Comparative Analysis of Multiclass Text Classification: A Study on the Performance of Zero-Shot Classification vs. Supervised Learning

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Abstract

This research delves into an extensive examination of supervised learning and zero-shot classification within multiclass text classification, aiming to discern their distinct attributes, limitations, and pioneering methodologies in the realm of machine learning. Employing a methodical framework, the study's principal objective revolves around in-depth scrutiny and comparative assessment of supervised learning vis-à-vis zero-shot classification techniques for multiclass text categorisation. The aim is to elucidate their competencies, constraints, and potential ramifications in practical applications. This study rigorously evaluates the dependence of supervised learning on labelled datasets in contrast to the innovative predictive capabilities of zero-shot classification without specific training through meticulous experimentation and comparative analysis. This evaluation employs a range of performance metrics, alongside leveraging the pioneering concept of self-training proposed by Gera et al., to conduct a comprehensive analysis. The empirical findings distinctly highlight the superior accuracy of supervised learning, specifically Logistic Regression, in comparison to zero-shot classification for the categorization of news articles. Notably, the introduction of Gera et al.'s self-training approach within the realm of zero-shot learning demonstrates a promising avenue for enhancing accuracy within this domain. This research significantly contributes to the burgeoning landscape of machine learning methodologies, emphasizing the structured nature and reliability of supervised learning while concurrently showcasing the potential of innovative strategies like self-training within zero-shot classification. These findings underscore the importance of structured approaches in supervised learning, while also emphasizing the potential of inventive methodologies in zero-shot classification to bolster accuracy and adaptability, not solely in text classification but also analogous tasks across various domains.

Keywords: Supervised Learning, Zero-Shot Classification, Multiclass Text Classification, Machine Learning Paradigms, Comparative Analysis, Self-Training, Logistic Regression, Performance Metrics, Natural Language Processing, Data Labeling

I. INTRODUCTION

Over the years, we have been prominent witnesses to the remarkable advancements covered within the realms of machine learning. The research in this field continues to prevail as new algorithms are being developed and computer scientists constantly migrate to more efficient and accurate models to produce high-quality results. This migration, however, does not leave behind the previous structures adopted which set a proper foundation for new developments and serve as a starting point for new developers. Two particularly useful learning methods for model development are supervised learning and zero-shot learning which are widely adopted when implementing machine learning frameworks across multiple disciplines.

Supervised learning is a much more popular learning style and is adopted more as it learns from labeled data. It has shown tremendous success in various applications from its predictions based on custom-labelled and finetuned models. However, acquiring labels for a large amount of data and targets such as the vast example of big data use cases does bring up worthy debates regarding comparison against other learning methods with issues of it being costly and impractical.

Zero-shot learning aims to analyze patterns and generate accurate models without direct training or manufactured labels. It may bridge the learning gap without supervised labels, but challenges persist in the semantic gap between seen and unseen data and its robustness in real-world use cases.

Both learning methodologies possess a high reputation and considerable promise in the world of machine learning, but there is still enough to analyze between within their approaches, limitations and real-world implications to fully assess their comparative nature. Our main objective was to explore this comparative nature with a suitable use case and make useful deductions on the outcome of the learning methods. After diving deep into their performance in a scenario regarding text classifications and natural language samples, this study allowed us to give make suitable deductions on where the strengths of each methodology lie, and which use cases they would be most fit for adoption.

The structure of this paper is as follows: Section 2 summarizes the inferences we've drawn after constructive review of closely related literary works and journals. Section 3 follows with the importance of this study, our motivation to take up such a case and what impact it could have. Section 4 takes us into the methodology and techniques used during our analysis and outlines a standard machine learning workflow. Section 5 summarizes the outcome of our findings and links to explanatory tables and statistics. Sections 6 and 7 reveal the limitations during the study and how we overcame these constraints accordingly. Section 8 rounds up our research in a comprehensive summary with Section 9 recognizing the factors and resources that supported this study. Finally, Sections 10 and 11 list our sources, references and supplementary materials that expand on our paper's content.

