of tasks. But their performance across different domains often suffers because there just aren't enough datasets, especially in e-commerce. Some of the biggest improvements in LLM performance have come from tabular datasets like WikiTable [Chen et al., 2021] and QTSumm [Zhao et al., 2023b], which help models do better on tasks like summarization. Even so, e-commerce still lacks high-quality datasets that capture the key details needed for fine-tuning models for these kinds of tasks [Macková and Pilát, 2024a].

E-commerce platforms usually present product data in formats like JSON, CSV, or TSV. While these formats are common, JSON in particular can make it tricky to fine-tune LLMs [Gao et al., 2024]. This makes it harder for models to generate accurate and contextually relevant reviews, which in turn makes it more difficult for users to understand the information and make informed decisions.

On top of that, the absence of specialized datasets means e-commerce platforms struggle to provide users with reliable and consistent information. Bad or incomplete reviews lead to poor customer experiences, higher return rates, and inefficiencies in operations.

1.3 Motivation

the motivation of the study realms in the necessity to data in the domain-specific of product reviews. As highlighted by [Macková and Pilát, 2024a] and [Wang et al., 2023], the shortage of targeted, high-quality datasets makes it challenging for LLMs to effectively handle structured product data. Fine-tuning provides a practical solution by adapting LLMs' general capabilities to meet the specific needs of e-commerce.

The goal of this project is to enhance the generation of attribute-specific product reviews using the newly introduced eC-Tab2Text dataset. Designed specifically for training LLMs like LLama2-chat [Touvron et al., 2023], StructLM [Zhuang et al., 2024], and Mistral [Jiang et al., 2023], this dataset captures a wide range of product attributes and user intents. Fine-tuning with this data aims to improve the models' accuracy, fluency, and overall quality of the generated reviews, ultimately leading to better customer engagement.

As e-commerce platforms face increasing competition, the demand for automated solutions that consistently ensure user satisfaction is growing. By addressing current gaps in attribute-specific review generation, models fine-tuned with eC-Tab2Text not only improve review quality but also pave the way for scalable, automated solutions across industries. This project showcases the potential of domain-specific datasets to make AI systems more effective and impactful in real-world applications.

1.4 Objectives

1.4.1 General Objective

Present a dataset for domain-specific in e-commerce applications, **eC-Tab2Text**, to enhance the performance of Large Language Models (LLMs) in generating accurate and product reviews.

1.4.2 Specific Objectives

- Recolect data of product specifications and reviews from pricebaba[1] to create the **eC-Tab2Text** dataset.
- Use the **eC-Tab2Text** dataset to fine-tune open-source LLMs: LLama2-chat, Mistral Instruct, and StructLM.
- Use text-based metrics (BLEU, METEOR, ROUGE-1, ROUGE-L, BERTScore) and model-based metrics (Faithfulness, fluency, correctness) to evaluate the performance of the fine-tune models
- To evaluate the models' robustness across several datasets, do cross-validation with QTSUMM dataset.

1.5 Contributions

Our main contributions are as follows:

- We present eC-Tab2Text, a novel domain-specific dataset for Table-to-text generation in the e-commetce domain. The dataset features attribute-rich product tables paired with user-specific queries and outputs.
- We fine-tune open-source LLMs on the eC-Tab2Text dataset, resulting in significant improvements in text generation performance across various metrics.

[1] https://pricebaba.com/

- We provide a detailed analysis of domain robustness by comparing models trained on eC-Tab2Text with those trained on QTSumm, hightlightning the critical need for domain-specific datasets to achieve superior performance in e-commerce applications.

Chapter 2

Theoretical Framework

2.1 E-commerce Product-related Databases

E-commerce is a vast industry that continues to grow rapidly, managing large amount of product data, users, reviews and transactions. To mantain the performance and the user experience, platforms integrated databases with advanced queries and big data techniques. Studies have shown that incorporating these types of queries into e-commerce systems can streamline the search process, making it more user-friendly overall [Muntjir and Siddiqui, 2016]. Big data tools, like Hadoop [Shvachko et al., 2010] or MPP distributed databases, are also being used to analyze customer reviews and buying habits. This helps businesses optimize product selection and create a better shopping experience for customers [Liang, 2020].

Due the problem of handling complex data formats, different frameworks has emerged. These frameworks are helping e-commerce platforms run more efficiently. Cloud-based systems like [1] allow sellers to maintain a centralized product catalog, making it easier to sync data across platforms and share rich product information [Tan and Teo, 2015]. Machine learning tools also presents alternatives to handle complex data, like TrendSpotter [Ryali et al., 2023], which can predict trending products by analyzing customer behavior in real time. This is a significant advancement for businesses trying to keep up with the ever-changing market.

2.2 Large Language Models (LLMs)

Large language models (LLMs) are a big step forward in natural language processing (NLP). These models, which have millions or even billions of settings [Zhao et al., 2023a], are trained on huge amounts of text. This allows them to handle tasks like translation, summarization, and sentiment analysis with impressive accuracy. LLMs are very flexible and can be used in many areas, such as improving recommendation

[1] https://www.theproductfolks.com/productpedia-product-management-glossary

systems, robotics, and telecommunications [Debbah, 2023, Fan et al., 2023].

LLMs are so powerful because their ability to learn from minimal data. They can tackle tasks they have never explicitly been trained on—a capability known as 'zero-shot' or 'few-shot' learning [Naveed et al., 2024]. This flexibility makes them increasingly valuable even outside traditional NLP applications.

2.3 Fine Tuning

Fine-tuning is a technique of taking a pre-trained model and tailoring it for a specific task [Zhang et al., 2022a]. A general-purpose language model can be fine-tuned on a smaller, domain-specific dataset to analyze e-commerce reviews more effectively.

2.3.1 The Basics

The process adjusts the model's parameters to minimize a loss function L on a smaller dataset D', leveraging the knowledge the model has already learned [Lalor et al., 2017]. The key is to make incremental changes to the model's weights without erasing its general-purpose capabilities.

2.3.2 Practical Fine-Tuning

Fine-tuning often employs gradient-based methods like Stochastic Gradient Descent (SGD). However, the low variability of some datasets may lead in overfitting problems which can degrade the model's performance on general tasks [Catani and Leifer, 2020].

2.3.3 Why It's Efficient

The main advantage of fine-tuning models is that is faster and requires less data compared to training a model from scratch, making it ideal for scenarios with limited computational resources [Xiao et al., 2023].

2.3.4 Mathematical Framework

Fine-tuning continue increasing the knowledge the model already learned during its initial training on a large dataset. In simple terms, this process involves adjusting the model's parameters (θ) to improve its performance on a specific task. The model starts with what it learned from the large dataset (D) and is then updated using a smaller, task-specific dataset (D'). This adjustment is guided by optimizing a loss function (L), which measures how well the model is doing [Liu et al., 2023a]. The objective can be expressed as:

$$\min_{\theta} L_{D'}(\theta)$$

where $L_{D'}$ represents the loss on the fine-tuning dataset. Gradient-based methods are used to adjust the pre-trained weights minimally but effectively to improve performance on the new task [Lalor et al., 2017].

2.3.5 Operational Fine-Tunings

Fine-tuning tries to making specific adjustments to the model so it can handle a new task better. It finds to add knowledge and rules related to the specific domain. The key is to make these changes without disrupting what the model already knows, so it stays stable and works consistently [Catani and Leifer, 2020].

2.3.6 Sample Complexity and Generalization

Fine-tuning depends on how similar the pre-training task is to the new one to achieve a good performance in the new task. Fine-tuning can significantly reduce the number of examples needed to train a model (called sample complexity), this is because the general data features the pre-trained model already knows for different task. Fine-tuning simply tweaks these features to suit the new task, often achieving good accuracy with fewer examples. This idea can be better understood by looking at how the model's ability to generalize improves after fine-tuning [Shachaf et al., 2021].

2.3.7 Gradient-Based Fine-Tuning

Fine-tuning often involves gradient-based optimization techniques. Stochastic Gradient Descent (SGD) in mostly cases is used to iteratively adjust the weights. The process can be sensitive to the initial learning rate and other hyperparameters [Vrbancic and Podgorelec, 2020]. However, for LLMs fine-tuning optimizers like AdamW [Loshchilov and Hutter, 2019] are often preferred due to their efficiency and stability.

