Zero-shot Text Classification With Generative Language Models

Raul Puri
NVIDIA
raulp@nvidia.com

Bryan Catanzaro
NVIDIA
bcatanzaro@nvidia.com

Abstract

This work investigates the use of natural language to enable zero-shot model adaptation to new tasks. We use text and metadata from social commenting platforms as a source for a simple pretraining task. We then provide the language model with natural language descriptions of classification tasks as input and train it to generate the correct answer in natural language via a language modeling objective. This allows the model to generalize to new classification tasks without the need for multiple multitask classification heads. We show the zero-shot performance of these generative language models, trained with weak supervision, on six benchmark text classification datasets from the torchtext library. Despite no access to training data, we achieve up to a 45% absolute improvement in classification accuracy over random or majority class baselines. These results show that natural language can serve as simple and powerful descriptors for task adaptation. We believe this points the way to new metalearning strategies for text problems.

1 Method

Our method reformulates text classification problems as multiple choice question answering. To enable our model to generalize to new classification tasks, we provide the model with a multiple choice question description containing each class in natural language, and train it to generate the correct answer, also in natural language, from the provided description. To better prepare our model to handle a wide variety of class descriptors, we utilize a pretrained GPT-2 (Radford et al., 2019) transformer model and finetune it on the task of multiple choice title prediction for the OpenWebText dataset (Peterson et al., 2019). This pretraining task trains the model to use common sense reasoning to select the most probable title or description of the text data from a provided list of rich natural language descriptions or classes, similar to the problem formulation of text classification. The wide variety of titles available in the pretraining dataset help simulate numerous automatically generated N-way text classification tasks to enable meta-learning. In initial studies we found that the diverse language found in title prediction was necessary to adapt to new tasks, and other pretraining tasks such as WebText subreddit prediction did not transfer at all.

For a given document, we randomly sample a number of titles $t \in [2, 15]$ with one title being the correct title. Half of the time we replace a single title with “none of the above”, and occasionally ($p = 1/t$) we choose to replace the correct title with “none of the above”. We prepend all selected titles to the document in the form of a multiple choice question, and train the model to generate the answer, similar to generative Question Answering (McCann et al., 2018). Example input representations for title prediction can be found in Table 1.

The model is optimized by computing a next token prediction language modeling loss, $\sum_t \mathcal{L}(w_t, P(\hat{w}_t|w_{[1,t-1]}))$, that optimizes over the entire concatenated input $w = [question, reference\_text, output\_answer]$ and the questions are generated according to a grammar. The input representation utilizes type tokens to segment the question, reference text, and answer. To

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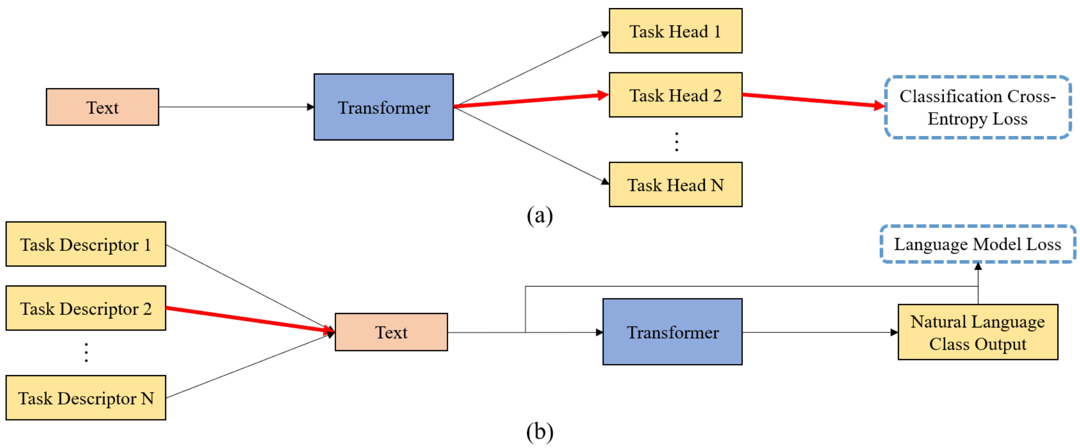

Figure 1: Comparison between existing multitask classifiers and our method. (a) Multitask classifiers have the model featurize text and send it to one of N task heads. (b) In our method, one of N task descriptors is prepended to the text and the model generates the answer in natural language.

