

# Zero-shot Topical Text Classification with LLMs - an Experimental Study

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## Abstract

Topical Text Classification (TTC) is an ancient, yet timely research area in natural language processing, with many practical applications. The recent dramatic advancements in large LMs raise the question of how well these models can perform in this task *in a zero-shot scenario*. Here, we share a first comprehensive study, comparing the zero-shot performance of a variety of LMs over *TTC*<sup>23</sup>, a large benchmark collection of 23 publicly available TTC datasets, covering a wide range of domains and styles. In addition, we leverage this new TTC benchmark to create LMs that are specialized in TTC, by fine-tuning these LMs over a subset of the datasets and evaluating their performance over the remaining, held-out datasets. We show that the TTC-specialized LMs obtain the top performance on our benchmark, by a significant margin. Our code and model are made available for the community.<sup>1</sup> We hope that the results presented in this work will serve as a useful guide for practitioners interested in topical text classification.

## 1 Introduction

The recent emergence of Transformer-based Language Models (LMs) has led to significant breakthroughs in various NLP tasks (Brown et al., 2020; Chung et al., 2022). In particular, LMs have shown dramatic performance improvements in text classification (e.g., Zhang et al. (2023)), which is one of the most common use cases considered by NLP practitioners. Notably, these improvements are also present in the challenging setting of zero-shot classification, where no labeled data are available for the target categories (Yin et al., 2019). Manual collection of labeled data is known to be notoriously costly, complicated, and time consuming, representing a major blocker in the adoption of text

classification solutions in practice. Hence, gaining a better understanding of the current performance of LMs in this zero-shot scenario is a timely issue with great practical importance.

Text classification is a relatively broad umbrella term, covering tasks such as (i) Sentiment Analysis (SA) in various forms (Liu, 2015); (ii) Style Detection - e.g., spam filtering (Cormack, 2008), authorship attribution, etc.; and (iii) Topical Text Classification (TTC), where the goal is to associate a text example with one or more topics out of a pre-defined set of topics, or categories (e.g., Lang (1995)).<sup>2</sup>

The zero-shot scenario is of crucial importance for the latter, TTC task. Specifically, for tasks such as SA, the categories are typically the same between different use cases – Positive, Negative, and Neutral. Hence, in principle, one can rely on existing SA labeled datasets to fine-tune the LM. In contrast, in TTC the list of categories is likely to change from one downstream task to another, hence relying on previously labeled datasets is not straightforward.

Thus, the main motivation for the present work relies on three intertwined pillars – (i) the special importance of the zero-shot setup for TTC; (ii) the wide range of practical TTC use cases – e.g., in domains such as customer-care, healthcare, and legal (Chalkidis et al., 2022); and (iii) the assumed potential of LMs to obtain strong zero-shot performance in TTC tasks.

Correspondingly, here we report the results of a comparative study - to the best of our knowledge, first of its kind - focused on the zero-shot TTC performance of a plethora of LMs over a large collection of TTC datasets. Specifically, we consider 23 datasets, across a variety of domains, styles and complexity levels, including news, legal contracts, chats and more.

<sup>2</sup>We use the terms topics and categories interchangeably throughout the paper.

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<sup>1</sup><https://github.com/IBM/zero-shot-topical-text-classification>

Moreover, while previous work used LMs for zero-shot TTC without specific tuning for this task, here, we suggest that specializing LMs in the TTC task can provide significant performance gains. To that end, we show that one can fine-tune a LM over existing TTC labeled datasets to significantly improve its performance over *new* TTC tasks, with categories never seen before. We show the value of this approach in zero-shot TTC by training the LM on a subset of the datasets, and evaluating its performance on the remaining, held-out datasets.

To summarize, the main contribution of this paper is three-fold: (1) We introduce *TTC*<sup>23</sup>, a heterogeneous collection of 23 TTC datasets, that we propose as a new benchmark for this task; (2) we share the results of a comprehensive comparative study of the zero-shot performance of various LMs at different sizes over *TTC*<sup>23</sup>, addressing both prediction performance and run-time considerations; and finally, (3) we show that *TTC*<sup>23</sup> can be leveraged to create models with significantly enhanced zero-shot performance in new TTC tasks.

## 2 Related Work

### 2.1 Zero-shot Topical Text Classification

Benchmarking TTC was highlighted in [Zhang et al. \(2015\)](#), introducing large-scale datasets, such as AG News, DBPedia and Yahoo Answers.

Zero-shot TTC has been mostly studied as part of a wider scope of zero-shot classification tasks in NLP. [Yin et al. \(2019\)](#) have shown the usefulness of leveraging LMs fine-tuned on NLI datasets for the purpose of zero-shot text classification in general, where topical text classification datasets were only one type of the evaluated tasks. [Halder et al. \(2020\)](#) introduced an approach named TARS, which unifies text classification tasks to a pairwise format, and is able to transfer knowledge from one dataset to another by leveraging the semantic relation between the text and the label in a zero or few-shot setting. [Zhong et al. \(2021\)](#) map text classification tasks into a pairwise question-answering format, where each class is given as a prompt in question format, with Yes/No labels. They also propose the concept of “meta-tuning”, suggesting that teaching a model how to solve different tasks in a unified format can help it to better generalize to unseen tasks. [Puri and Catanzaro \(2019\)](#) proposed using generative models for zero-shot text classification. They formulated the text classification tasks, including TTC, as a multiple-choice

question answering problem, and used the GPT-2 model.

A recently introduced approach for creating zero-shot learners is instruction-tuning ([Sanh et al., 2021](#); [Chung et al., 2022](#); [Longpre et al., 2023](#)) in which zero-shot generalization is enabled by mapping natural language tasks into human-readable instructions and finetuning pretrained models with a multitask mixture of datasets covering a wide variety of tasks. A prominent example for this approach is Flan-T5, which was trained over 1800 tasks, including at least 4 datasets that are topical in nature. While the works mentioned above aimed to create a versatile zero-shot model that can perform well over a wide range of downstream tasks, our aim here is to explore whether honing-in on a narrower scope of downstream tasks, namely topical text classification, can enable us to improve the zero-shot performance on this type of task only.

A previous paper that focused specifically on benchmarking TTC is the work of [Schopf et al. \(2023\)](#), which conducted an evaluation of zero-shot TTC by comparing similarity-based and NLI-based models on 4 TTC datasets. In our work we expand the set of benchmark datasets and evaluated models, and further suggest to improve upon them via task-specific fine-tuning.

### 2.2 Evaluation of large LMs

There is a recent rise in attention to evaluation of large LMs in several contexts. [Kocoń et al. \(2023\)](#) and [Chen et al. \(2023\)](#) evaluated ChatGPT and GPT-3.5, respectively, on a range of NLP tasks, e.g., sentiment analysis, emotion recognition, and question answering, while [Chalkidis \(2023\)](#) did so for ChatGPT specifically on datasets in the legal domain. [Zhang et al. \(2023\)](#) evaluated Flan-UL2, Flan-T5-XXL, GPT3.5, and ChatGPT on tasks associated with sentiment analysis, finding that Flan-UL2 achieves comparable or even better results than GPT-3.5 or ChatGPT, despite being magnitudes smaller. [Wadhwa et al. \(2023\)](#) evaluated GPT-3 and Flan-T5-Large on relation extraction in a few-shot and supervised setting. [Parikh et al. \(2023\)](#) evaluated Flan-T5-XXL and GPT-3 on zero-shot intent detection on 4 benchmark datasets, finding that they achieve comparable results.

### 3 Approaches to Zero-shot Topical Text Classification

#### 3.1 Existing Approaches

There are several approaches for dealing with zero-shot TTC. Here we briefly describe a collection of popular methods, highlighting their commonalities and differences. What all the approaches have in common is the key idea of casting different tasks onto a single meta-problem. Using this casting, a model that was trained to solve the meta-problem can also be used to solve other, unseen tasks. The three main meta-problems that have been suggested in the context of text classification are: Natural Language Inference (NLI), Question Answering (QA), and Instruction Tuning. Figure 1 shows how a TTC example is mapped onto each meta-problem.

**Natural Language Inference (NLI).** In this approach, initially proposed by Yin et al. (2019), pre-trained NLI encoder-only models are used as zero-shot text classifiers. These models are pre-trained using large manually labeled datasets for textual entailment, such as the MNLI dataset (Williams et al., 2018). The method operates by treating the text to be classified as the NLI premise and constructing a hypothesis for each candidate topic. The hypothesis template depends on the target task, where for TTC, the template is usually of the form “this text is about <topic>”. The entailment and contradiction probabilities predicted by the NLI model are converted to label probabilities for this topic.

**Question-Answering (QA).** In this approach, different tasks are translated into yes/no questions. Zhong et al. (2021) created a large question answering meta-dataset from a collection of manually annotated datasets of different NLP classification tasks, all framed as question answering problems. Next, they used these data to train a binary model for yes/no question answering.