2.3.8 Computational Efficiency

In computational focus, apply fine-tuning methods are efficient compared to training a model from scratch. By starting with a pre-trained model, the number of training epochs and the amount of data required are significantly reduced. This reduce of amount of data and number of training epochs leads to less computational requirements that, in some cases, permit to execute and train models locally [Shi et al., 2023]. Fine-tuning allows for the practical deployment of advanced models in resource-constrained environments by focusing computational resources on the most impactful aspects of training [Xiao et al., 2023].

2.4 JSON-Tuning

JSON-Tuning is an approach that taking advantage of JSON (JavaScript Object Notation) data structure to training LLMs with a more comprehensive and consistent data. This method improves accuracy and efficiency which agilize how data is fed into the model and reduces the workload during fine-tuning [Zheng et al., 2024].

One of the key benefits of JSON-Tuning is its ability to reduce redundancy and simplify data management. This allows the models to reduce time in inference and training having more consistency in the contexts they are leaining [Gao et al., 2024].

2.5 Evaluation Metrics

2.5.1 BLEU (Bilingual Evaluation Understudy)

Measures n-gram overlap between machine-generated and reference text [Reiter, 2018]. Mathematically, the BLEU score is calculated using the formula:

$$\text{BLEU} = BP \cdot \exp\left(\sum_{n=1}^{N} w_n \log p_n\right)$$

where:

- BP is the brevity penalty to penalize short translations.
- w_n is the weight for n-gram precision.
- p_n is the precision for n-grams of length n.

Brevity penalty BP is defined as:

$$BP = \begin{cases} 1 & \text{if } c > r \\ e^{(1-\frac{r}{c})} & \text{if } c \leq r \end{cases}$$

where c is the length of the candidate translation and r is the length of the reference translation [Reiter, 2018].

2.5.2 ROUGE (Recall-Oriented Understudy for Gisting Evaluation)

Focuses on recall, measuring the overlap of reference text in generated output [Ng and Abrecht, 2015].

1. **ROUGE-N [Maples, 2017]**: Measures the n-gram recall between the candidate and reference summaries.

$$\text{ROUGE-N} = \frac{\sum_{S\in\text{RefSummaries}} \sum_{gram_n \in S} \text{Count}_{match}(gram_n)}{\sum_{S\in\text{RefSummaries}} \sum_{gram_n \in S} \text{Count}(gram_n)}$$

where $gram_n$ is any n-gram, and $\text{Count}_{match}(gram_n)$ is the maximum number of n-grams co-occurring in a candidate and reference summary.

2. **ROUGE-L [Lin, 2004]**: Measures the longest common subsequence (LCS) based statistics, capturing sentence-level structure similarity.

$$\text{ROUGE-L} = \frac{LCS(C, R)}{\text{length}(R)}$$

where $LCS(C, R)$ is the length of the longest common subsequence between candidate C and reference R [Ng and Abrecht, 2015].

3. **ROUGE-1 and ROUGE-2**: Specifically measure the overlap of unigrams and bigrams, respectively, between the candidate and reference summaries [Ganesan, 2018].

2.5.3 METEOR (Metric for Evaluation of Translation with Explicit ORdering)

Incorporates synonyms and paraphrases for evaluating translations [Agarwal and Lavie, 2008]. The final score is a harmonic mean of unigram precision and recall, favoring recall:

$$\text{METEOR [Lavie et al., 2004]} = \frac{10 \cdot P \cdot R}{9 \cdot P + R}$$

where:

- P is the precision of unigrams.
- R is the recall of unigrams.

This metric also incorporates a penalty function for longer alignment chunks to address issues of word ordering [Agarwal and Lavie, 2008].

2.5.4 BERTScore

Uses contextual embeddings to assess semantic similarity between generated and reference texts [Zhang* et al., 2020].

The mathematical formulation is the following:

$$F_{\text{BERT [Zhang* et al., 2020]}} = 2 \cdot \frac{P_{\text{BERT}} \cdot R_{\text{BERT}}}{P_{\text{BERT}} + R_{\text{BERT}}}.$$

According with the Hugginface space [2] and [Zhang* et al., 2020], BERTScore can produce three different metrics:

- **Precision**: The fraction of correctly labeled positive examples out of all of the examples that were labeled as positive.
- **Recall**: The fraction of the positive examples that were correctly labeled by the model as positive.
- **F1-score**: The harmonic mean of the precision and recall.

[2] https://huggingface.co/spaces/evaluate-metric/bertscore

2.6 Faithfulness, Fluency and Correctness in LLMs

Faithfulness, fluency and correctness are metrics usually used in the evaluation of large language models (LLM) systems as model-based metrics. Using these metrics it is possible to evaluate the performance of the output generated capturing the context of all the text instead of the words-metrics [Lyu et al., 2024].

2.6.1 Faithfulness

Faithfulness evaluate the model ability of creating outputs using factual infromation given by the context avoiding generating information that its origin is unknown [Jacovi and Goldberg, 2020].

Faithfulness can be measured in a few ways:

- **Reference-based evaluation**: This compares the model's output to a reference or correct answer. If the output matches the source text, it is considered faithful [Parcalabescu and Frank, 2024].

- **Model-based evaluation**: Specialized models like Prometheus [Kim et al., 2024c] or G-eval Liu et al. [2023b] check if the output is consistent with the input and spot any deviations [Gat et al., 2024].

- **Human evaluation**: People manually review the output to see if it accurately represents the input. This method often involves subjective scoring of factual accuracy [Jacovi and Goldberg, 2020].

2.6.2 Correctness

Correctness metric especially evaluate the structure of the output, if the syntaxis is correct, follows grammar rules and mantaining some coherence in the text [Varshney et al., 2022].

Correctness can be evaluated by:

- Linguistic accuracy: Focused on the gramar and context of the text [Varshney et al., 2022].

- Semantic accuracy: Evaluate if the output is meaningful and coherent within the context of the task [Steen et al., 2023].

- Automatic metrics: Metrics such as BLEU, ROUGE, or METEOR can be used too to measure how closely the generated output matches the reference text in terms of word overlap, sequence structure, and linguistic integrity [Gat et al., 2024].

- Model-based evaluation: Correctness can be evaluated with Prometheus or G-eval too[Kim et al., 2024c].

2.6.3 Fluency

Fluency evaluate how nmatural the text generated is, focuse on the smoothness, easy-reading, and how much the text is human-like. Evaluate the sentences too check the logical flow of the text. Fluency is a critical metric for evaluating LLM outputs in tasks such as conversational agents, creative writing, and summarization, where readability and user engagement are paramount [Yin et al., 2022].

Fluency can be evaluated through various approaches:

- **Linguistic coherence**: Assessing the logical progression and connectivity of sentences in the generated text, ensuring that the output is cohesive and makes sense within the context [Gat et al., 2024].
- **Grammatical accuracy**: Evaluate the gramatical errors that may involved in reducing the fluemcy of the reading [Varshney et al., 2022].
- **Stylistic consistency**: Focuse on the tone, formality, and vocabulary of the outputs are consistent with the intended style of the task [Yao and Koller, 2024].
- **Human evaluation**: It is possible to ask human to score the text's fluency based on readability and naturalness, often providing insights that complement automatic metrics [Jacovi and Goldberg, 2020].
- **Model-based evaluation**: Employing models or tools like Prometheus to assess linguistic quality and stylistic alignment [Kim et al., 2024c].

Fluency is particularly relevant in applications requiring user interaction, if the fluency is poor it can lead to misunderstandings, reduced trust, and disengagement of the users. Fluency ensures that the output is not only accurate but also appealing and easy to comprehend [Jacovi and Goldberg, 2020].

2.7 Cross-Validation Evaluation

To check how well our models can generalize and handle new data, we use a cross-validation approach. Cross-validation is a widely used technique that splits the data into multiple subsets (folds) and alternates between training and testing on these folds [Jiang and Wang, 2017, Carmack et al., 2012, Bergmeir and Benítez, 2012]. This helps measure the model's performance on unseen data. In this study, we take it a step further by using a variant of cross-validation that tests model robustness on completely different datasets [Barratt and Sharma, 2018].