Dataset	Question	Text	Answer
Title Prediction Pretraining	Which of these choices best describes the following document? : “ A pool For All Bodies ” , “ Lawmakers say they’d take pay cut, but they can’t ” , “ Raiders’ Gareon Conley faces civil suit ” , “ Prolific cybercriminal suspected of spreading ransomware arrested by Polish Police [Europol] ”	Story highlights Members of Congress also preparing for potential sharp cuts in federal spending\n\nBut lawmakers will not see any change to their annual salary of $174,000...	Lawmakers say they’d take pay cut, but they can’t
AGNews Zero-shot Classification	How is the text best described? : “ Science & Technology ” , “ Business ” , “ Sports ” , or “ World News ”	An Entertaining Holiday Pick \n Hastings, a multimedia retailer, trims losses and raises full-year guidance.	Business

Table 1: Example inputs for pretraining and downstream tasks. The descriptor questions are concatenated to the text samples and the language model generates the remaining output answer text. Class descriptors for the 5 other downstream classification tasks can be found in appendix A.4.1

encode positional information, the input uses learned positional embeddings that reset to position 0 at the start of the answer. This is described in more detail in the appendix section A.1.

For our analysis of zero shot classification we examine the performance of our model at various sizes on several of the torchtext classification datasets. When transferring the model we provide all the given dataset’s classes (typically ranging from 2-15 classes) to the model in the multiple choice question format and prompt it to generate out the correct class. Furthermore, we ensure that downstream tasks do not contain "none of the above" options. We use greedy autoregressive decoding to generate our output text. Example inputs for each of our downstream tasks are shown in Table 1.

1.1 Dataset

We build upon prior work collecting large language modeling datasets from the internet. Namely, we extend the OpenWebText corpus (Peterson et al., 2019) by annotating the documents with subreddits and titles in natural language. The OpenWebText dataset is collected by scraping outbound weblinks from reddit that have more than 3 karma score. We annotate each outbound weblink with the title of the Reddit post, and the subreddit that the link was posted in. Weblinks can appear in multiple posts across different subreddits, so for a given link we aggregate a list of all it’s related subreddits and titles. Detailed dataset statistics can be found in appendix section A.3. To create training data we sample a random document, multiple titles including one of the documents corresponding titles, and arrange the input as described in the previous section. We evaluate the trained model on the DBPedia, AGNews, Yahoo Answers, SST-2, Amazon-2, and Yelp-2 text classification datasets (Socher et al., 2013; Lehmann et al., 2015). The classes and class descriptors used for each of these tasks can be found in appendix section A.4.1. To experiment with different class descriptions and model architectures, we create a small validation set of 2000 random training set examples for each of the downstream tasks. We evaluate our design choices on these validation sets before reporting final accuracies on the entire test set.

2 Related Work

Zero and few shot learning have been the subject of many studies. Some works have looked at meta-learning for machine translation in low resource languages (Gu et al., 2018), iteratively guiding policies with language (Co-Reyes et al., 2018) for instruction following (Branavan et al., 2009; Chen and Mooney, 2011), and generating WikiSQL-style structured queries from natural language queries (Huang et al., 2018). Radford et al. (2018, 2019) show that large scale language models can be used in a multitask zero shot capacity by allowing the model to generate output text in an autoregressive manner given a prompt with the task description. They demonstrate that larger transformer language models perform better than smaller models in zero shot settings. However, their models are never explicitly trained for zero shot text classification. To perform classification, the authors propose appending a prompt token to the text and restricting the output vocabulary to the tokens of possible answers. This effectively turns the output vocabulary into a pretrained task-specific classification head. Unlike our approach their work requires manual intervention and does not take advantage of task descriptors to modulate output behavior. The Multitask Question Answering Network (McCann et al., 2018) study also investigates zero shot performance of multitask generative language models prompted with descriptor questions. However, they only analyze zero shot classification performance between tasks of identical domains (SST-2 and Amazon-2) that are trained with supervised learning and identical prompts. Using identical prompts and supervised learning prevents a true analysis of the model's ability to adapt to unseen task descriptors.