**Instruction Tuning.** Another approach for dealing with zero-shot text classification is by treating the classification task as a sequence generation task, where the target task is phrased as an input prompt and the text generated by the model is the predicted label. A well-known approach for improving the zero-shot performance of generative models is instruction tuning. This approach leverages the intuition that NLP tasks can be described via natural language instructions. Following this intuition, models are fine-tuned on a collection of

tasks described via instructions. The instructions are fed to the model as input prompts.

#### 3.2 Our Approach

Most available solutions for zero-shot TTC are based on models that were designed to solve a wider range of tasks. We propose to create models specialized at TTC by leveraging the large amount of publicly available topical datasets. A large collection of such datasets from various domains and styles is used to create a rich and diverse meta-dataset for TTC, that can be used to fine-tune existing zero-shot models, adapting them to the specific task of TTC.

The details on how we process the datasets and fine-tune different types of zero-shot models on them are presented next, in Sections 4 and 5.

### 4 The TTC<sup>23</sup> Benchmark

Our aim was to gather a diverse set of datasets containing multiple domains and styles that could serve as a training set for fine-tuning models, and also as a TTC evaluation benchmark. We collected datasets for TTC by searching on huggingface, kaggle, as well as in related papers, focusing on datasets where the input is between one and a few sentences, in English, and labeled in a multi-class or multi-label setting. The collection covers, among others, the following domains and styles: legal – both formal (e.g., LEDGAR) and informal (e.g., Legal Advice Reddit); finance – both from the news (Reuters) and tweets (Financial Tweets); News items – both headlines (News Category Classification Headline) and discussion threads (20 Newsgroups); and Chatbot queries – in banking (Banking77) and multi-domain (Massive).

Overall we collected 23 datasets, presented in Table 1.

#### 4.1 Converting Datasets from Different Tasks

Our collection primarily includes datasets associated with detecting the main theme or topic in a given text. To enrich the diversity of the collection, we also considered datasets which were originally targeted at a separate task. For *Banking77*, *Clinic150*, and *Massive*, originally curated for the task of intent detection, we took the intent as the gold label; for *Argument Topic* and *Claim Stance Topic*, which contain arguments associated with debatable topics, we took the debatable topic as the gold label; and for *Contract NLI*, which was orig-

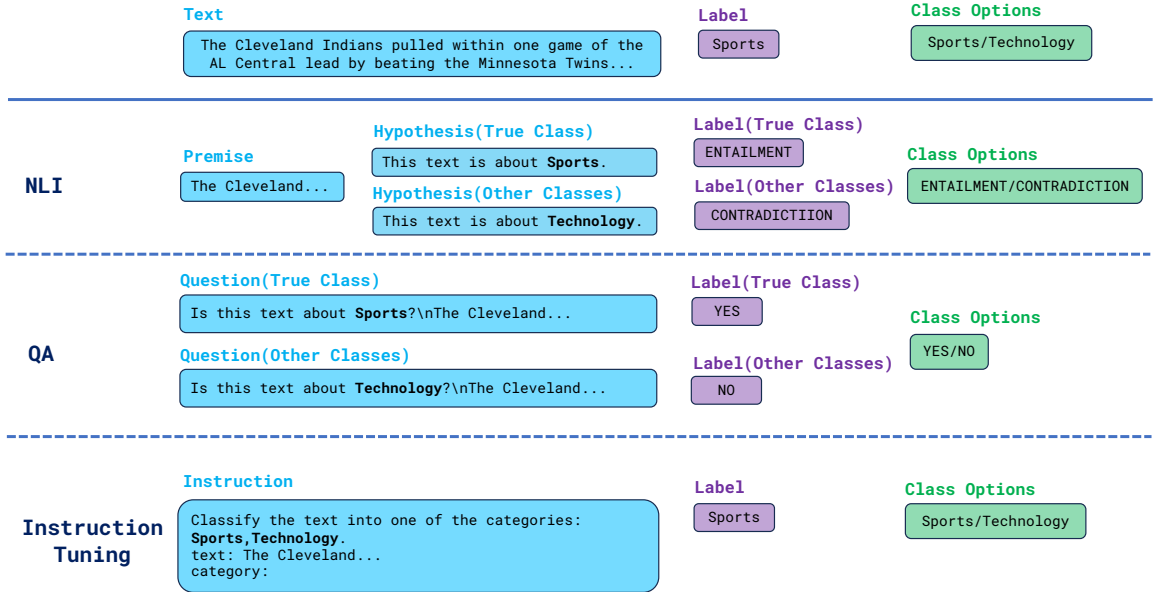


Figure 1: Framing topical text classification as each of the meta-problems representing the common zero-shot approaches.

Dataset	Size	# Classes	Multi-label	Domain
20 Newsgroups (Lang, 1995)	19.0k	20	No	General
AG News (Zhang et al., 2015)	142.6k	4	No	General
Argument Topic (Gretz et al., 2020)	10.4k	71	No	General
Banking77 (Casanueva et al., 2020)	14.5k	77	No	Finance/Banking
Claim Stance Topic (Bar-Haim et al., 2017)	2.6k	55	No	General
Clinical150 (Larson et al., 2019)	25.5k	150	No	General
Contract NLI (Koreeda and Manning, 2021)	7.5k	17	Yes	Legal
CUAD (Hendrycks et al., 2021)	8.8k	37	Yes	Legal
DBPedia (Zhang et al., 2015)	650k	14	No	Legal
Eli5-category (Gao et al., 2021)	91.6k	10	No	General
Financial Tweets (Jia, 2022)	23.6k	20	No	Finance/Banking
HeadQA (Vilares and Gómez-Rodríguez, 2019)	8.1k	6	No	Medical
Law Stack Exchange (Li et al., 2022)	2.8k	16	No	Legal
LEDGAR (Chalkidis et al., 2022)	88.5k	99	No	Legal
Legal Advice Reddit (Li et al., 2022)	108.8k	11	No	Legal
Massive (FitzGerald et al., 2022; Bastianelli et al., 2020)	18.5k	60	No	General
Medical Abstracts (Schopf et al., 2023)	15.5k	5	No	Medical
News Category Classification Headline (Misra and Grover, 2021; Misra, 2022)	229.5k	40	No	General
Reuters (Apté et al., 1994)	13.1k	20	Yes	Finance/Banking
Sentiment (Jacobs, Gilles and Hoste, Veronique, 2022)	7.5k	18	Yes	Finance/Banking
Unfair ToS (Chalkidis et al., 2022)	11.6k	8	Yes	Legal
Xglue (Liang et al., 2020)	130.0k	10	No	General
Yahoo Answers (Yin et al., 2019)	145.4k	10	No	General

Table 1: List of datasets in the  $TTC^{23}$  benchmark collection.

inally curated for identifying entailment between premises and hypotheses in contracts, we took the category of the hypothesis as the gold label.

## 4.2 Data Formatting

To ease data processing, we converted all datasets to a unified format containing a single text column and a single label column, where each label

contains zero or more categories (depending on the dataset). For datasets that originally did not contain a train-dev-test split, we created one.

## 4.3 Label Cleansing and Rephrasing

Zero-shot TTC relies on a good semantic representation of the topic. For it to be effective, this representation should be clear and grammatically sound,



and also consistent between different datasets. This led us to rephrase the categories in the following ways (see Appendix E for the full list of changes):

1. We rephrased categories that were in an unreadable or technical format (e.g., in 20 Newsgroups, we rephrased `alt.atheism` to `atheism`).
2. We rephrased categories that might not be grammatically correct when prepended with a prompt (e.g., in ClinC150, we rephrased `find_phone` to `finding a phone`).
3. We removed examples associated with categories that do not convey semantic information (e.g., `topic general` in LEDGAR).
4. For the Reuters dataset, many categories were either acronyms or required domain expertise to parse. Thus, we kept examples associated with the top-20 prevalent categories in the dataset, and rephrased these categories to make them more readable.
5. We performed further cleansing across all datasets to remove underscores and convert to lower case.

## 5 Experimental Setup

Next we describe the setup in which we evaluate the different methods for zero-shot TTC.

### 5.1 Datasets

We use the *TTC*<sup>23</sup> benchmark described in Section 4 containing 23 datasets – 18 multi-class and 5 multi-label – for training and evaluation.

### 5.2 Evaluating Fine-tuned Models on *TTC*<sup>23</sup>

#### 5.2.1 Leave-one-fold-out

To evaluate fine-tuned models in a zero-shot setting, we split *TTC*<sup>23</sup> into  $k$  folds and employ a leave-one-fold-out setup, where we train on  $k-1$  folds and evaluate on the remaining fold.

We consider two fold-splits:

**In-domain.** In this split, different folds share datasets from the same domain. The motivation for this split is to evaluate how well a model performs when tested on a similar domain that was present in training. We split to 3 folds containing 8, 8, and 7 datasets, respectively. Unless stated otherwise, this fold-split is used for all experiments. The folds are presented in Appendix A.

**Out-of-domain.** In this split, different folds do not share datasets from the same domain. The motivation for this split is to evaluate how well a model performs when tested on a domain not present in training. We determined for each dataset its domain manually, ending up with 4 folds, as presented in Table 1.