2.7.1 Cross-Validation with Alternate Datasets

To ensure the robustness of a model or dataset to fine-tune an LLM, we perform cross-validation using two separate datasets, A and B. The idea is to train a model on one dataset and test it on the other, making sure the model works well across different types of data. Specifically:

- Train a model, M_A, on dataset A and test it on dataset B.
- Train another model, M_B, on dataset B and test it on dataset A.

If the models perform well on the alternate datasets, it means they have learned meaningful patterns rather than just memorizing the training data.

2.7.2 Mathematical Formulation

Let $\mathcal{D}_A = \{(x_i^A, y_i^A)\}_{i=1}^{n_A}$ and $\mathcal{D}_B = \{(x_i^B, y_i^B)\}_{i=1}^{n_B}$ represent two datasets with n_A and n_B samples. The cross-validation process involves:

1. **Training Models**:

$$M_A = \text{train}(\mathcal{D}_A), \tag{2.1}$$

$$M_B = \text{train}(\mathcal{D}_B). \tag{2.2}$$

2. **Cross-Dataset Testing**: - Test M_A on $\mathcal{D}_B$ to calculate the error $E(M_A, \mathcal{D}_B)$. - Test M_B on $\mathcal{D}_A$ to calculate the error $E(M_B, \mathcal{D}_A)$.

3. **Performance Metrics**: We evaluate each model's performance on the alternate dataset using metrics like accuracy, precision, recall, or mean squared error (MSE). For example, if we use MSE:

$$\text{MSE}_{M_A \to B} = \frac{1}{n_B} \sum_{i=1}^{n_B} \left(y_i^B - M_A(x_i^B) \right)^2, \tag{2.3}$$

$$\text{MSE}_{M_B \to A} = \frac{1}{n_A} \sum_{i=1}^{n_A} \left(y_i^A - M_B(x_i^A) \right)^2. \tag{2.4}$$

By comparing errors from in-domain and out-of-domain tests (e.g., $E(M_A, \mathcal{D}_A)$ vs. $E(M_A, \mathcal{D}_B)$), we can assess if the models generalize well or are overfitting to specific data patterns.

2.7.3 Discussion of Cross-Dataset Validation Results

Analyzing the cross-dataset performance of M_A and M_B helps us understand how robust and adaptable these models are. If they perform consistently across datasets, it shows they can transfer what they have learned and aren not overly biased toward any specific dataset. This makes the models more reliable for broader applications.

2.8 Summary

This chapter explores how machine learning and advanced data systems are transforming e-commerce. From improving search results using big data to predicting trends with machine learning, these technologies enhance the shopping experience.

It also highlights the role of large language models in NLP, showing how fine-tuning and techniques like JSON-Tuning make them adaptable to specific domains. Finally, it emphasizes the importance of evaluation metrics and validation techniques for ensuring models are accurate and reliable in real-world scenarios with word-based metrics and model-based ones.

Chapter 3

State of the Art

3.1 Pretrained Models and Their Applications

Pre-trained language models have seen remarkable advancements, leveraging large datasets and sophisticated training methodologies to achieve significant improvements in various natural language processing (NLP) tasks. Pre-trained models such as BERT, GPT, and their variants have revolutionized the field by providing robust, general-purpose representations that can be fine-tuned for specific tasks with minimal additional training data [Chen et al., 2022]. Techniques like function-preserving initialization and advanced knowledge initialization in Bert2BERT exemplify innovative methods to enhance the efficiency of pre-training larger models by reusing smaller pre-trained models, reducing computational costs and carbon footprints associated with training from scratch [Chen et al., 2022].

3.1.1 Applications in Specialized Fields

The application of pre-trained models in domains such as clinical information extraction has demonstrated their versatility and effectiveness. For instance, large language models like GPT-3 have been utilized to decode complex medical jargon and abbreviations in electronic health records, significantly improving the extraction of actionable medical information without extensive manual labeling [Agrawal et al., 2022]. Similarly, in e-commerce, pre-trained models like GPT-4 and LLama2 have been employed to extract structured data, such as product attribute values, from unstructured text, enabling better product search and comparison features [Brinkmann et al., 2024].

3.1.2 Advancements in Structured Data Models

Pre-trained language models have transformed structured data extraction and utilization in e-commerce. Traditional methods like BERT often require extensive task-specific training data and face limitations in generalizing to unseen attribute values [Brinkmann et al., 2024]. In contrast, modern LLMs like GPT-4 and LLama2 excel in zero-shot and few-shot scenarios, offering robust solutions for attribute extraction with minimal training [Brinkmann et al., 2024]. Additionally, synthetic data generation has been integrated into structured data models, addressing data sparsity and improving model performance by enhancing training datasets with diverse and realistic examples [Skondras et al., 2023].

3.1.3 Sequence-to-Sequence Architectures

Research has shown that integrating pre-trained language model representations into sequence-to-sequence architectures can yield substantial gains in tasks like neural machine translation and abstractive summarization. For example, incorporating pre-trained embeddings into the encoder network of transformer models has significantly enhanced translation accuracy, particularly in low-resource settings, demonstrating improvements in BLEU scores and overall model performance [Edunov et al., 2019].

3.1.4 E-commerce Systems and Personalized Solutions

E-commerce systems increasingly leverage pre-trained models like E-BERT, which integrates domain-specific knowledge to improve recommendation accuracy, aspect extraction, and product classification [Zhang et al., 2021]. Fine-tuned models like LLama2 have demonstrated effectiveness in generating enhanced product descriptions validated by metrics such as NDCG, click-through rates, and human assessments [Zhou et al., 2023]. Furthermore, combining collaborative filtering with LLMs has advanced recommendation systems, enabling personalized and accurate suggestions for users [Xu et al., 2024].

3.2 Structured Datasets and Their Importance

Structured datasets in formats like JSON, CSV, and TSV are essential for training LLMs to handle organized data effectively, with JSON being particularly popular for its clear structure and web compatibility [Singha et al., 2023]. Key datasets include QTSUMM, which supports structured summarization [Zhao et al., 2023b], and PROMAP, which standardizes product attributes for improved e-commerce interoperability [Macková and Pilát, 2024b]. WikiTableT focuses on table-based question answering, TabFact trains models for factual verification using paired tables and true/false statements [Chen et al., 2020b], and datasets like ToTTo [Parikh et al., 2020] and LogicNLG [Chen et al., 2020a] extend LLM capabilities by generating coherent, contextually relevant, and logically sound text from structured inputs. The eC-Tab2Text dataset advances Query-Focused Table Summarization specifically for e-commerce data, addressing challenges like diverse product attributes and user-specific queries. These datasets collectively enhance structured data transformation into human-centric narratives, improving search accuracy and recommendation systems in query-specific applications. Additionally, synthetic data generation increases their utility by addressing data shortages and aiding model generalization [Suri et al., 2023].

3.2.1 Notable Structured Datasets

- **QTSUMM Dataset**: Supports structured summarization and information retrieval by providing JSON-formatted entries tailored for query-focused tasks [Zhao et al., 2023b].
- **PROMAP Dataset**: Focuses on product attribute mapping, improving e-commerce interoperability by standardizing product attributes across descriptions [Macková and Pilát, 2024b].
- **WikiTableT**: Designed for table-based question answering, this dataset contains structured tabular data from Wikipedia to enhance knowledge retrieval [Chen et al., 2021].
- **TabFact**: Pairs tables with true/false statements for fact verification tasks, helping reduce hallucinations in model outputs [Chen et al., 2020c].