Recent work in meta-learning has centered around gradient based meta learning strategies such as Model Agnostic Meta-Learning or MAML (Finn et al., 2017). However, parallel work such as Memory Augmented Neural Networks (Santoro et al., 2016) and Simple Neural Attentive Learners (Mishra et al., 2017) demonstrate the effectiveness of architecture based meta-learning. This is similar to our work except that our models receive weak supervision in the form of class labels and a question in natural language instead of similar class examples. We show throughout this work that melding techniques from NLP and architecture based meta-learning allows our model to adapt to new language classification tasks.

Lastly, similar to our work, concurrent research investigates models capable of handling tasks with different class counts and output mappings. Bansal et al. (2019) combine prototypical networks and MAML to adapt to NLP tasks with different numbers of labels. Raffel et al. (2019) propose a unified multitask language model that uses weakly-supervised task labels to generate task outputs with natural language. By doing so, the resulting model is capable of performing a diverse set of tasks including classification, natural language inference, question answering, and abstractive summarization. Furthermore, the authors demonstrate the viability of this approach by scaling the model to 11 billion parameters and achieving state of the art accuracy. However, neither of these works examine the ability of a unified model to adapt to new task descriptors in a zero-shot fashion.

3 Results

To test the ability of our pretrained models to adapt to new tasks and tasks descriptions, we transfer the models to 6 classification tasks. We provide three baselines the first two of which are designed to expose dataset bias: random guessing, majority class (mode of the training dataset), and directly finetuning a 355 million parameter classification model on the downstream tasks. In our experiments we investigate the effect of two components of the pretraining process on downstream task performance: model scale and data scale. Table 2 shows that increasing model size leads to improved performance on downstream tasks. In some scenarios smaller models are barely able to perform better

Model	SST-2	AGNews	DBPedia	Yahoo	Amazon-2	Yelp-2	Average
Random Guess˜	50.6	27.4	7.27	10.2	52.9	50.4	33.1
Majority Class˜	49.9	25.3	7.6	9.9	49.3	49.2	31.9
117M All Data	51.8 / 0	40.2 / .00	39.6 / .25	26.1 / .97	50.3 / .001	50.1 / 0	43.0 / .202
355M 1/4 Data	61.7 / 0	**68.3 / .51**	**52.5 / .03**	**52.2 / .64**	64.5 / .001	58.5 / 0	59.6 / .197
355M All Data	**62.5 / 0**	65.5 / .01	44.8 / .62	49.5 / .30	**80.2 / 0**	**74.7 / 0**	**62.9 / .176**
355M Finetuned˜	93.23	94.87	99.0	72.79	97.115	94.479	91.91
SOTA	96.8*	95.51*	99.38*	76.26**	97.6*	98.45*	94

Table 2: Zero shot transfer results. Seperated by a slash, each column contains test accuracies and (when applicable) the percentage of out of vocabulary test answers. Provided baseline models include random guessing˜, majority class˜, and finetuning˜ baselines. State of the art results held by *XLNet (Yang et al., 2019) and **DRNN (Wang, 2018).

than random. For DBPedia the 355M GPT-2 model leads to a 45.2% absolute accuracy improvement over random. In tasks with several classes such as DBPedia, AGnews, and Yahoo Answers the model performs noticeably better than random; however, they struggle to break past 50% and no task comes close to achieving either finetuned or SOTA accuracies. Contextualizing these results with the results of the binary classification tasks like SST-2, Amazon-2, and Yelp-2 we hypothesize that the model can narrow down unlikely classes, but struggles to choose between the two most plausible options due to its lack of formal supervision.

These results also show that restricting the size of the dataset and available document-title pairs leads to a reduction in overall task performance averaged across all tasks. This highlights the need for pretraining across a diverse set of tasks and language. Table 2 demonstrates that the robustness of our generative model is also similarly dictated by model and pretraining dataset size. Although rare across all pretrained models, the out of distribution answers (generated answers that are not valid classes) diminish with larger pretrained models and data. The most common out of vocab answer is an empty string where the model decides to immediately predict the end of text token. Other out of vocab answers are typically rearrangements of valid answer tokens. These are rare with greedy decoding, but become more frequent when using other sampling methods such as top-k (Fan et al., 2018) or top-p nucleus sampling (Holtzman et al., 2019). In the case of Yahoo Answers the model can combine two categories such as "Education & Reference" with "Science & Mathematics" to output "Education & Mathematics". We perform further studies examining the relationship between question descriptions, tokenization, accuracy, and out of vocabulary answers in appendix section A.4.2. These studies showcase the model's ability to adapt to different descriptions, but expose issues with controllability. Nevertheless, with this model the practitioner's burden is shifted away from designing effective zero-shot multitask architectures, to data problem design.