#### 5.2.2 Building a Unified Dataset

When fine-tuning a model in the leave-one-fold-out setup, we create merged train and dev sets. The merged train set is comprised of the train sets of all datasets in the folds we train on (and likewise, the merged dev set). For the train set, we also sample at most 100 examples from each category to prevent over-dominance of highly populated categories. For evaluation, we consider the test sets of all datasets in the held-out fold separately, and they are not sampled.

For building the merged train/dev sets for NLI-based models, we convert the positive examples to a pairwise format, where each example contains the text input and the hypothesis template “This text is about <topic>.”, separated by [SEP], with an ENTAILMENT label. In case the example contains multiple positive topics (in a multi-label setting), we create multiple pairwise positive examples, one for each positive topic.

For each positive pairwise example we add a negative pairwise example whose topic is selected at random from the categories of this dataset (excluding the positive topics of this example), with a CONTRADICTION label.

For instruction-tuned models, we similarly merge the datasets in the training folds. The input for each text is comprised of the instruction, the candidate categories, and the text, and the output is the target category. If the example originally contains more than one category, we choose one randomly. Examples with no categories are ignored in training. We use the instruction in Figure 1.

### 5.3 Inference

**Encoder-only Models.** For all encoder-only models we run a pairwise inference of each example with all candidate categories.

**Encoder-Decoder Models.** For instruction-tuned models, when evaluating multi-class datasets we construct the same instruction that contains the task description and all candidate categories, and ask the model to generate the predicted category.

Classification tasks are a special case of a generation task where the generated tokens are expected to come from a pre-defined list of categories. Thus, we implemented a logits processor that restricts the calculation of tokens to take into account only the tokens that are permitted according to the candidate categories. This avoids generating texts which cannot be exactly matched to any category and improves the performance. For example, if there are two candidate categories, “world news” and “tv and film”, and the first generated token is “world”, the second token must be “news”.

Multi-label datasets have been relatively less explored in the context of using instruction-tuned models for classification. We propose to frame the classification as a binary classification task. Instead of asking the model to generate a single category name out of a pre-defined list of candidates (as in the multi-class setting), we present the model with each candidate category separately, along side its negation (e.g., *sports*, *not sports*), and ask the model to choose between the two. The score for each <text, category> pair is the probability given by the model for generating that category name.

## 5.4 Models

We consider the following off-the-shelf models:

**S-BERT** (Reimers and Gurevych, 2019). In addition to the approaches in Section 3, we also evaluate S-BERT. We use the all-mpnet-base-v2 model.

**QA-based.** We use the RoBERTa-Large-QA model released in Zhong et al. (2021).<sup>3</sup> For each inferred pair, we calculate the probability of the label “Yes”. We use a single label description (question), ‘*Is this text about <topic>?*’, which is one of the manually annotated label descriptions used by Zhong et al. (2021), and matches the TTC task. Three of the *TTC*<sup>23</sup> datasets were part of the training set of this model, thus we also report results on a subset of *TTC*<sup>23</sup> that excludes them.

**NLI-based.** We use RoBERTa-large-NLI (Liu et al., 2019)<sup>4</sup> and DeBERTa-large-NLI (He et al., 2021).<sup>5</sup> For each inferred pair, we calculate the probability of the label ENTAILMENT divided by the probability of the label CONTRADICTION.

<sup>3</sup><https://huggingface.co/ruiqi-zhong/roberta-large-meta-tuning-test>

<sup>4</sup><https://huggingface.co/roberta-large-mnli>

<sup>5</sup><https://huggingface.co/MoritzLaurer/DeBERTa-v3-large-mnli-fever-anli-ling-wanli>

**Instruction-tuned models.** We evaluate Flan-T5-Large/XL/XXL. Four of the datasets in *TTC*<sup>23</sup> were part of Flan’s training, thus we also report results on a subset of *TTC*<sup>23</sup> that excludes them. Given that datasets may contain a large set of candidate categories, increasing the size of the prompt, we use a sequence length of 2048. We use a greedy decoding method, since our aim is to generate the tokens representing the most probable class.

We also evaluate models fine-tuned over *TTC*<sup>23</sup> in the leave-one-fold-out setup described above. Implementation details can be found in Appendix B. We consider the following fine-tuned models:

1. NLI-based FT. We fine-tune RoBERTa-large-NLI and DeBERTa-large-NLI.
2. Instruction-tuned FT. We fine-tune Flan-T5-XXL. In order to be able to fine-tune this model, we use the efficient fine-tuning approach of Low Rank Adapters (LoRA) (Hu et al., 2021). We fine-tune the model for 3 epochs and use the dev set for early stopping.

### 5.4.1 Decoder-only Models

Recent advancements exhibited in GPT-4 and ChatGPT suggest they could be suitable for TTC as well. However, there are several issues associated with evaluating these models. First, assessing the zero-shot performance of the GPT family is challenging due to its undisclosed training data, potentially encompassing supervised training from our evaluation datasets. Second, given its paid nature, extensive inference at the scale presented in this work is not only costly but also non-reproducible should the service evolve in the future. Thus, we excluded them from this paper.

## 5.5 Metrics

**Multi-class.** For multi-class datasets, we take the highest scoring predicted category per example, and report macro-averaged f1 over all categories.

**Multi-label.** For multi-label datasets, to avoid sensitivity to any decision threshold, we report macro-average AUC-ROC over all categories.

We report the average of 3 seeds.

## 6 Results and Analysis

We present results averaged on all datasets in Table 2 and full results in Tables 4 and 5 in the Appendix.

Model	Model Type	#Params	MC	MC*	MC**	ML
<i>Off-the-shelf Models</i>						
S-BERT		110M	52.66	51.89	54.15	85.49
RoBERTa-Large-QA	QA-based	355M	-	-	54.21	88.12
RoBERTa-Large-NLI	NLI-based	355M	51.05	47.89	51.26	82.97
DeBERTa-Large-NLI	NLI-based	435M	54.40	51.08	55.15	88.26
Flan-T5-Large	Instruction-tuned	770M	-	54.89	-	86.57
Flan-T5-XL	Instruction-tuned	3B	-	61.39	-	89.47
Flan-T5-XXL	Instruction-tuned	11B	-	64.79	-	89.72
<i>Models fine-tuned on TTC<sup>23</sup></i>						
RoBERTa-Large-NLI FT	NLI-based	355M	58.59	57.51	59.34	90.64
DeBERTa-Large-NLI FT	NLI-based	435M	64.00	63.14	65.36	<b>93.19</b>
Flan-T5-XXL FT	Instruction-tuned	11B	-	<b>67.32</b>	-	89.56

Table 2: TTC results over 18 multi-class and 5 multi-label datasets in  $TTC^{23}$ . Top: off-the-shelf zero-shot models. Bottom: fine-tuned models over  $TTC^{23}$  in leave-one-fold-out. MC stands for multi-class datasets, and ML for multi-label datasets. MC\* are the subset of 14 datasets not included in Flan models training. MC\*\* are the subset of 15 datasets not included in the QA model training. For MC\*/\*\* we report macro-f1 and for ML macro-AUC-ROC, averaged over all respective datasets.

## 6.1 Off-the-shelf Models

Considering the top part of Table 2, Flan-T5-XXL model is clearly the best zero-shot model for TTC. As expected, the performance of Flan-based models increases with model size (see MC\* column). Note, that QA and Flan models were trained on multiple tasks (including TTC ones), making them a stronger baseline compared to the NLI-based models which were trained on a single and somewhat different entailment task. It is also worth noting that S-BERT is competitive with off-the-shelf encoder-only models, representing a much faster cost-effective alternative when resources are limited.<sup>6</sup>

## 6.2 Impact of Fine-Tuning on $TTC^{23}$

The results of models fine-tuned over  $TTC^{23}$  in leave-one-fold-out setup are presented at the bottom of Table 2. Remarkably, fine-tuning RoBERTa and DeBERTa models significantly improves their macro-f1 performance on MC datasets by 8 and 10 points, respectively; and by 10 and 12 points, respectively, over the MC\* datasets. Fine-tuning Flan-T5-XXL yields a more moderate, yet significant improvement of 2.5 f1 points on the MC\* datasets, leading to the top zero-shot performance in our MC experiments with an impressive macro-

averaged f1 score of 67.32. As can be seen in Table 4, it is the best model for 10/14 of the MC\* datasets. Interestingly, DeBERTa-Large-NLI FT outperforms the much larger Flan-T5-XL, which further highlights the advantage of the task-specific training.

Focusing on encoder-only models, and the MC\*\* column, fine-tuning on  $TTC^{23}$  yields better performance compared to the QA-based model, that uses a different training scheme.

## 6.3 Comparison to Leave-one-domain-out

We compare the results of our in-domain setup to an out-of-domain setup, where the evaluated datasets in each fold come from a domain not present in the training data, using DeBERTa-Large-NLI FT. This enables to quantify the impact of domain similarity between train and test on model performance. The results are in Table 3. When moving to an out-of-domain setup macro-f1 and macro-AUC-ROC drop by 1-2 points, as expected. The out-of-domain setup is more challenging, but not necessarily more realistic. Given that we envision a model trained on hundreds of classes and multiple domains, it might be reasonable to assume that in real-world applications this model will be tested over datasets it is already somewhat familiar with.