II. RELATED WORK

We reviewed various literary works relating to supervised learning and zero-shot learning as benchmarks and important sources in various aspects of our work. Key factors that facilitate the foundation of our research are emphasized in papers produced by Akritidis & Bozanis (2013), Xian et al. (2017) and Gera et al. (2022).

Supervised learning methods were duly investigated by Akritidis and Bozanis, especially with a focus on classification in research articles. Their work involved creating supervised models which classified research articles based on their subject or discipline which is almost identical to our use case methodology in our research problem as it involves natural language inference. They considered a big dataset while incorporating more target values which they deemed to be of greater influence during the model formation. They were able to conclude on a robust model boasting over 90% accuracy which would be useful in the industry. An evaluation on this learning method in relative comparison with other methods for standard adoption is the discourse of our research.

Gera et al., however, took up the scope of zero-shot learning with a great belief in its movement levelling the quality of supervised learning methods. They surely are right about labels being obstacles, especially in large datasets but finding the avoidance of producing substandard models is what matters most. They emphasized the use of self-training methods being adopted by the zero-shot models to bridge the gap in effectiveness with supervised learning. Considering this adaptation in our study can help increase the level of learning we are comparing while also finding ways to tackle current limitations. This would support the movement to have a large general model which has been a prominent goal for the community.

Xian et al. expanded on zero-shot learning by analyzing the pros and cons of its methods, assessing the evaluation protocols, and eliminating the extreme concerns. They concluded on the relative performances of state-of-the-art zero shot learning methods for a comprehensive comparison. Several tests on numerous datasets of varying sizes permitted them to gain useful inferences regarding the individual methods. This was important due to the lack of proper evaluation protocols and standard when comparing the zero-shot methods from the past and present. Their research methodology complements our approach of an analytical metric comparison between learning methods, except theirs is within zero-shot methods while ours cross compares with one of a completely different nature.

The previously referenced papers serve as suitable evidence regarding the impact of different machine learning methods in the real world. Further studies continue to improve existing models and find ways to bridge the semantic gaps and limitations they possess. These insights help facilitate the methodology we adopt and collaboratively contribute to our research's foundation.

III. MOTIVATION

The conducted research is driven by the challenges faced in the domains of zero-shot and supervised learning, especially in the case of handling unlabeled classes in machine learning models. Numerous models rely on accurately labeled data for successful training processes which could prove to be costly and impractical. This limitation affects the applicability and scalability of machine learning models in real-world use cases.

Exploring and advancing the methodologies of zero-shot learning to overcome the constraints of the supervised approach sets the motivation for our research. Experimenting how the various learning methods perform on popular study of text classification fosters our understanding on the areas where each learning method could be utilized better. This study will contribute to significant efforts in revolutionizing general models to solve issues such as data scarcity and oversized processing. Our findings will also facilitate those interested in applying innovative solutions and developing robust AI systems which could be utilized in other machine learning areas such as image recognition, natural language processing, and medical diagnostics.

In summary, bridging a gap between zero shot and supervised learning paradigms will increase the potential of the use of machine learning models in real-world use cases and foster AI-driven technologies to tackle complex problems.

IV. METHODOLOGY

In this section, we provide a comprehensive overview of the methodological approach undertaken to address the central research: “How do zero-shot classification and supervised learning compare in the realm of multiclass text classification?” As outlined in the introduction, our broader goal is to enhance our understanding of the performance difference between these two approaches and to contribute valuable insights into how to improve the efficiency of text classification in the field of natural language processing.

To contextualize our methodology, it is crucial to revisit the primary objective set forth in the introduction. Our research stems from the pressing need to explore innovative techniques for handling multiclass text classification tasks effectively. As we delve into the methodology, we will outline the steps taken to rigorously compare the performance of zero-shot classification and supervised learning in achieving this objective. The context provided will reinforce the importance of our investigation within the broader landscape of machine learning and text classification methodologies.

In addressing the central research question regarding the comparative performance of zero-shot classification and supervised learning in multiclass text classification, our methodological approach involves a thorough analysis of their respective techniques, strengths, and limitations.