4 Conclusion and Future Work

In this work, we present a novel pretraining method for zero shot language classification through a generative language model classifier. By generating classifications through natural language, the model eliminates the need for multiple task-specific classification heads, making the model far more general and flexible. Increasing model and data scale further demonstrates that the capabilities of recent transformer language models are sufficient to extract meaningful feature representations that allow us to better generalize and adapt to new tasks. These results highlight the potential of natural language as learning and adaptation signals in future applications.

Currently this work is employed for zero-shot classification. Future extensions should investigate the ability of gradient based metalearning to adapt to task descriptors, either through K-shot support-based learning or by taking gradient steps on the task descriptors themselves as in Metz et al. (2018). Additionally, future work could extend the text classification task to other language problems such as question answer or instruction following. Applying this technique in other settings will require addressing its current limitations with respect to controllability, available data and task diversity.

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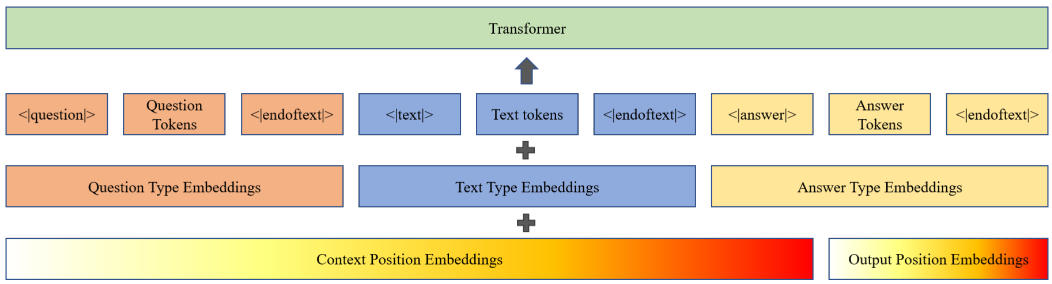
A Appendix

A.1 Input Representation and Training Details

A.1.1 Input Tokens



To form the input representation, the question, text, and answer tokens are concatenated together. Each set of tokens has a <|endoftext|> token appended to the end, and has a special prompt token prepended to the set. The special tokens for the three fields are respectively <|question|>, <|text|>, and <|answer|>. In addition to prompt tokens, each segment of the input also has unique type token embeddings added. There are three different type tokens total, one for each segment of the input. Lastly, to encode positional information in our input representation we utilize two sets of position embeddings. One range of position ids up to and including the <|answer|> prompt token, and another set of ids starting from 0 at the beginning of the answer tokens. These ranges are depicted by the colored gradient in the figure above. This helps the transformer distinguish between the context and the generated output.

A.1.2 Multiple Choice Format

We maintain a list of approximately 25 multiple choice question formats as shown below. At training and evaluation time we randomly sample a question format and fill the brackets with the desired classes. We format the classes as a comma separated list with double quotation marks to help segment the answers from the rest of the question text. We ensure that spaces are put between the answers and the quotation marks to avoid any unwanted byte pair merges: “ `class1` ” , “ `class2` ” , or “ `class3` ”. Examples of this formatting can be seen in Table 1.