Table 3.1 shows a comparison between eC-Tab2Text and existing table-to-text generation datasets, highlighting the diversity and scope of structured data available for training and evaluation. This table is adapted from [Zhao et al., 2023b]

Table 3.1: Comparison between eC-Tab2Text and existing table-to-text generation datasets. Adapted from [Zhao et al., 2023b]

Dataset	Table Source	# Tables / Statements	# Words / Statement	Explicit Control
		Single-sentence Table-to-Text		
ToTTo [Parikh et al., 2020]	Wikipedia	83,141 / 83,141	17.4	Table region
LOGICNLG [Chen et al., 2020a]	Wikipedia	7,392 / 36,960	14.2	Table regions
HiTab [Cheng et al., 2022]	Statistics web	3,597 / 10,672	16.4	Table regions & reasoning operator
		Generic Table Summarization		
ROTOWIRE [Wiseman et al., 2017]	NBA games	4,953 / 4,953	337.1	✗
SciGen [Moosavi et al., 2021]	Sci-Paper	1,338 / 1,338	116.0	✗
NumericNLG [Suadaa et al., 2021]	Sci-Paper	1,355 / 1,355	94.2	✗
		Table Question Answering		
FeTaQA [Nan et al., 2022]	Wikipedia	10,330 / 10,330	18.9	Queries rewritten from ToTTo
		Query-Focused Table Summarization		
QTSumm [Zhao et al., 2023b]	Wikipedia	2,934 / 7,111	68.0	Queries from real-world scenarios
eC-Tab2Text (*ours*)	e-Commerce products	1,452 / 3354	56.61	Queries from e-commerce products

3.2.2 Advancements Through Synthetic Data Generation

Synthetic data generation techniques have enhanced the versatility of structured datasets, addressing data shortages and improving generalization capabilities. For example, synthetic data generated by LLMs like ChatGPT has been used in resume classification to augment real-world datasets, resulting in improved model accuracy and robustness across various applications [Skondras et al., 2023].

3.3 Evaluation Metrics for LLMs

Evaluating the performance of large language models requires comprehensive metrics that reflect their capabilities across different dimensions. Traditional metrics like BLEU and ROUGE assess the quality of text generation by comparing outputs to reference texts [Zhang et al., 2022b]. However, newer methods have introduced specialized metrics for diverse tasks.

3.3.1 Faithfulness and Correctness

Faithfulness measures the factual accuracy of generated content by ensuring that outputs are grounded in input data [Madsen et al., 2022]. Correctness focuses on syntactic and grammatical quality, ensuring coherence and linguistic accuracy [Yao and Koller, 2024]. Advanced evaluators like G-Eval and Prometheus provide automated scoring for these metrics, enhancing large-scale evaluation processes [Kim et al., 2024c].

Chapter 4

Methodology

The methodology will outline the systematic process used to create and evaluate the **eC-Tab2Text dataset**, which is designed to enhance the performance of Large Language Models (LLMs) in generating accurate and meaningful product reviews for e-commerce applications.

This process spans from the initial data acquisition and preparation to the fine-tuning and evaluation of LLMs. Each stage is essential to ensuring that the dataset effectively bridges the gap between structured product data and user-centric textual reviews.

The methodology is summarized in a flowchart (Figure 4.1). This structured approach guarantees a comprehensive and reproducible pathway for leveraging LLMs to transform structured product data into human-readable reviews while addressing challenges such as data sparsity and domain-specific needs.

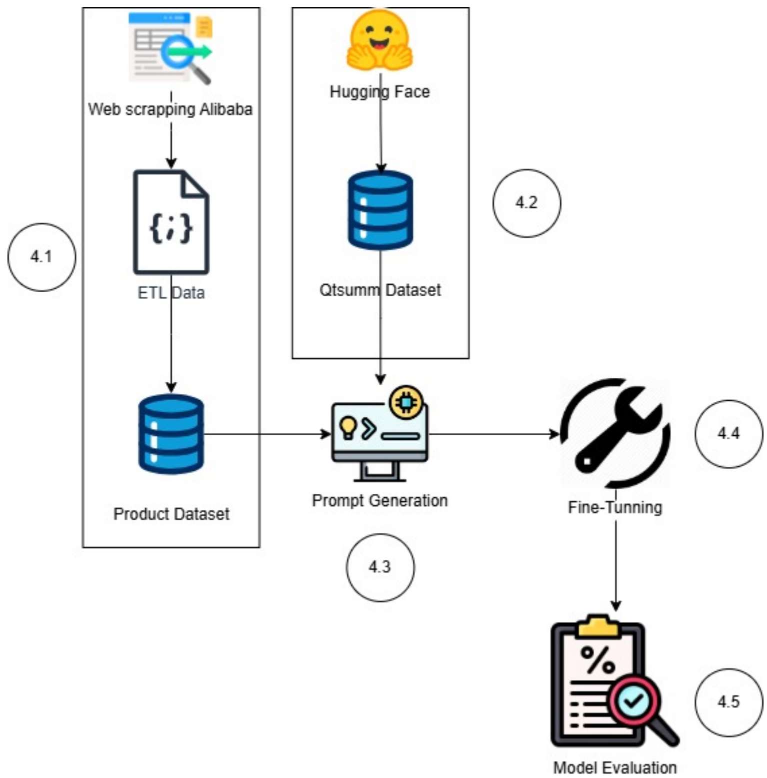


Figure 4.1: Methodology Flowchart

4.1 Dataset Preparation

4.1.1 Data Sources

The eC-Tab2Text dataset was constructed using product reviews and specifications extracted from the Pricebaba website. This source provides detailed information on electronic devices, such as mobile phones and laptops, including expert reviews and structured product attributes. The study focused exclusively on mobile phone data due to the richness of the descriptions and expert evaluations. Each review contained sections on pros and cons and feature-specific details, such as camera performance, battery life, and display quality.

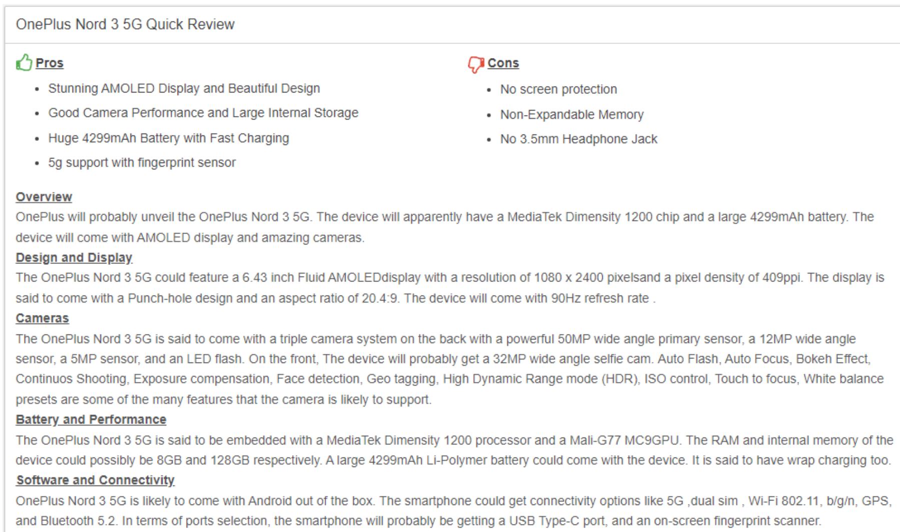
4.1.2 Data Extraction and Format

Data was extracted using web scraping techniques and stored in JSON format to maintain structure and compatibility with modern data processing workflows. Two JSON files were created:

- **Reviews JSON:** Captures attributes like pros, cons, and detailed textual descriptions.

- **Specifications JSON:** Contains key-value pairs for both key specifications and full technical details.

Figures 4.2 and 4.3 illustrate the data structures.



OnePlus Nord 3 5G Quick Review

Pros

- Stunning AMOLED Display and Beautiful Design
- Good Camera Performance and Large Internal Storage
- Huge 4299mAh Battery with Fast Charging
- 5g support with fingerprint sensor

Cons

- No screen protection
- Non-Expandable Memory
- No 3.5mm Headphone Jack

Overview

OnePlus will probably unveil the OnePlus Nord 3 5G. The device will apparently have a MediaTek Dimensity 1200 chip and a large 4299mAh battery. The device will come with AMOLED display and amazing cameras.

Design and Display

The OnePlus Nord 3 5G could feature a 6.43 inch Fluid AMOLEDdisplay with a resolution of 1080 x 2400 pixelsand a pixel density of 409ppi. The display is said to come with a Punch-hole design and an aspect ratio of 20.4:9. The device will come with 90Hz refresh rate .

Cameras

The OnePlus Nord 3 5G is said to come with a triple camera system on the back with a powerful 50MP wide angle primary sensor, a 12MP wide angle sensor, a 5MP sensor, and an LED flash. On the front, The device will probably get a 32MP wide angle selfie cam. Auto Flash, Auto Focus, Bokeh Effect, Continuos Shooting, Exposure compensation, Face detection, Geo tagging, High Dynamic Range mode (HDR), ISO control, Touch to focus, White balance presets are some of the many features that the camera is likely to support.