## 6.4 Does Category Similarity Help?

As an additional measure for evaluating the impact of training data on model performance, we explore

<sup>6</sup>In addition to the models presented here, we experimented with the Llama family of models. Our trials in zero-shot classification with them on  $TTC^{23}$  yielded significantly inferior results, leading to its exclusion.

whether high performance on categories in the test fold is correlated with the occurrence of semantically similar categories in the train set. To that end, for each category in a test fold we find the score of its most similar category in the train folds using S-BERT. The correlation between these scores and the respective f1 scores in the DeBERTa-Large-NLI FT run is insignificant (-0.03). Furthermore, in an anecdotal inspection, we observe relatively low performance for categories in the test fold even though the exact same category name was included in the train folds. E.g., the category *greeting* appears both in *Clinic150* and *Massive*, however the f1 results for this category are lower compared to other categories. Thus, overall it seems that the semantic similarity of a category name to another category included in the training data has no significant influence over performance, possibly due to the magnitude and diversity of the training data we consider.

## 6.5 Run-time Analysis

When choosing which model to run, a relevant aspect for a practitioner is run-time. To this end, we analyze the run-time of the different models. Each of the models we consider uses a different technique for running predictions: S-BERT calculates the embeddings of the input texts and categories separately and calculates their cosine similarity. Flan-T5-XXL concatenates all the candidate categories to a single prompt with additional tokens for instruction, and runs one inference on each input text – thus, the number of categories directly impacts the prompt length. DeBERTa-Large-NLI prepends a short template to each text, and runs inference for each category separately. Thus, the number of categories directly impacts the number of inferences per input text.

Inference over large datasets naturally takes more time than inference on smaller datasets. To compare run-time between datasets of different sizes, we measure the throughput using the Kchar/s (kilo characters per second) metric, dividing the total length of the dataset input by the run-time.

We use an A100 GPU with 40GB of memory. For each method, we pick the inference batch size that allows minimal run-time as measured in seconds. We use fp16 quantization for both DeBERTa-Large-NLI and Flan-T5-XXL.

The average throughput of S-BERT, DeBERTa-Large-NLI, and Flan-T5-XXL is 118.73, 21.67,

Model	MC	ML
DeBERTa-Large-NLI FT	64.00	93.19
DeBERTa-Large-NLI FT (OOD)	61.83	92.04

Table 3: TTC over 18 multi-class and 5 multi-label datasets in  $TTC^{23}$ , comparing in-domain (top) to out-of-domain (bottom) fold-splits.

and 8.02 Kchar/s respectively. Full analysis is available in Table 6 in the Appendix. Next, we share a few observations that emerge from this analysis.

There is large variance between different datasets, as text length and number of categories impact the throughput. For example, Flan-T5-XXL’s throughput on Clinic150 is 0.43 Kchars/s compared to 22.1 Kchars/s on Legal Advice Reddit. Similar variance is seen in other models.

For most datasets, the throughput of DeBERTa-Large-NLI is higher, i.e., better than that of Flan-T5-XXL, despite making more inference calls per text. For example, in Xglue the throughput of DeBERTa-Large-NLI is more than 4 times greater than with Flan-T5-XXL. The only exception to this is LEDGAR, which contains long texts and a large number of categories. For this dataset, the throughput of Flan-T5-XXL is two times larger. This is presumably because Flan-T5-XXL processes the long text only once, and concatenates the candidate categories to a single inference, while DeBERTa-Large-NLI infers the text repeatedly for each candidate category. Coupled with the results discussed in Section 6.2, this analysis highlights the run-time vs. quality trade-off, as the superior quality of Flan-T5-XXL comes at the cost of longer run-time.<sup>7</sup>

For S-BERT, the effect of calculating category embeddings and cosine similarity is negligible, and the model does not use any prompt. Aside from the fact that it is the smallest model, S-BERT naturally has the best throughput across all datasets, at the cost of lower f1.

## 7 Conclusions

TTC is an ancient problem in computer science research, dating back to 1961 (Maron, 1961). The recent advancements in large LMs led us to explore how well they perform on this problem in a zero-shot setting. In this paper we introduce a comprehensive evaluation of existing approaches to zero-shot TTC over a diverse set of datasets,  $TTC^{23}$ . Our results indicate that large LMs indeed

<sup>7</sup>Note, Flan-T5-XXL also has relatively high hardware constraints, though we did not analyze this aspect in detail.



exhibit a significant improvement over the smaller encoder-only models that were the main focus on previous studies on zero-shot TTC (e.g., (Yin et al., 2019; Schopf et al., 2023)).

Furthermore, we show that fine-tuning RoBERTa and DeBERTa models as well as Flan-T5-XXL over existing TTC datasets can significantly boost their respective zero-shot performance on *new* TTC datasets, with category names not included in the training data. In other words, even LLMs that represent very strong baselines, can be further significantly improved with additional fine-tuning focused on the target task. Our run-time analysis has shown that this superior performance comes with a cost of additional run-time, something the practitioner needs to take into account.

Our fine-tuned Flan-T5-XXL model obtained very impressive zero-shot performance - macro-averaged f1 of 67.32 when averaging across 14 multi-class datasets. Nonetheless, these results are typically still not satisfactory in practice, and we expect that a traditional process of collecting labeled data for the target task under consideration to further fine-tune the model would be required. That said, a strong zero-shot TTC model can serve as an excellent starting point to perform domain adaptation on a target dataset, e.g., by means of self-training (Gera et al., 2022) or active learning (Ein-Dor et al., 2020; Shnarch et al., 2022), as we plan to explore in future work.

## 8 Ethics and Broader Impact

This paper is submitted in the wake of a tragic terrorist attack perpetrated by Hamas, which has left our nation profoundly devastated. On October 7, 2023, thousands of Hamas terrorists infiltrated the Israeli border, launching a brutal assault on 22 Israeli villages. They methodically moved from home to home brutally torturing and murdering more than a thousand innocent lives, spanning from infants to the elderly. In addition to this horrifying loss of life, hundreds of civilians were abducted and taken to Gaza. The families of these abductees have been left in agonizing uncertainty, as no information, not even the status of their loved ones, has been disclosed by Hamas.

We fervently call for the immediate release of all those who have been taken hostage and urge the academic community to unite in condemnation of these unspeakable atrocities committed by Hamas.

We call all to join us in advocating for the prompt and safe return of the abductees, as we stand together in the pursuit of justice and peace.

## 9 Limitations

The approach taken in this work has a few limitations:

1. For reasons detailed in Section 5.4.1, we do not present an evaluation of decoder-only models such as GPT-4 or ChatGPT.
2. For Flan-based models, it could be that with better prompt engineering, e.g., including trying few-shot prompts, one could improve their performance.
3. Our approach for classification of multi-label datasets with the generative models is a rough attempt to adapt these models to this setup. It could be that other approaches for multi-label classification could be utilized, e.g., by asking the model to generate zero or more categories.
4. We analyze the potential impact of the training data on model performance in Sections 6.3 and 6.4. However, perhaps there are other, more subtle ways in which the training data impacts the performance which are not directly evaluated in this work.
5. We do not attempt to fine-tune the QA-based model, which could have benefited from it as well.
6. We consider datasets containing sentences, paragraphs, or short sections. We do not test our approach on document-level inputs, though in theory this should be feasible.
7. This type of work entails several degrees of freedom – what templates to use, which datasets to evaluate on, what hyper-parameters to tune, which runtime measures to consider, etc. We attempted to prioritize them in order to cover the issues we consider most important. However, dedicating more time and effort to these items could have yielded additional insights.

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## A In-domain Folds

In the in-domain fold-split, these are the folds we considered:

Fold1: Reuters, Claim Stance Topic, Unfair ToS, HeadQA, Banking77, AG News, Yahoo Answers.

Fold2: Argument Topic, CUAD, DBPedia, News Category Classification Headline, Eli5-category, Financial Tweets, Law Stack Exchange, Massive.

Fold3: Clinc150, 20 Newsgroups, Contract NLI, LEDGAR, Legal Advice Reddit, Medical Ab-stracts, Xglue, Sentivent.

## B Model Implementation

For DeBERTa-based models, we fine-tune for 3 epochs without early-stopping using a learning-rate of  $5e-6$ , a batch-size of 32, and a maximum sequence length of 256.

For RoBERTa-based models, we use a maxi-mum sequence length of 128, which is the limit of the RoBERTa-Large-QA released model. For the RoBERTa-Large-NLI model, we fine-tune for 3 epochs without early stopping using a learning-rate of  $1e-5$ , and a batch-size of 32.

When fine-tuning Flan-T5-XXL with LoRA, we adapt only the q (query) and v (value) projections in the transformer, and set rank=16, alpha=32 and dropout=0.05. We set the learning rate to  $3e-5$ , the batch size to 16, the gradient accumulation steps to 16, the input sequence length to 512, the warmup steps to 2 and use a paged Adamw optimizer.