- To which category does the following document belong? : {}
- To which category does the following text belong? : {}
- To which category does the text belong? : {}
- To which category does the article belong? : {}
- How would you describe the following document? : as {}
- How would you describe the text? : as {}
- How would you describe the following text? : as {}
- Which best describes the text? : {}
- Which best describes the document? : {}
- Which best describes the following document? : {}
- Which best describes the following text? : {}
- The following document is _ ? : {}
- The following text is _ ? : {}
- The text is _ ? : {}
- The document is _ ? : {}
- How is the text best described? : {}
- How is the document best described? : {}

- How is the following text best described? : {}
- How is the following document best described? : {}
- Which of these choices best describes the text? : {}
- Which of these options best describes the text? : {}
- Which of these choices best describes the document? : {}
- Which of these options best describes the document? : {}
- Which of these categories best describes the following document? : {}
- Which of these choices best describes the following document? : {}
- Which of these options best describes the following text? : {}

A.2 Training Hyperparameters

To train our model we follow a procedure largely based on the training procedures described in Radford et al. (2019) with a few differences. All training is performed with a maximum sequence length of 512 tokens. In the full dataset training setting we utilize a learning rate of 4×10^{-5} and a batch size of 128. When training with a quarter of the dataset we then used a learning rate of 3×10^{-5} and a batch size of 32. Our learning rate has a warmup period over 1% of the total training iterations before decaying according to a single cycle cosine decay schedule over 10 epochs. We utilize an Adam optimizer (Kingma and Ba, 2014) with decoupled weight decay (Loshchilov and Hutter, 2019) $\lambda = 0.01$. All our models are trained efficiently on V100 GPUs by utilizing mixed precision training with dynamic loss scaling (Micikevicius et al., 2017). Additionally, we use global gradient norm clipping of 1.0 to improve the stability of training large models. Lastly, we utilize attention and hidden state dropout (Srivastava et al., 2014) values of 0.1.

A.3 Training Data Statistics

We provide class frequency statistics shown below to highlight the diversity of the dataset used for pretraining.

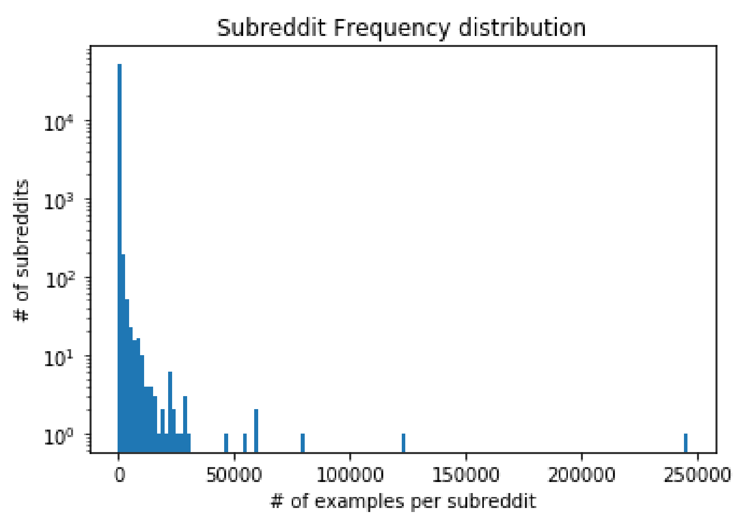


Figure 2: Subreddit Class Distribution. The number of times a subreddit occurs (frequency) is presented on the x-axis. The y-axis corresponds to the number of subreddits that appear at a certain frequency.

The data is distributed according to a power law distribution clustered around <1000 samples per subreddit, with a long tail reaching up to 245000 samples for a given subreddit. Zooming into the distribution (shown below) we find that there are approximately 9400 subreddits with 20 or more samples out of 50700 subreddit. Out of the 9400 subreddit two thirds have fewer than 100 samples. This level of diversity is ideal for a meta learning or domain adaptation dataset.

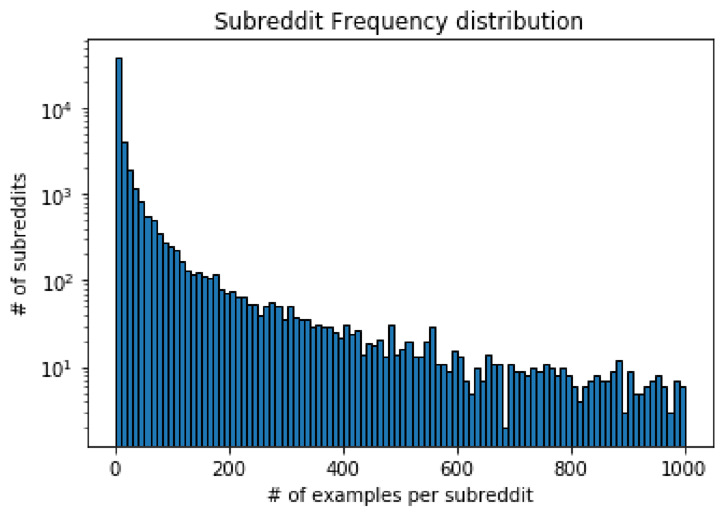


Figure 3: Enlarged Subreddit Class Distribution.