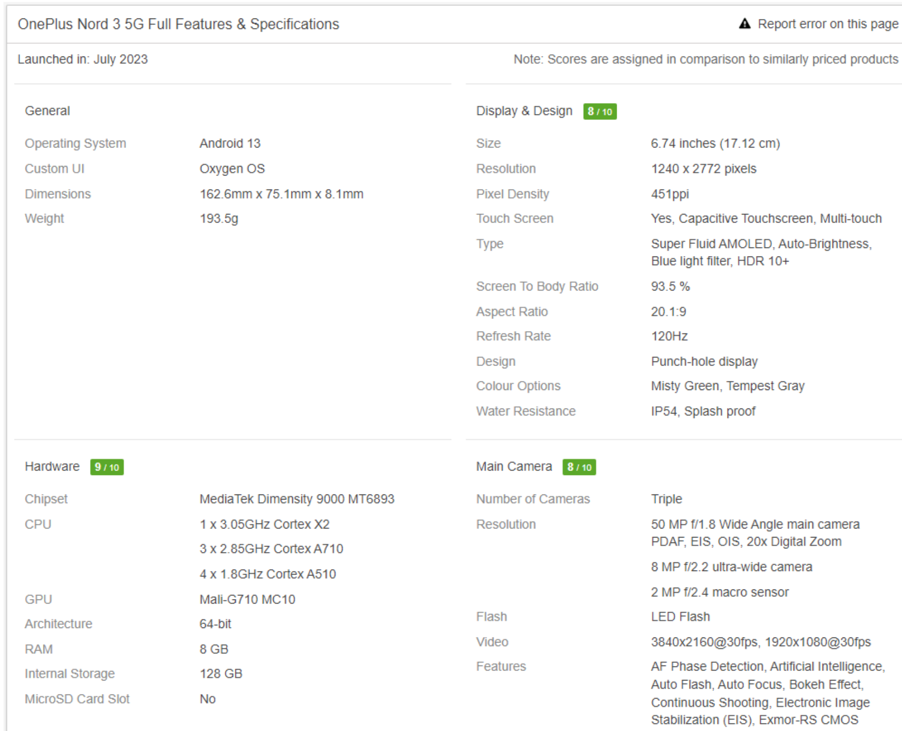
Battery and Performance

The OnePlus Nord 3 5G is said to be embedded with a MediaTek Dimensity 1200 processor and a Mali-G77 MC9GPU. The RAM and internal memory of the device could possibly be 8GB and 128GB respectively. A large 4299mAh Li-Polymer battery could come with the device. It is said to have wrap charging too.

Software and Connectivity

OnePlus Nord 3 5G is likely to come with Android out of the box. The smartphone could get connectivity options like 5G ,dual sim , Wi-Fi 802.11, b/g/n, GPS, and Bluetooth 5.2. In terms of ports selection, the smartphone will probably be getting a USB Type-C port, and an on-screen fingerprint scanner.

Figure 4.2: pricebaba reviews structure [Pricebaba.com, 2023]



OnePlus Nord 3 5G Full Features & Specifications

Report error on this page

Launched in: July 2023

Note: Scores are assigned in comparison to similarly priced products

General	
Operating System	Android 13
Custom UI	Oxygen OS
Dimensions	162.6mm x 75.1mm x 8.1mm
Weight	193.5g

Display & Design 8 / 10	
Size	6.74 inches (17.12 cm)
Resolution	1240 x 2772 pixels
Pixel Density	451ppi
Touch Screen	Yes, Capacitive Touchscreen, Multi-touch
Type	Super Fluid AMOLED, Auto-Brightness, Blue light filter, HDR 10+
Screen To Body Ratio	93.5 %
Aspect Ratio	20.1:9
Refresh Rate	120Hz
Design	Punch-hole display
Colour Options	Misty Green, Tempest Gray
Water Resistance	IP54, Splash proof

Hardware 9 / 10	
Chipset	MediaTek Dimensity 9000 MT6893
CPU	1 x 3.05GHz Cortex X2 3 x 2.85GHz Cortex A710 4 x 1.8GHz Cortex A510
GPU	Mali-G710 MC10
Architecture	64-bit
RAM	8 GB
Internal Storage	128 GB
MicroSD Card Slot	No

Main Camera 8 / 10	
Number of Cameras	Triple
Resolution	50 MP f/1.8 Wide Angle main camera PDAF, EIS, OIS, 20x Digital Zoom 8 MP f/2.2 ultra-wide camera 2 MP f/2.4 macro sensor
Flash	LED Flash
Video	3840x2160@30fps, 1920x1080@30fps
Features	AF Phase Detection, Artificial Intelligence, Auto Flash, Auto Focus, Bokeh Effect, Continuous Shooting, Electronic Image Stabilization (EIS), Exmor-RS CMOS

Figure 4.3: pricebaba specifications structure [Pricebaba.com, 2023]

4.1.3 Data Format

The chosen format for data representation is JSON, as this format allows for structured and easy-to-process data representation. Two JSON files will be used to represent the data: one for the reviews and another for the product specifications. This last one will contains two parts per product: the key values, which means the most important data of the product, and the full specifications. Each JSON file will contain an array of objects, where each object will represent a product along with its respective reviews or specifications. The structure of the JSON files is outlined below:

Listing 4.1: JSON Data Format Product specification

```
{
    "url": {
        "keys_specifications": [],
        "full_specifications": [
            "Launch Date": "Launch Date",
            "General": {
                "subcategories1": [
                    "value1"
                    ],
                "subcategories2": [
                    "value1",
                    "value2"
                    ],
                ...
            },
            "Characteristic1": {
                "subcategories1": [
                    "value1"
                    ],
                "subcategories2": [
                    "value1",
                    "value2"
                    ],
                ...
            },
            "Characteristic2": {
                "subcategories1": [
                    "value1"
                    ],
                "subcategories2": [
                    "value1",
                    "value2"
                    ],
                ...
            },
            ...
        ]
    },
}
```

Listing 4.2: JSON Data Format reviews

```
{
    "url": {
        "text": {
            "Characteristic1": ["Description1"],
            "Characteristic2": ["Description2"],
            ...
        },
        "Pros": [
            "Pro 1",
            "Pro 2",
            "Pro 3"
        ],
        "Cons": [
            "Con 1",
            "Con 2",
            "Con 3"
        ]
    },
}
```

4.1.4 Data Cleaning and Normalization

To ensure consistency and usability, the extracted data underwent rigorous cleaning and normalization:

- Standardizing all values to lowercase.
- Replacing special characters (e.g., ‘&‘ with ‘and‘).
- Reordering keys for logical and contextual coherence.

For instance, the key ‘Display & Design‘ was transformed into ‘Design and Display‘ to improve readability.

4.1.5 Data Integration

The reviews and specifications JSON files were merged into a unified dataset by matching entries based on their unique product URLs. This ensured that each product’s reviews and specifications were consolidated into a single cohesive data entry.

4.1.6 Data Filtering

Irrelevant and redundant entries were removed to refine the dataset further:

- Discarding reviews with no textual content in the ‘text‘ field.
- Removing specifications containing only generic data, such as entries labeled ‘General‘.
- Excluding overly simplistic reviews categorized as ‘Overview‘.

4.1.7 Data Splitting

The finalized dataset was divided into training and testing sets with an 80%-20% split. This ensured a sufficient volume of data for training while retaining a reliable subset for evaluation.

4.2 Prompt Structuration

4.2.1 Prompts for Dataset 1 (eC-Tab2Text)

Prompts were carefully designed to guide models in generating detailed, contextually relevant reviews based on specific product attributes. Each prompt instructed the model to utilize key product features from the JSON-structured data and generate reviews adhering to the given keys. For example, a prompt could ask the model to focus on "Design and Display" and "Battery." The dataset was expanded to approximately 12k high-quality prompts through key permutation strategies, facilitating extensive training and evaluation.