## C Full MC Results

Tables 4 and 5 present the full results of our evalu-ation over TTC<sup>23</sup>.

## D Runtime Results

Table 6 presents the runtime analysis over all multi-class datasets of TTC<sup>23</sup>.

## E Rephrasing Labels



Dataset	S-BERT	RoBERTa-Large-NLI	RoBERTa-Large-NLI FT	RoBERTa-Large-QA	DeBERTa-Large-NLI	DeBERTa-Large-NLI FT	Flan-Large	Flan-XL	Flan-XXL	Flan-XXL FT
20 News-group	59.68	50.42	53.53	41.16	56.63	66.87	57.1	62.33	62.28	<b>72.2</b>
AG News	59.85	70.63	76.69		68.67	<b>79.55</b>				
Argument Topic	95.46	84.75	94.7	76.38	89.38	96.65	88.64	94.49	95.73	<b>97.83</b>
Banking77	60.42	36.91	56.99	48	49.96	66.3	55.6	62.76	66.59	<b>68.89</b>
Claim Stance Topic	69.82	42.98	75.75	50.35	56.94	78.75	73.23	75.99	82.21	<b>87.28</b>
Clinic150	69.15	51.87	71.98	54.1	54.73	79.06	61.4	72.92	79.11	<b>83.47</b>
DBPedia	68.88	82.56	82.54	84.1	<b>92.76</b>	90.18				
Eli5-category	45.36	48.89	39.47	50.97	53.06	50.64	50.3	49.25	56.34	<b>57.11</b>
Financial Tweets	30.21	32.32	46.61	40.82	27.94	48.68	46.97	<b>53.82</b>	52	49.48
HeadQA	40.94	41.35	30.97	<b>45.83</b>	44.24	36.81				
Law Stack Exchange	45.73	54.03	57.54	54.86	57.66	59.94	52.35	52.78	58.17	<b>62.94</b>
LEDGAR	23.28	33.77	46.44	37.61	18.5	48.99	31.89	44.73	47.73	<b>55.86</b>
Legal Advice Reddit	56.78	63.69	66.69	68.76	67.45	72.21	62.56	67.94	75.59	<b>77.99</b>
Massive	50.61	48.78	58.31	50.9	54.22	66.61	46.22	61.27	64.82	<b>68.54</b>
Medical Abstracts	58.4	53.39	53.74	54.34	53.6	59.13	54.04	62.48	<b>63.71</b>	60.69
News Category Classification Headline	24.06	25.5	28.57		24.77	30.53	29.34	33.04	<b>37.64</b>	36.91
Xglue	37.56	43.12	54.82	54.97	50.24	59.58	58.83	<b>65.67</b>	65.13	63.25
Yahoo Answers	51.64	54.02	59.23		58.42	<b>61.59</b>				

Table 4: Full results of all models on 18 MC TTC<sup>23</sup> datasets.

Dataset	S-BERT	RoBERTa-Large-NLI	RoBERTa-Large-NLI FT	RoBERTa-Large-QA	DeBERTa-Large-NLI	DeBERTa-Large-NLI FT	Flan-T5-Large	Flan-T5-XL	Flan-T5-XXL	Flan-T5-XXL FT
Contract NLI	75.55	71.8	80.33	76.31	74.95	<b>87.10</b>	75.85	76.66	75.42	76.17
CUAD	88.49	86.04	94.65	92.10	88.96	<b>96.71</b>	92.27	93.66	92.46	92.39
Reuters	93.58	88.2	97.35	97.26	96.12	<b>98.31</b>	87.83	93.62	95.2	94.7
Sentiment	78.75	80.75	83.79	86.18	85.52	85.71	81.88	85.32	<b>87.17</b>	86.29
Unfair ToS	91.06	88.05	97.08	88.73	95.76	98.10	95.04	98.08	<b>98.36</b>	98.23

Table 5: Full results of all models on 5 ML TTC<sup>23</sup> datasets.

<b>Dataset</b>	<b># Categories</b>	<b>Average Text Length</b>	<b>S-BERT</b>	<b>Deberta-Large-NLI</b>	<b>Flan-T5-XXL</b>
20 Newsgroups	20	1925.64	274.96	21.94	15.19
AG News	4	232.49	87.12	54.33	13.78
Argument Topic	71	116.73	64.91	2.97	1.72
Banking77	77	59.04	29.16	1.45	0.85
Claim Stance Topic	55	79.47	43.13	2.68	1.00
Clinc150	150	38.02	25.82	0.57	0.43
DBPedia	14	280.08	104.60	17.60	5.87
Eli5-category	10	82.88	44.21	15.21	4.30
Financial Tweets	20	135.74	59.96	8.15	3.10
HeadQA	6	116.80	39.22	28.81	4.05
Law Stack Exchange	16	849.40	129.22	20.82	18.33
LEDGAR	99	715.78	117.31	3.91	8.37
Legal Advice Reddit	11	1292.77	202.30	37.16	22.51
Massive	60	31.36	22.25	1.24	0.68
Medical Abstracts	5	1185.45	182.09	72.57	17.66
News Category Classification	40	59.09	38.30	3.15	1.39
Headline					
Xglue	10	3971.01	589.28	71.59	16.42
Yahoo Answers	10	508.63	83.47	26.05	8.84

Table 6: Throughput in Kchars/sec on a Tesla A100 with 40Gb.

<b>dataset</b>	<b>class name</b>	<b>rephrased class name</b>	<b>rephrased type</b>
claim stance topic	the one-child policy of the republic of China	the one-child policy of the republic of china	lower case
claim stance topic	make physical education compulsory	physical education	motion to topic
claim stance topic	subsidize the growing of tobacco	the growing of tobacco	motion to topic
claim stance topic	American Jobs Act	american jobs act	lower case
claim stance topic	all nations have a right to nuclear weapons	all nations a right to nuclear weapons	motion to topic
claim stance topic	subsidize poor communities	poor communities	motion to topic
claim stance topic	institute a mandatory retirement age	a mandatory retirement age	motion to topic
claim stance topic	re-engage with Myanmar	re-engage with myanmar	lower case
claim stance topic	build the Keystone XL pipeline	the keystone xl pipeline	motion to topic
claim stance topic	Israel's 2008-2009 military operations against Gaza	israel's 2008-2009 military operations against gaza	lower case
claim stance topic	build high rises for housing	high rises for housing	motion to topic
claim stance topic	the blockade of Gaza	the blockade of gaza	lower case
claim stance topic	Holocaust denial	holocaust denial	lower case
claim stance topic	the creation of private universities in the UK	the creation of private universities in the uk	lower case
claim stance topic	ASEAN	asean	lower case
claim stance topic	implement playoffs in collegiate level American football	implement playoffs in collegiate level american football	lower case
claim stance topic	unleash the free market	the free market	motion to topic
claim stance topic	have children	children	motion to topic
claim stance topic	build hydroelectric dams	hydroelectric dams	motion to topic

Table 7: Label cleaning.

dataset	class name	rephrased class name	rephrased type
argument topic	Intelligence tests bring more harm than good	intelligence tests	motion to topic
argument topic	Surrogacy should be banned	surrogacy	motion to topic
argument topic	We should ban cosmetic surgery	cosmetic surgery	motion to topic
argument topic	We should abolish capital punishment	capital punishment	motion to topic
argument topic	We should ban cosmetic surgery for minors	cosmetic surgery for minors	motion to topic
argument topic	We should ban human cloning	human cloning	motion to topic
argument topic	We should limit executive compensation	executive compensation	motion to topic
argument topic	We should ban naturopathy	naturopathy	motion to topic
argument topic	We should abolish the three-strikes laws	the three-strikes laws	motion to topic
argument topic	We should legalize organ trade	organ trade	motion to topic
argument topic	We should prohibit flag burning	flag burning	motion to topic
argument topic	We should adopt gender-neutral language	gender-neutral language	motion to topic
argument topic	We should subsidize Wikipedia	wikipedia	motion to topic
argument topic	We should legalize cannabis	cannabis	motion to topic
argument topic	We should introduce compulsory voting	compulsory voting	motion to topic
argument topic	We should limit judicial activism	judicial activism	motion to topic
argument topic	We should adopt a multi-party system	multi-party system	motion to topic
argument topic	We should adopt libertarianism	libertarianism	motion to topic
argument topic	Homeschooling should be banned	homeschooling	motion to topic

Table 8: Label cleaning.

dataset	class name	rephrased class name	rephrased type
argument topic	We should subsidize student loans	student loans	motion to topic
argument topic	We should subsidize stay-at-home dads	stay-at-home dads	motion to topic
argument topic	Payday loans should be banned	payday loans	motion to topic
argument topic	Assisted suicide should be a criminal offence	assisted suicide	motion to topic
argument topic	Holocaust denial should be a criminal offence	holocaust denial	motion to topic
argument topic	Social media brings more harm than good	social media	motion to topic
argument topic	We should ban private military companies	private military companies	motion to topic
argument topic	The use of public defenders should be mandatory	the use of public defenders	motion to topic
argument topic	We should abandon the use of school uniform	the use of school uniform	motion to topic
argument topic	Foster care brings more harm than good	foster care	motion to topic
argument topic	We should ban targeted killing	targeted killing	motion to topic
argument topic	We should fight for the abolition of nuclear weapons	the abolition of nuclear weapons	motion to topic
argument topic	We should ban algorithmic trading	algorithmic trading	motion to topic
argument topic	We should ban whaling	whaling	motion to topic
argument topic	The vow of celibacy should be abandoned	the vow of celibacy	motion to topic
argument topic	We should legalize prostitution	prostitution	motion to topic
argument topic	We should adopt a zero-tolerance policy in schools	zero-tolerance policy in schools	motion to topic
argument topic	We should abolish zoos	zoos	motion to topic
argument topic	We should abandon marriage	marriage	motion to topic

Table 9: Label cleaning.