Lastly we show the most common subreddits along with their subreddit frequency in Table A.3. We find that half of the top fifteen subreddits are politically related. This skew may lead to possible biases in the training process. A plausible explanation for this bias can be found in the way the dataset is collected. Since we heuristically filter for reputable outbound links it is likely that we choose subreddits where people post outside news.

Subreddit	Frequency
r/politics	245308
r/worldnews	122884
r/The_Donald	80042
r/todayilearned	59892
r/news	59166
r/technology	54860
r/science	46452
r/Conservative	30823
r/POLITIC	28310
r/conspiracy	28293
r/india	27892
r/environment	26816
r/atheism	25999
r/programming	24020
r/Libertarian	23711

Table 3: Subreddit Frequency.

A.4 Downstream Task Setup

A.4.1 Class Descriptors

Listed below are the class descriptions used for each classification task.

Dataset	Classes
SST-2	Positive Sentiment, Negative Sentiment
AGNews	Science & Technology, Business, Sports , World News
DBPedia	Company, Mean Of Transportation, Film, Office Holder, Written Work, Animal, Natural Place, Artist, Plant, Athlete, Album, Building, Village, Educational Institution
Yahoo Answers	Family & Relationships, Business & Finance, Health, Society & Culture, Education & Reference, Entertainment & Music, Science & Mathematics, Computers & Internet, Sports, Politics & Government
Yelp-2	Positive polarity, Negative polarity
Amazon-2	Positive polarity, Negative polarity

A.4.2 Descriptor Selection

The ability of our model to adapt to new tasks and its behavior for a given input is controlled by the input descriptor questions it receives. In this section we investigate the impact that question formulation has on downstream task performance. Specifically, we modify the provided class descriptions for several tasks and observe the effects this has on the 355 million parameter model's downstream task performance:

- For binary classification tasks like SST-2, Amazon-2, Yelp-2 we move away from `Positive Sentiment` and `Negative Sentiment`, or `Positive polarity` and `Negative polarity`. Instead we simply use `positive` and `negative` as in McCann et al. (2018).
- For DBPedia we revert to the original class descriptions provided by the dataset and remove all whitespace (eg. `Mean Of Transportation` becomes `MeanOfTransportation`).
- For AGNews we also revert to the original class descriptions and change `World News` to `World` and `Science & Technology` to `Sci/Tech`.

Table A.4.2 shows that the choice of class description has a significant impact on performance. In the worst case poor class descriptions can lead to an absolute 27% drop in accuracy and 44% increase in out of vocabulary answers. In the cases of binary classification tasks and AGNews we hypothesize performance is negatively impacted by incomplete task descriptions: `positive` and `World` do not explicitly convey positive sentiment or World News. Empirical observations in Figure 4 show that the model either selects plausibly overlapping categories in the case of AGNews, or responds with a completely out of vocabulary answer as in the case of sentiment analysis. For DBPedia and AGNews, concatenating words together drastically changes the resulting bytepair tokenization despite the descriptions still being human readable. This changes the semantic understanding that the model receives and as a result the model completely avoids selecting it. In some cases the model may not have ever trained the subword embeddings corresponding to those tokens. This section highlights that our language modeling technique, while general, is subject to errors arising from problem formulation and requires careful control to craft questions that elicit desired effects. Remedying these issues will be a goal of future work.

Descriptor Set	SST-2	AGNews	DBPedia	Amazon-2	Yelp-2
Good Descriptors	63.22 / 0	69.04 / .478	53.85 / .056	81.22 / .056	74.35 / 0
Bad Descriptors	35.91 / 44.3	62.61 / 0	44.99 / .050	64.3 / 22.1	68.02 / 23.4

Table 4: Validation Set Accuracy/Out of Vocabulary Answer Percentages. We compare performance on the validation set with two different sets of descriptors: one deemed good and one deemed bad. We showcase the importance of selecting appropriate descriptors for a task.