For this purpose, instructions with the following structure will be created:

Listing 4.3: Prompt structuration

```
"Given following json that contains specifications of a product,
    generate a review of the key characteristics with json format.
    Follow the structure on Keys to write the Output:
### Product: Product for JSON specifications
### Keys: Combination of the keys of the JSON reviews
### Output: reviews for JSON reviews accordingly to the keys"
```

it means that instructions will be generated for each permutation of the review keys. For example, if there is a review with the keys Design and Display', Camera', Battery', Performance', Software', i' instructions are chosen from the possible combinations of these keys, where i' is the number of instructions desired to be generated. This approach ensures that the model generates reviews according to the different characteristics of the products. An example of key selection could be that if a product has the keys Design and Display', Camera', Battery', Performance', Software', then the keys Design and Display', Camera' might be selected to generate one instruction, and for another instruction for the same product, the keys Design and Display', Battery' might be selected, and so on.

With these combinations of keys for generating instructions, from the original 7,400 data points, 60,700 instructions are obtained that will be used to train the models. These instructions are the final dataset, which is available on Hugginface.

4.2.2 Prompts for Dataset 2 (QTSUMM)

This dataset will be use to applied a cross-validation technique to evaluate the models. The data will be obtained for an existing dataset that is not product-based, but it is focused on structured data in JSON format. The dataset is QTSUMM [Zhao et al.,

Topic	Value
Input	
# Samples	11,994
Avg # Attributes	59.8
Max # Attributes	68
Output	
# Queries	3354
Avg # words/query	56.61

Table 4.1: Statistics of eC-Tab2Text dataset

2023b], which contains the columns: table, which contains JSON format data; query, which is the 'keys' the model will use to generate the output; and summary, the expected output. The dataset is structured as shown in Figure 4.4, where each object contains the columns especified before. This dataset will be used to generate prompts for the models to evaluate their performance.

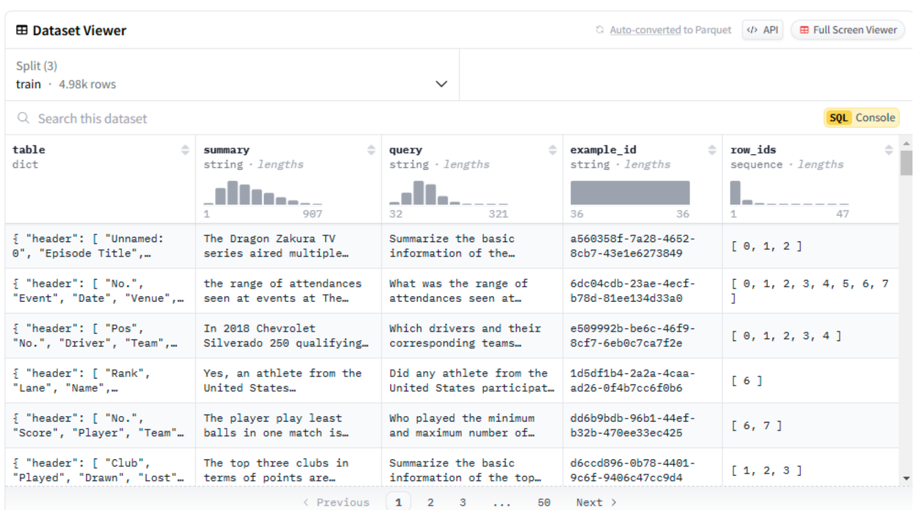


table dict	summary string · lengths	query string · lengths	example_id string · lengths	row_ids sequence · lengths
	1 907	32 321	36 36	1 47
{ "header": ["Unnamed: 0", "Episode Title",…	The Dragon Zakura TV series aired multiple…	Summarize the basic information of the…	a560358f-7a28-4652-8cb7-43e1e6273849	[0, 1, 2]
{ "header": ["No.", "Event", "Date", "Venue",…	the range of attendances seen at events at The…	What was the range of attendances seen at…	6dc04cdb-23ae-4ecf-b78d-81ee134d33a0	[0, 1, 2, 3, 4, 5, 6, 7]
{ "header": ["Pos", "No.", "Driver", "Team",…	In 2018 Chevrolet Silverado 250 qualifying…	Which drivers and their corresponding teams…	e509992b-be6c-46f9-8cf7-6eb0c7ca7f2e	[0, 1, 2, 3, 4]
{ "header": ["Rank", "Lane", "Name",…	Yes, an athlete from the United States…	Did any athlete from the United States participat…	1d5df1b4-2a2a-4caa-ad26-0f4b7cc6f0b6	[6]
{ "header": ["No.", "Score", "Player", "Team"…	The player play least balls in one match is…	Who played the minimum and maximum number of…	dd6b9bdb-96b1-44ef-b32b-470ee33ec425	[6, 7]
{ "header": ["Club", "Played", "Drawn", "Lost"…	The top three clubs in terms of points are…	Summarize the basic information of the top…	d6ccd896-0b78-4401-9c6f-9406c47cc9d4	[1, 2, 3]

Figure 4.4: QTSUMM dataset structure [Zhao et al., 2023b]

For QTSUMM, prompts were structured similarly but adapted to its unique characteristics. The 'prompts' column in QTSUMM was filled with data derived from the 'table', 'query', and 'summary' columns, ensuring the model understood instructions regardless of the dataset used.

For the QTSUMM dataset, the 'prompts' column will be filled with data as follows:

Listing 4.4: Prompt structuration

```
"Given following json that contains specifications of a product,
    generate a review of the key characteristics with json format.
    Follow the structure on Keys to write the Output:
### Product: Column table of JSON specifications
### Keys: Column query of the dataset
### Output: Column summary of the dataset"
```

The 'prompt' as shown have the same format for both dataset, but the data used to fill them are different. This will allows the models understands the instructions no matter the dataset used to train or evaluate them.

4.3 Model Fine-Tuning

The eC-Tab2Text dataset provides a diverse and robust set of inputs and outputs, as summarized in Table 4.1. The input JSON files contain rich attribute-based product specifications, with an average of 59.8 attributes per product and a maximum of 68 attributes for the most detailed entries. On the output side, the queries are designed to be concise and precise, with an average word count of 22.5 per query, enabling focused evaluation and training of the LLMs.

4.3.1 eC-Tab2Text Evaluation

Model Fine-Tuning. To evaluate the effectiveness of the eC-Tab2Text dataset, three state-of-the-art Large Language Models (LLMs) were fine-tuned:

- **Llama2-chat 7B**: This model is specifically designed for interactive tasks and demonstrates advanced conversational capabilities through fine-tuning on instruction-based datasets [Touvron et al., 2023].
- **StructLM 7B**: A pre-trained model optimized for structured text processing and table-to-text generation, StructLM uses a transformer architecture with enhancements for structured data encoding, showcasing its robustness in domain-specific text generation tasks [Zhuang et al., 2024].
- **Mistral_Instruct 7B**: Known for its high adaptability, this model leverages supervised fine-tuning with diverse instruction-following datasets, achieving state-of-the-art performance in multi-modal and domain-adapted text generation [Jiang et al., 2023].

The fine-tuning process involved training the models with eC-Tab2Text's curated dataset to assess their capabilities in generating high-quality, contextually accurate outputs tailored to e-commerce applications. By aligning with studies emphasizing the importance of instruction tuning and domain-specific dataset alignment to enhance LLM performance [Zhang et al., 2023, Chang et al., 2024], the models were configured with parameters optimized for computational efficiency, as detailed in Table 4.2. The fine-tuning focused on adapting the models to handle the domain-specific tasks of generating detailed and attribute-focused product reviews.

Hyperparameter	Value
Learning Rate	2×10^{-4}
Batch Size	2
Epochs	1
Gradient Accumulation Steps	1
Weight Decay	0.001
Max Sequence Length	900

Table 4.2: Hyperparameter settings for fine-tuning.

Furthermore, the ‘BitsAndBytesConfig‘ library from Hugging Face’s ‘transformers‘ has been utilized for model optimization. These additional hyperparameters are shown in Table 4.3.

Hyperparameter	Value
bnb_4bit_compute_dtype	float16
bnb_4bit_quant_type	nf4
use_nested_quant	False

Table 4.3: Hyperparameters Selection BitsAndBytes

Metrics. Evaluation metrics are essential for assessing the quality of text generation models. The most widely used metrics include:

- **BLEU (Bilingual Evaluation Understudy)** [Papineni et al., 2002]: Commonly used in machine translation and natural language generation, BLEU measures the overlap of n-grams between generated and reference texts. Despite its popularity, BLEU has limitations, particularly in capturing semantic similarity and evaluating beyond exact matches [Reiter, 2018].