<b>dataset</b>	<b>class name</b>	<b>rephrased class name</b>	<b>rephrased type</b>
argument topic	We should abandon television	television	motion to topic
argument topic	We should abolish intellectual property rights	intellectual property rights	motion to topic
argument topic	We should end mandatory retirement	retirement	motion to topic
argument topic	We should abolish the right to keep and bear arms	the right to keep and bear arms	motion to topic
argument topic	Blockade of the Gaza Strip should be ended	blockade of the gaza strip	motion to topic
argument topic	We should subsidize vocational education	vocational education	motion to topic
argument topic	We should stop the development of autonomous cars	the development of autonomous cars	motion to topic
argument topic	We should ban the use of child actors	the use of child actors	motion to topic
argument topic	We should adopt an austerity regime	austerity regime	motion to topic
argument topic	We should adopt atheism	atheism	motion to topic
argument topic	We should end affirmative action	affirmative action	motion to topic
argument topic	We should prohibit women in combat	women in combat	motion to topic
argument topic	We should ban the Church of Scientology	the church of scientology	motion to topic
argument topic	We should legalize sex selection	sex selection	motion to topic
argument topic	We should prohibit school prayer	school prayer	motion to topic
argument topic	Entrapment should be legalized	entrapment legalized	motion to topic
argument topic	We should close Guantanamo Bay detention camp	guantanamo bay detention camp	motion to topic
argument topic	We should ban factory farming	factory farming	motion to topic
argument topic	We should end racial profiling	racial profiling	motion to topic

Table 10: Label cleaning.

<b>dataset</b>	<b>class name</b>	<b>rephrased class name</b>	<b>rephrased type</b>
argument topic	We should ban telemarketing	telemarketing	motion to topic
argument topic	Homeopathy brings more harm than good	homeopathy	motion to topic
argument topic	We should ban missionary work	missionary work	motion to topic
argument topic	We should cancel pride parades	cancel pride parades	motion to topic
argument topic	We should legalize polygamy	polygamy	motion to topic
argument topic	We should abolish safe spaces	safe spaces	motion to topic
argument topic	We should oppose collectivism	collectivism	motion to topic
argument topic	We should fight urbanization	fight urbanization	motion to topic
argument topic	We should ban fast food	fast food	motion to topic
argument topic	We should subsidize embryonic stem cell research	embryonic stem cell research	motion to topic
argument topic	We should subsidize space exploration	space exploration	motion to topic
argument topic	We should end the use of economic sanctions	the use of economic sanctions	motion to topic
argument topic	We should abolish the Olympic Games	the olympic games	motion to topic
argument topic	We should subsidize journalism	journalism	motion to topic
clinc150	translate	translation	grammatical
clinc150	meaning_of_life	meaning of life	cleaning
clinc150	insurance_change	insurance change	cleaning
clinc150	find_phone	finding a phone	grammatical
clinc150	travel_alert	travel alert	cleaning
clinc150	pto_request	pto request	cleaning
clinc150	improve_credit_score	improving credit score	grammatical
clinc150	fun_fact	a fun fact	grammatical
clinc150	change_language	changing language	grammatical
clinc150	replacement_card_duration	replacement card duration	cleaning
clinc150	application_status	application status	cleaning

Table 11: Label cleaning.

<b>dataset</b>	<b>class name</b>	<b>rephrased class name</b>	<b>rephrased type</b>
clinc150	flight_status	flight status	cleaning
clinc150	flip_coin	flipping a coin	grammatical
clinc150	change_user_name	changing user name	grammatical
clinc150	where_are_you_from	where you are from	grammatical
clinc150	shopping_list_update	shopping list update	cleaning
clinc150	what_can_i_ask_you	what i can ask you	grammatical
clinc150	maybe	not being sure	grammatical
clinc150	oil_change_how	how to change oil	grammatical
clinc150	restaurant_reservation	restaurant reservation	cleaning
clinc150	confirm_reservation	confirming reservation	grammatical
clinc150	freeze_account	freezing account	grammatical
clinc150	rollover_401k	rollover 401k	cleaning
clinc150	who_made_you	who made you	cleaning
clinc150	user_name	user name	cleaning
clinc150	next_song	next song	cleaning
clinc150	restaurant_suggestion	a restaurant suggestion	grammatical
clinc150	rewards_balance	rewards balance	cleaning
clinc150	pay_bill	paying a bill	grammatical
clinc150	spending_history	spending history	cleaning
clinc150	pto_request_status	pto request status	cleaning
clinc150	credit_score	credit score	cleaning
clinc150	new_card	new card	cleaning
clinc150	lost_luggage	lost luggage	cleaning
clinc150	oil_change_when	when to change oil	grammatical
clinc150	yes	assertion	grammatical
clinc150	travel_suggestion	travel suggestion	cleaning
clinc150	todo_list_update	todo list update	cleaning
clinc150	change_speed	changing speed	grammatical
clinc150	tire_pressure	tire pressure	cleaning
clinc150	no	negation	grammatical
clinc150	nutrition_info	nutrition info	cleaning
clinc150	carry_on	carry ons	grammatical
clinc150	pto_used	pto used	cleaning
clinc150	schedule_maintenance	scheduling maintenance	grammatical
clinc150	travel_notification	travel notification	cleaning
clinc150	sync_device	sync device	cleaning
clinc150	thank_you	thank you	cleaning
clinc150	roll_dice	roll dice	cleaning
clinc150	food_last	food expiration	grammatical
clinc150	cook_time	cook time	cleaning
clinc150	reminder_update	reminder update	cleaning
clinc150	report_lost_card	reporting a lost card	grammatical

Table 12: Label cleaning.

<b>dataset</b>	<b>class name</b>	<b>rephrased class name</b>	<b>rephrased type</b>
clinc150	ingredient_substitution	ingredient substitution	cleaning
clinc150	make_call	making a call	grammatical
clinc150	todo_list	todo list	cleaning
clinc150	change_accent	changing an accent	grammatical
clinc150	bill_due	bill due	cleaning
clinc150	damaged_card	damaged card	cleaning
clinc150	restaurant_reviews	restaurant reviews	cleaning
clinc150	do_you_have_pets	a question about your pets	grammatical
clinc150	schedule_meeting	scheduling a meeting	grammatical
clinc150	gas_type	gas type	cleaning
clinc150	plug_type	plug type	cleaning
clinc150	tire_change	tire change	cleaning
clinc150	exchange_rate	exchange rate	cleaning
clinc150	next_holiday	next holiday	cleaning
clinc150	change_volume	changing volume	grammatical
clinc150	who_do_you_work_for	whom do you work for	grammatical
clinc150	credit_limit	credit limit	cleaning
clinc150	how_busy	waiting time	grammatical
clinc150	accept_reservations	accepting reservations	grammatical
clinc150	order_status	order status	cleaning
clinc150	pin_change	pin change	cleaning
clinc150	account_blocked	account blocked	cleaning
clinc150	what_song	what song	cleaning
clinc150	international_fees	international fees	cleaning
clinc150	last_maintenance	last maintenance	cleaning
clinc150	meeting_schedule	meeting schedule	cleaning
clinc150	ingredients_list	ingredients list	cleaning
clinc150	report_fraud	reporting fraud	grammatical
clinc150	measurement_conversion	measurement conversion	cleaning
clinc150	smart_home	smart home	cleaning
clinc150	book_hotel	booking a hotel	grammatical
clinc150	current_location	current location	cleaning
clinc150	min_payment	min payment	cleaning
clinc150	whisper_mode	whisper mode	cleaning
clinc150	canceling	cancel	grammatical
clinc150	international_visa	international visa	cleaning
clinc150	pto_balance	pto balance	cleaning
clinc150	reset_settings	reset settings	cleaning
clinc150	what_is_your_name	what your name is	grammatical
clinc150	direct_deposit	direct deposit	cleaning
clinc150	interest_rate	interest rate	cleaning
clinc150	credit_limit_change	credit limit change	cleaning
clinc150	what_are_your_hobbies	what your hobbies are	grammatical

Table 13: Label cleaning.