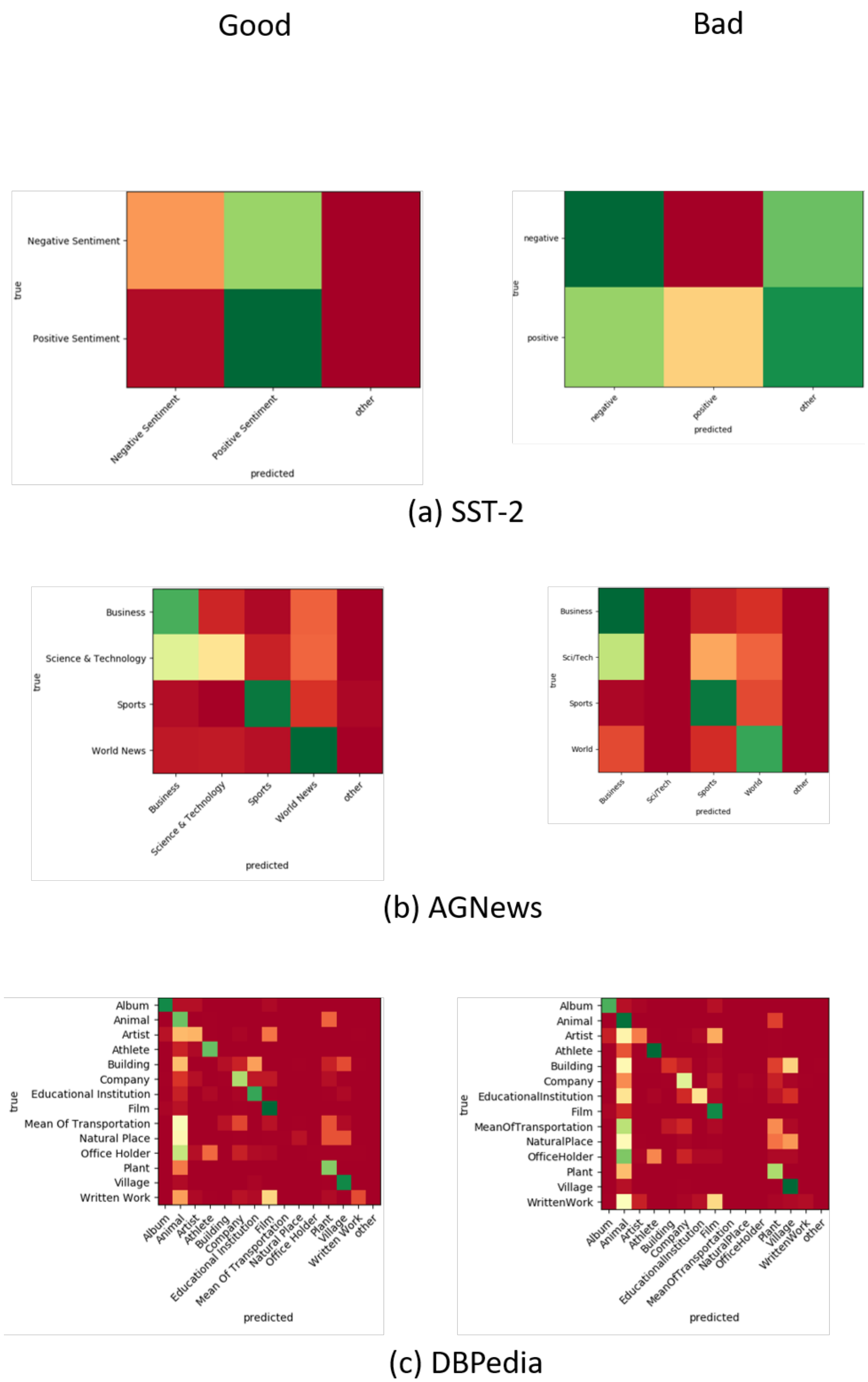


Figure 4: Confusion matrices for several classification tasks. The left column corresponds to the first row in Table A.4.2, and the right column corresponds to the second row. The color represents the prediction frequency with green being the highest, red the lowest, and yellow in the middle.