- **ROUGE (Recall-Oriented Understudy for Gisting Evaluation)** [Lin, 2004]: Focuses on recall-oriented evaluation by comparing the overlap of n-grams, word sequences, and word pairs between generated summaries and reference texts. It is highly effective for summarization tasks [Ganesan, 2018].

- **METEOR (Metric for Evaluation of Translation with Explicit ORdering)**[Lavie and Agarwal, 2007]: Incorporates stemming, synonymy, and flexible matching, providing a more nuanced evaluation than BLEU. It strongly correlates with human judgments, especially in translation tasks [Dobre, 2015].

- **BERTScore** [Zhang* et al., 2020]: Leverages contextual embeddings from pre-trained transformer models to measure semantic similarity between generated and reference texts. Unlike n-gram-based metrics, BERTScore captures meaning and context, offering a robust evaluation for text generation tasks [Zhang* et al., 2020].

Prometheus Evaluation (Hallucination) To evaluate model-based metrics, the Prometheus framework [Kim et al., 2024c] was employed, utilizing structured prompts for three key evaluation criteria: fluency, correctness, and faithfulness [1]. The primary framework leverages an Absolute System Prompt, which defines the role of the evaluator and ensures objective, consistent assessments based on established rubrics. This Absolute System Prompt, shown in Listing4.5, forms the foundation for all evaluations across metrics.

Listing 4.5: Absolute System Prompt [Kim et al., 2024c]

```
You are a fair judge assistant tasked with providing clear, objective
    feedback based on specific criteria, ensuring each assessment
    reflects the absolute standards set for performance.
```

The task descriptions for evaluating fluency, correctness, and faithfulness share a similar structure, as shown in Listing4.6,4.7. These instructions define the evaluation process, requiring detailed feedback and a score between 1 and 5, strictly adhering to a given rubric.

Listing 4.6: Task description used for evaluation of faithfulness [Kim et al., 2024c]

```
###Task Description:
An instruction (might include an Input inside it), a response to
    evaluate, a reference answer that gets a score of 5, and a score
    rubric representing a evaluation criteria are given.
1. Write a detailed feedback that assess the quality of the response
    strictly based on the given score rubric, not evaluating in general
    .
2. After writing a feedback, write a score that is an integer between 1
     and 5. You should refer to the score rubric.
3. The output format should look as follows: "Feedback: (write a
    feedback for criteria) [RESULT] (an integer number between 1 and 5)
    "
4. Please do not generate any other opening, closing, and explanations.
5. Only evaluate on common things between generated answer and
    reference answer. Don't evaluate on things which are present in
    reference answer but not in generated answer.
```

Listing 4.7: Task description used for evaluation of fluency and correctness [Kim et al., 2024c]

```
###Task Description:
An instruction (might include an Input inside it), a response to
    evaluate, a reference answer that gets a score of 5, and a score
    rubric representing a evaluation criteria are given.
1. Write a detailed feedback that assess the quality of the response
    strictly based on the given score rubric, not evaluating in general
    .
2. After writing a feedback, write a score that is an integer between 1
     and 5. You should refer to the score rubric.
```

[1]https://github.com/prometheus-eval/prometheus-eval

```
3. The output format should look as follows: "Feedback: (write a
    feedback for criteria) [RESULT] (an integer number between 1 and 5)
    "
4. Please do not generate any other opening, closing, and explanations.
```

Instructions for Evaluation Prometheus prompts are customized for each evaluation metric. Below are the specialized structures and rubrics for fluency, faithfulness, and correctness.

Faithfulness This metric ensures the generated response aligns with both the provided context and reference answers. The evaluation structure incorporates specific rubrics for relevance and information consistency.

Listing 4.8: Prompt structured correctness [Kim et al., 2024c]

```
###The instruction to evaluate:
Evaluate the fluency of the generated JSON answer.
###Context:
{Prompt}
###Existing answer (Score 5):
{reference_answer}
###Generate answer to evaluate:
{response}
###Score Rubrics:
"score1_description":"If the generated answer is not matching with any
    of the reference answers and also not having information from the
    context.",
"score2_description":"If the generated answer is having information
    from the context but not from existing answer and also have some
    irrelevant information.",
"score3_description":"If the generated answer is having relevant
    information from the context and some information from existing
    answer but have additional information that do not exist in context
     and also do not in existing answer.",
"score4_description":"If the generated answer is having relevant
    information from the context and some information from existing
    answer.",
"score5_description":"If the generated answer is matching with the
    existing answer and also having information from the context."}
###Feedback:
```

Fluency This metric evaluates the grammatical accuracy and readability of the generated response.

Listing 4.9: Prompt structured fluency [Kim et al., 2024c]

```
###The instruction to evaluate: Evaluate
the fluency of the generated JSON answer
###Response to evaluate: {response}
###Reference Answer (Score 5):
{reference_answer}
###Score Rubrics:
```

```
"score1_description":"The generated JSON answer is not fluent and is
    difficult to understand.",
"score2_description":"The generated JSON answer has several grammatical
     errors and awkward phrasing.",
"score3_description":"The generated JSON answer is mostly fluent but
    contains some grammatical errors or awkward phrasing.",
"score4_description":"The generated JSON answer is fluent with minor
    grammatical errors or awkward phrasing.",
"score5_description":"The generated JSON answer is perfectly fluent
    with no grammatical errors or awkward phrase
###Feedback:
```

Correctness This metric assesses the logical accuracy and coherence of the generated response compared to the reference.

Listing 4.10: Prompt estructured correctness [Kim et al., 2024c]

```
###The instruction to evaluate:
Your task is to evaluate the generated answer and reference answer for
    the query: {Prompt}
###Response to evaluate:
{response}
###Reference Answer (Score 5):
{reference_answer}
###Score Rubrics:
"criteria": "Is the model proficient in generate a coherence response",
"score1_description": "If the generated answer is not matching with any
     of the reference answers.",
"score2_description": "If the generated answer is according to
    reference answer but not relevant to user query.",
"score3_description": "If the generated answer is relevant to the user
    query and reference answer but contains mistakes.",
"score4_description": "If the generated answer is relevant to the user
    query and has the exact same metrics as the reference answer, but
    it is not as concise.",
"score5_description": "If the generated answer is relevant to the user
    query and fully correct according to the reference answer.

###Feedback:
```

Cross-Validation. Performed to validate the robustness and generalizability of the fine-tuned models by testing them across distinct datasets. This process ensured the models could adapt effectively to different structured data scenarios while maintaining high performance. Specifically, the same three models fine-tuned on the eC-Tab2Text dataset (**Llama2-chat 7B**, **StructLM 7B**, and **Mistral_Instruct 7B**) were trained and evaluated on the QTSumm dataset [Zhao et al., 2023b], using identical hyperparameters as detailed in Section 4.3.1.

QTSumm Dataset.**[Zhao et al., 2023b]** Designed for query-focused summarization tasks, it includes structured JSON data, queries, and summaries. This dataset provided an ideal contrast to eC-Tab2Text, as its focus lies on general-purpose summarization rather than product-specific reviews. The models were trained using prompts structured similarly to those used with the eC-Tab2Text dataset. The key distinction in the QTSumm setup was the row-level content included in the prompts, as outlined in 4.11. This alignment ensured training consistency while leveraging the QTSumm dataset's unique characteristics.

Listing 4.11: Prompt structuration for QTSumm

```
"Given following json that contains specifications of a product,
    generate a review of the key characteristics with json format.
    Follow the structure on Keys to write the Output:
### Product: Column table of JSON specifications
### Keys: Column query of the dataset
### Output: Column summary of the dataset"
```

4.4 Resume

This section provides a detailed overview of the methodology used for generating product reviews on e-commerce platforms using Large Language Models (LLMs). It describes the entire process from data collection and preparation, where data was generated from scratch, meticulously cleaned, and structured for further processing.

The section continues by detailing the model tuning techniques, including the selection of hyperparameters and optimization methods, tailored to match the computational limits of the hardware. This phase was essential for adapting the models to produce relevant product reviews. The effectiveness of these fine-tuned models was then measured using evaluation metrics such as BLEU, METEOR, and ROUGE to assess the quality of generated reviews against actual product reviews.