<b>dataset</b>	<b>class name</b>	<b>rephrased class name</b>	<b>rephrased type</b>
clinc150	book_flight	booking a flight	grammatical
clinc150	shopping_list	shopping list	cleaning
clinc150	bill_balance	bill balance	cleaning
clinc150	share_location	sharing location	grammatical
clinc150	redeem_rewards	redeem rewards	cleaning
clinc150	play_music	asking to play music	grammatical
clinc150	calendar_update	calendar update	cleaning
clinc150	are_you_a_bot	asking if you are a bot	grammatical
clinc150	expiration_date	expiration date	cleaning
clinc150	update_playlist	updating playlist	grammatical
clinc150	cancel_reservation	canceling reservation	grammatical
clinc150	tell_joke	telling a joke	grammatical
clinc150	change_ai_name	changing ai name	grammatical
clinc150	how_old_are_you	how old you are	grammatical
clinc150	car_rental	car rental	cleaning
clinc150	jump_start	jump start	cleaning
clinc150	meal_suggestion	meal suggestion	cleaning
clinc150	order_checks	ordering checks	grammatical
clinc150	card_declined	a declined card	grammatical
cuad	Filename		deletion
cuad	Document Name		deletion
cuad	Document Name-Answer		deletion
cuad	Parties		deletion
cuad	Parties-Answer		deletion
cuad	Agreement Date		deletion
cuad	Agreement Date-Answer		deletion
cuad	Effective Date		deletion
cuad	Effective Date-Answer		deletion
cuad	Expiration Date-Answer		deletion
cuad	Renewal Term-Answer		deletion
cuad	Notice Period To Terminate Renewal- Answer		deletion
cuad	Governing Law-Answer		deletion
cuad	Most Favored Nation- Answer		deletion
cuad	Competitive Restriction Exception-Answer		deletion
cuad	Non-Compete-Answer		deletion
cuad	Exclusivity-Answer		deletion
cuad	No-Solicit Of Customers- Answer		deletion
cuad	No-Solicit Of Employees- Answer		deletion
cuad	Non-Disparagement- Answer		deletion
cuad	Termination For Convenience-Answer		deletion

Table 14: Label cleaning.

<b>dataset</b>	<b>class name</b>	<b>rephrased class name</b>	<b>rephrased type</b>
cuad	Rofr/Rofo/Rofn-Answer		deletion
cuad	Change Of Control-Answer		deletion
cuad	Anti-Assignment-Answer		deletion
cuad	Revenue/Profit Sharing-Answer		deletion
cuad	Price Restrictions-Answer		deletion
cuad	Minimum Commitment-Answer		deletion
cuad	Volume Restriction-Answer		deletion
cuad	Ip Ownership Assignment-Answer		deletion
cuad	Joint Ip Ownership-Answer		deletion
cuad	License Grant-Answer		deletion
cuad	Non-Transferable License-Answer		deletion
cuad	Affiliate License-Licensor-Answer		deletion
cuad	Affiliate License-Licensee-Answer		deletion
cuad	Unlimited/All-You-Can-Eat-License-Answer		deletion
cuad	Irrevocable Or Perpetual License-Answer		deletion
cuad	Source Code Escrow-Answer		deletion
cuad	Post-Termination Services-Answer		deletion
cuad	Audit Rights-Answer		deletion
cuad	Uncapped Liability-Answer		deletion
cuad	Cap On Liability-Answer		deletion

Table 15: Label cleaning.

<b>dataset</b>	<b>class name</b>	<b>rephrased class name</b>	<b>rephrased type</b>
cuad	Liquidated Damages-Answer		deletion
cuad	Warranty Duration-Answer		deletion
cuad	Insurance-Answer		deletion
cuad	Covenant Not To Sue-Answer		deletion
cuad	Third Party Beneficiary-Answer		deletion
20 newsgroup	alt atheism	atheism	readability
20 newsgroup	comp graphics	computer graphics	readability
20 newsgroup	comp os ms-windows misc	microsoft windows	readability
20 newsgroup	comp sys ibm pc hardware	pc hardware	readability
20 newsgroup	comp sys mac hardware	mac hardware	readability
20 newsgroup	comp windows x	windows x	readability
20 newsgroup	misc forsale	for sale	readability
20 newsgroup	rec autos	cars	readability
20 newsgroup	rec motorcycles	motorcycles	readability
20 newsgroup	rec sport baseball	baseball	readability
20 newsgroup	rec sport hockey	hockey	readability
20 newsgroup	sci crypt	cryptography	readability
20 newsgroup	sci electronics	electronics	readability
20 newsgroup	sci med	medicine	readability
20 newsgroup	sci space	space	readability
20 newsgroup	soc religion christian	christianity	readability
20 newsgroup	talk politics guns	guns	readability
20 newsgroup	talk politics mideast	middle east	readability
20 newsgroup	talk politics misc	politics	readability
20 newsgroup	talk religion misc	religion	readability
banking77	activate my card	activating my card	grammatical
banking77	age limit	age limit	cleaning
banking77	apple pay or google pay	apple pay or google pay	cleaning
banking77	atm support	atm support	cleaning
banking77	automatic top up	automatic top up	cleaning
banking77	balance not updated after bank transfer	balance that has not been updated after a bank transfer	grammatical
banking77	balance not updated after cheque or cash deposit	balance that has not been updated after cheque or cash deposit	grammatical

Table 16: Label cleaning.

<b>dataset</b>	<b>class name</b>	<b>rephrased class name</b>	<b>rephrased type</b>
banking77	beneficiary not allowed	a beneficiary who is not allowed	grammatical
banking77	cancel transfer	canceling a transfer	grammatical
banking77	card about to expire	a card that is about to expire	grammatical
banking77	card acceptance	card acceptance	cleaning
banking77	card arrival	card arrival	cleaning
banking77	card delivery estimate	card delivery estimation	grammatical
banking77	card linking	card linking	cleaning
banking77	card not working	card not working	cleaning
banking77	card payment fee charged	a card payment fee that was charged	grammatical
banking77	card payment not recognised	card payment not recognised	cleaning
banking77	card payment wrong exchange rate	card payment wrong exchange rate	cleaning
banking77	card swallowed	card swallowed	cleaning
banking77	cash withdrawal charge	cash withdrawal charge	cleaning
banking77	cash withdrawal not recognised	cash withdrawal not recognised	cleaning
banking77	change pin	changing pin	grammatical
banking77	compromised card	compromised card	cleaning
banking77	contactless not working	contactless not working	cleaning
banking77	country support	country support	cleaning
banking77	declined card payment	declined card payment	cleaning
banking77	declined cash withdrawal	a declined cash withdrawal	grammatical
banking77	declined transfer	declined transfer	cleaning
banking77	direct debit payment not recognised	direct debit payment not recognised	cleaning
banking77	disposable card limits	disposable card limits	cleaning
banking77	edit personal details	editing personal details	grammatical
banking77	exchange charge	exchange charge	cleaning
banking77	exchange rate	exchange rate	cleaning
banking77	exchange via app	exchange via app	cleaning
banking77	extra charge on statement	extra charge on statement	cleaning
banking77	failed transfer	failed transfer	cleaning
banking77	fiat currency support	fiat currency support	cleaning
banking77	get disposable virtual card	getting disposable virtual card	grammatical
banking77	get physical card	getting physical card	grammatical
banking77	getting spare card	getting spare card	cleaning
banking77	getting virtual card	getting virtual card	cleaning
banking77	lost or stolen card	lost or stolen card	cleaning
banking77	lost or stolen phone	lost or stolen phone	cleaning

Table 17: Label cleaning.

<b>dataset</b>	<b>class name</b>	<b>rephrased class name</b>	<b>rephrased type</b>
banking77	order physical card	ordering physical card	grammatical
banking77	passcode forgotten	forgotten passcode	grammatical
banking77	pending card payment	pending card payment	cleaning
banking77	pending cash withdrawal	pending cash withdrawal	cleaning
banking77	pending top up	pending top up	cleaning
banking77	pending transfer	pending transfer	cleaning
banking77	pin blocked	blocked pin	grammatical
banking77	receiving money	receiving money	cleaning
banking77	Refund not showing up	refund not showing up	cleaning
banking77	request refund	refund request	grammatical
banking77	reverted card payment?	reverted card payment	grammatical
banking77	supported cards and currencies	supported cards and currencies	cleaning
banking77	terminate account	terminating account	grammatical
banking77	top up by bank transfer charge	top up by bank transfer charge	cleaning
banking77	top up by card charge	top up by card charge	cleaning
banking77	top up by cash or cheque	top up by cash or cheque	cleaning
banking77	top up failed	failed top up	grammatical
banking77	top up limits	top up limits	cleaning
banking77	top up reverted	top up reverted	cleaning
banking77	topping up by card	topping up by card	cleaning
banking77	transaction charged twice	transaction charged twice	cleaning
banking77	transfer fee charged	charged transfer fee	grammatical
banking77	transfer into account	transferring into account	grammatical
banking77	transfer not received by recipient	transfer not received by recipient	cleaning
banking77	transfer timing	transfer timing	cleaning
banking77	unable to verify identity	being unable to verify identity	grammatical
banking77	verify my identity	verifying my identity	grammatical
banking77	verify source of funds	verifying source of funds	grammatical
banking77	verify top up	verifying top up	grammatical

Table 18: Label cleaning.