Chapter 5

Experiments and Results

In this chapter, the results obtained from the implementation of the methodology described in the previous chapter are presented. First, the hyperparameters used for training the models are introduced. Subsequently, the results obtained by the models are presented. Finally, the evaluation of the models based on the evaluation metrics is shown, and the obtained results are discussed.

5.1 Hyperparameters

Table 5.1 shows the hyperparameters used to train the models. As these are preliminary evaluations, the *bitsandbytes* options used were those defined by an example of training an optimized LLM model. For the rest of the hyperparameters, a default configuration was used.

Hyperparameter	**Value**
Learning Rate	2e-4
Batch Size	2
Epochs	1
max_grad_norm	0.3
gradient_accumulation_steps	1
weight_decay	0.001
warmup_ratio	0.03
lr_scheduler_type	cosine
optim	adam
max_seq_length	900
bnb_4bit_compute_dtype	float16
bnb_4bit_quant_type	nf4
use_nested_quant	False

Table 5.1: Hyperparameters Selection

Mode	Models	BLEU	METEOR	ROUGE-1	ROUGE-L	BERTScore	Correctness	Faithfulness	Fluency
Base	Llama2	1.39	3.59	5.57	4.09	66.49	32.18	37.68	32.47
	StructLM	6.21	11.96	20.09	15.34	82.56	64.30	70.08	63.10
	Mistral	4.19	9.55	25.64	18.99	82.12	77.02	81.16	76.5
	GPT-4o-mini	7.14	16.12	29.44	19.47	83.75	**80.89**	**83.92**	**80.81**
	Gemini-1.5-flash	8.8	15.18	30.38	21.51	84.05	78.79	83.04	78.54
Fine-tuned	Llama2	29.36	40.2	48.36	39.25	90.05	61.38	63.78	61.47
	StructLM	31.06	42.3	49.42	40.58	90.9	69.70	72.46	69.93
	Mistral	**38.89**	**49.43**	**56.64**	**48.32**	**92.18**	73.07	76.63	73.03

Table 5.2: Results of Trained vs. Base Models: LLAMA2, StructLM, and Mistral_Instruct

Dataset Trained	Dataset Tested	Models	BLEU	METEOR	ROUGE-1	ROUGE-L	BERTScore	Correctness	Faithfulness	Fluency
QTSumm	QTSumm	Llama2	13.32	32.38	26.3	19.22	86.47	51.09	57.30	48.98
		StructLM	6.6	22.04	13.52	10.04	84.5	41.14	48.92	39.68
		Mistral	10.1	28.57	20.7	15.51	85.65	49.99	57.73	50.71
	eC-Tab2Text	Llama2	17.47	40.2	35.69	21.14	85.41	63.98	71.40	64.07
		StructLM	3.73	17.42	10.41	6.77	82.91	36.69	60.81	37.03
		Mistral	13.97	26.88	28.58	17.08	84.83	58.35	69.81	58.95
eC-Tab2Text	QTSumm	Llama2	29.4	40.21	48.43	39.25	90.05	61.38	63.78	61.47
		StructLM	31.06	42.3	49.42	40.58	90.9	69.70	72.46	69.93
		Mistral	38.89	49.43	56.64	48.32	92.18	73.07	76.63	73.03
	eC-Tab2Text	Llama2	6.5	22.77	7.79	16.59	81.93	48.42	48.66	48.55
		StructLM	10.15	30.59	30.59	23.04	85.13	58.71	56.60	58.26
		Mistral	10.39	18.11	30.27	24.24	84.23	64.83	61.14	64.51

Table 5.3: Results of Trained vs. Base Models: LLAMA2, StructLM, and Mistral_Instruct

5.1.1 Issues Encountered with the Development Environment

During the training of the models, several issues were encountered with the development environment. Firstly, it was found that the Nvidia RTX 4070 Ti Super leaks in VRAM for the models if there where not quantizied. Secondly, the training time upscales 24h per model and more than 20h for testing each one. In order to find a solution for these problems it was necesary quantized the models to 4-bits.

5.2 Experiments

Table 5.2 and Table 5.3 collectively illustrate the performance comparisons of models across various metrics and datasets. Mistral_Instruct, fine-tuned with our dataset, demonstrates superior performance in text-based metrics and achieves the highest scores among standard and trained models in model-based metrics. Furthermore, Table 5.3 highlights the robustness of our dataset by comparing models trained with it against those trained with the QTSUMM dataset. Models trained with our dataset consistently outperform those trained on QTSUMM in both tasks, with Mistral_Instruct leading in performance, followed by StructLM.

The results indicate improved model performance in generating reviews that align closely with product characteristics. Fine-tuned LLMs demonstrate enhanced interaction with structured data compared to baseline models.

5.3 Discussion

Dataset Datasets used for fine-tuning large language models (LLMs) typically contain over 1,000 instances to effectively train the models ([Liu et al., 2024]). Similarly, our dataset includes a sufficient number of instances to accomplish the fine-tuning task. However, while the current dataset has demonstrated robustness in identifying key points across different tasks, increasing the variety of product types would likely enhance the model's accuracy and improve its ability to extract valuable insights from a broader range of product categories.

Model-based Evaluation While both Prometheus models are capable of reasoning to generate feedback for various tasks, they exhibit limitations in effectively performing pairwise ranking ([Kim et al., 2024a], [Kim et al., 2024c]). In our evaluation, we utilized metrics such as faithfulness through the Prometheus-Eval [1] template. However, responses occasionally display an error margin of +/- 1 in scoring, depending on the input, and may even vary when provided with identical inputs [Kim et al., 2024b]. This variability highlights that the performance of the Mistral_Instruct model, both fine-tuned and raw, remains comparable in terms of reasoning ability also in comparison with close-source models as it is demonstrate with GPT4-o. However, the fine-tuned model demonstrates an improved capacity to format responses in a more structured and coherent manner, underscoring the benefits of fine-tuning for task-specific output refinement.

5.4 Resume

This section outlines the experimental setup used to evaluate the proposed methodologies, including details about the hyperparameters and configurations of the trained models. The primary focus was to assess the performance differences between the base models and the specifically trained models using various metrics such as BLEU, METEOR, ROUGE, faithfullness and correctness scores. The experiments demonstrated significant improvements in the trained models all metrics, showcasing the effectiveness of the training process tailored to the consumer technology product dataset.

[1] https://github.com/prometheus-eval/prometheus-eval

Chapter 6

Conclusiones y Trabajos Futuros

6.1 Conclusions

This study highlights the impact of fine-tuning Large Language Models (LLMs) using the eC-Tab2Text dataset, a domain-specific resource for e-commerce applications. By consolidating structured product data and addressing limitations of datasets like QTSUMM, eC-Tab2Text enables robust, attribute-specific product reviews. Fine-tuning models such as LLama2-chat, StructLM, and Mistral_Instruct significantly improved text-based and model-based metrics, with Mistral_Instruct consistently outperforming others. These findings validate the importance of tailored datasets in enhancing LLM performance and pave the way for future expansions into broader product categories and dynamic workflows.

6.2 Limitations and Future Work

This study faced several system and resource constraints that influenced the methodology and evaluation process. First, the VRAM limitations necessitated capping the maximum token length at 900 for the Mistral_Instruct model to ensure uniform hyperparameter settings across all models. While this standardization allowed for consistent comparisons, it may have constrained the ability of some models to generate longer, potentially more nuanced outputs.

Second, the evaluation relied on open-source methods, which, although competitive with closed-source approaches, may not fully capture all facets of model performance. Closed-source evaluation tools such as G-Eval[Liu et al., 2023b] could provide complementary insights and a more comprehensive understanding of the models' capabilities in future studies. Incorporating such tools would strengthen the robustness of the evaluation process.

Additionally, due to hardware limitations, the Llama2-chat model was employed for evaluation instead of more advanced models like Llama3, which require significantly higher VRAM for deployment. This choice, while practical, highlights the need for further exploration using state-of-the-art models to better assess eC-Tab2Text's full potential. Future research can expand on this work by leveraging newer LLM architectures and enhanced computational resources to validate and further refine the dataset's performance.

These limitations underscore the need for continued advancements in computational infrastructure and access to cutting-edge tools to unlock the complete potential of domain-specific datasets like eC-Tab2Text.

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