<b>dataset</b>	<b>class name</b>	<b>rephrased class name</b>	<b>rephrased type</b>
banking77	virtual card not working	virtual card not working	cleaning
banking77	visa or mastercard	visa or mastercard	cleaning
banking77	why verify identity	why identity verification is necessary	grammatical
banking77	wrong amount of cash received	wrong amount of cash received	cleaning
banking77	wrong exchange rate for cash withdrawal	wrong exchange rate for cash withdrawal	cleaning
dbpedia	Artist	artist	lower case
dbpedia	Plant	plant	lower case
dbpedia	Album	album	lower case
dbpedia	Animal	animal	lower case
dbpedia	Mean-Of-Transportation	mean of transportation	readability
dbpedia	NaturalPlace	natural place	readability
dbpedia	Athlete	athlete	lower case
dbpedia	OfficeHolder	office holder	readability
dbpedia	Company	company	lower case
dbpedia	Film	film	lower case
dbpedia	Educational-Institution	educational institution	readability
dbpedia	WrittenWork	written work	readability
dbpedia	Building	building	lower case
dbpedia	Village	village	lower case
ledgar	general		deletion
law stack exchange	contract-law	contract law	cleaning
law stack exchange	constitutional-law	constitutional law	cleaning
law stack exchange	criminal-law	criminal law	cleaning
law stack exchange	tax-law	tax law	cleaning
law stack exchange	civil-law	civil law	cleaning
law stack exchange	intellectual-property	intellectual property	cleaning
massive	datetime query	getting date or time details	grammatical
massive	iot hue lightchange	changing hue light	grammatical
massive	transport ticket	getting a transport ticket	grammatical
massive	takeaway query	getting a takeaway	grammatical
massive	qa stock	stock	grammatical
massive	general greet	greeting	grammatical
massive	recommendation events	event recommendation	grammatical
massive	music dislikeness	music dislikeness	cleaning
massive	iot wemo off	turning off wemo	grammatical

Table 19: Label cleaning.

<b>dataset</b>	<b>class name</b>	<b>rephrased class name</b>	<b>rephrased type</b>
massive	cooking recipe	cooking recipes	grammatical
massive	qa currency	currency	grammatical
massive	transport traffic	transport traffic	cleaning
massive	general quirky	quirky issues	grammatical
massive	weather query	the weather	grammatical
massive	audio volume up	turning up the volume	grammatical
massive	email addcontact	adding email contact	grammatical
massive	takeaway order	a takeaway order	grammatical
massive	email querycontact	getting email contact	grammatical
massive	iot hue lightup	increasing hue light	grammatical
massive	recommendation locations	location recommendations	grammatical
massive	play audiobook	playing an audio book	grammatical
massive	lists createoradd	creating or adding lists	grammatical
massive	news query	the news	grammatical
massive	alarm query	getting alarm details	grammatical
massive	iot wemo on	turning wemo on	grammatical
massive	general joke	a joke	grammatical
massive	qa definition	definitions	grammatical
massive	social query	social media	grammatical
massive	music settings	music settings	cleaning
massive	audio volume other	audio volume	grammatical
massive	calendar remove	removing from calendar	grammatical
massive	iot hue lightdim	dimming hue light	grammatical
massive	calendar query	getting calendar details	grammatical
massive	email sendemail	sending en email	grammatical
massive	iot cleaning	cleaning	grammatical
massive	audio volume down	turning down volume	grammatical
massive	play radio	playing the radio	grammatical
massive	cooking query	cooking details	grammatical
massive	datetime convert	converting date or time	grammatical
massive	qa maths	math	grammatical
massive	iot hue lightoff	turning off hue light	grammatical
massive	iot hue lighton	turning on hue light	grammatical
massive	transport query	getting transport details	grammatical
massive	music likeness	music likeness	cleaning
massive	email query	getting email details	grammatical
massive	play music	playing music	grammatical
massive	audio volume mute	muting audio volume	grammatical
massive	social post	posting on social media	grammatical
massive	alarm set	setting an alarm	grammatical
massive	qa factoid	factoids	grammatical
massive	calendar set	setting the calendar	grammatical

Table 20: Label cleaning.



<b>dataset</b>	<b>class name</b>	<b>rephrased class name</b>	<b>rephrased type</b>
massive	play game	playing a game	grammatical
massive	alarm remove	removing an alarm	grammatical
massive	lists remove	removing from lists	grammatical
massive	transport taxi	transport taxi	cleaning
massive	recommendation movies	movie recommendations	grammatical
massive	iot coffee	making coffee	grammatical
massive	music query	getting music details	grammatical
massive	play podcasts	playing podcasts	grammatical
massive	lists query	getting lists details	grammatical
ag news	World	world	lower case
ag news	Sci/Tech	science and technology	readability
ag news	Sports	sports	lower case
ag news	Business	business	lower case
yahoo answers	Sports	sports	lower case
yahoo answers	Health	health	lower case
yahoo answers	Family & Relationships	family and relationships	readability
yahoo answers	Science & Mathematics	science and mathematics	readability
yahoo answers	Education & Reference	education and reference	readability
yahoo answers	Entertainment & Music	entertainment and music	readability
yahoo answers	Society & Culture	society and culture	readability
yahoo answers	Business & Finance	business and finance, "ô	readability
yahoo answers	Politics & Government	politics and government	readability
yahoo answers	Computers & Internet	computers and internet	readability
xglue	foodanddrink	food and drink	readability
sentivent	cs r/brand	brand	readability
reuters	pet-chem		deletion
reuters	income		deletion
reuters	strategic-metal		deletion
reuters	lei		deletion
reuters	rand		deletion
reuters	coconut-oil		deletion
reuters	nkr		deletion
reuters	oat		deletion
reuters	propane		deletion
reuters	saudriyal		deletion

Table 21: Label cleaning.

<b>dataset</b>	<b>class name</b>	<b>rephrased class name</b>	<b>rephrased type</b>
reuters	sorghum		deletion
reuters	tea		deletion
reuters	cotton-oil		deletion
reuters	nat-gas	nat gas	cleaning
reuters	fuel		deletion
reuters	citruspulp		deletion
reuters	nzdlr		deletion
reuters	stg		deletion
reuters	sun-meal		deletion
reuters	cruzado		deletion
reuters	dfl		deletion
reuters	castorseed		deletion
reuters	rice		deletion
reuters	corn gluten feed		deletion
reuters	cpi		deletion
reuters	meal-feed		deletion
reuters	gnp	gross national product	readability
reuters	ship	ships	readability
reuters	acq	acquisition	readability
reuters	barley		deletion
reuters	lin-oil		deletion
reuters	corn-oil		deletion
reuters	silver		deletion
reuters	soy-meal		deletion
reuters	tapioca		deletion
reuters	orange		deletion
reuters	plywood		deletion
reuters	lead		deletion
reuters	tin		deletion

Table 22: Label cleaning.

dataset	class name	rephrased class name	rephrased type
reuters	f-cattle	f cattle	cleaning
reuters	linseed		deletion
reuters	pork-belly		deletion
reuters	jobs		deletion
reuters	naphtha		deletion
reuters	rye		deletion
reuters	lumber		deletion
reuters	dkr		deletion
reuters	platinum		deletion
reuters	money-supply	money supply	cleaning
reuters	rape-meal		deletion
reuters	coconut		deletion
reuters	gas		deletion
reuters	heat		deletion
reuters	retail		deletion
reuters	ipi		deletion
reuters	ringgit		deletion
reuters	copra-cake		deletion
reuters	zinc		deletion
reuters	rapeseed		deletion
reuters	cpu		deletion
reuters	fishmeal		deletion
reuters	soy-oil		deletion
reuters	veg-oil	vegetable oil	readability
reuters	yen		deletion
reuters	carcass		deletion
reuters	lin-meal		deletion
reuters	red-bean		deletion
reuters	jet		deletion
reuters	wpi		deletion
reuters	castor-oil		deletion
reuters	copper		deletion
reuters	wool		deletion
reuters	cocoa		deletion
reuters	groundnut-oil		deletion
reuters	peseta		deletion
reuters	palm-oil		deletion
reuters	dmk		deletion
reuters	bop		deletion
reuters	l-cattle		deletion
reuters	instal-debt		deletion
reuters	iron-steel		deletion
reuters	reserves		deletion
reuters	rubber		deletion
reuters	rape-oil		deletion
reuters	housing		deletion
reuters	inventories		deletion
reuters	potato		deletion
reuters	hog		deletion
reuters	earn	earnings	readability
reuters	skr		deletion
reuters	sun-oil		deletion
reuters	palladium		deletion
reuters	sunseed		deletion
reuters	can		deletion
reuters	soybean		deletion
reuters	cotton		deletion
reuters	austldr		deletion
reuters	palmkernel		deletion
reuters	groundnut		deletion
reuters	alum		deletion
reuters	money-fx	money foreign exchange	readability
reuters	nickel		deletion

Table 23: Label cleaning.