Zero-shot classification stands out as an intriguing approach due to its unique ability to perform classification without reliance on a pre-trained model with labeled data. This distinctive feature offers a notable advantage, significantly expediting the data collection and preparation stages in the data science cycle. By eliminating the need for a specifically labeled dataset during the training phase, zero-shot classification presents a promising avenue for scenarios where obtaining labeled data is challenging or time-consuming.

In our analysis of zero-shot classification, we delve into the underlying mechanisms that enable its capability to generalize to unseen classes. This involves an examination of semantic embeddings, transfer learning, and the utilization of external knowledge sources, all contributing to the model's adaptability to novel categories without explicit training.

In parallel, we investigate supervised learning, a widely adopted method for text classification. Unlike zero-shot classification, supervised learning relies on labeled datasets for training, where the model learns to recognize patterns associated with predefined classes. We explore the conventional yet robust approach of supervised learning, emphasizing its reliance on a comprehensive training set to achieve optimal performance.

The choice to focus on zero-shot classification and supervised learning stems from their prevalence in text classification tasks and the contrasting nature of their methodologies. By dissecting these methods, we aim to provide a nuanced understanding of their advantages and limitations, offering insights into when one approach might be more suitable than the other. This comparative analysis lays the groundwork for informed decision-making in real-world applications of multiclass text classification.

This methodology section is designed to provide a comprehensive understanding of our research approach in comparing zero-shot classification and supervised learning for multiclass text classification. We will delve into key aspects, including data collection, experimental design, and data analysis. The scope extends beyond a mere presentation of techniques; it encompasses an in-depth exploration of the intricacies associated with each method, shedding light on their applicability and performance nuances.

Our chosen methodology aligns seamlessly with the overarching research objectives outlined in the introduction. By scrutinizing the techniques employed in zero-shot classification and supervised learning, we aim to unravel the strengths and limitations of each approach. This alignment is pivotal in unraveling the comparative performance of these methods, providing valuable insights for practitioners and researchers engaged in text classification tasks.

As we embark on the detailed exploration of our methodology, the subsequent sections will unfold the intricacies of our research approach. The following discussions will sequentially address data collection strategies, the intricacies of our experimental design, and the meticulous process of data analysis. By delving into these components, we aim to provide a comprehensive view of our research methodology, elucidating how each facet contributes to our pursuit of understanding the nuanced dynamics between zero-shot classification and supervised learning in multiclass text classification tasks.

1.1. Data

Table 1 *Dataset Details: news-data from AriseTv*

Dataset name	source	training size	test size	language	columns
news-data	AriseTv	4,690	828	English	Title, Excerpt, Category, Labels

A. Zero-shot classification

For our zero-shot classification approach, we leveraged the bart-large-mnli model, a variant of BART (Bidirectional and Auto-Regressive Transformers) pretrained on the MultiNLI (MNLI) dataset. The MNLI dataset, known as Multi-Genre Natural Language Inference, comprises over 400,000 sentence pairs annotated with textual entailment information across various genres.

The zero-shot classification technique is rooted in the methodology proposed by Yin et al. (2019), utilizing pre-trained NLI models as ready-made zero-shot sequence classifiers. Specifically, the approach frames the sequence to be classified as the NLI premise and constructs a hypothesis from each candidate label. For instance, to evaluate whether a sequence belongs to the "politics" class, a hypothesis like "This text is about politics" is generated. The entailment and contradiction probabilities predicted by the NLI model are then converted to label probabilities.

The chosen model, bart-large-mnli, allows us to seamlessly integrate this zero-shot approach. It is pretrained on the MNLI dataset, making it proficient in understanding the relationships between sequences. This model is particularly effective, especially when applied to larger pre-trained models like BART and Roberta.

The core model employed for zero-shot learning is the bart-large-mnli model. It is specifically designed for sequence-pair classification tasks, making it well-suited for the zero-shot text classification method based on natural language inference.

We used the default hyperparameters, the bart-large-mnli model was trained with a batch size of 16, a learning rate of 5e-5, and over three epochs. The maximum sequence length considered was 128, with training, evaluation, and continuous evaluation during training set to True. Saved steps were implemented every 2000 steps, with warm-up steps at 1000. Weight decay and epsilon for the Adam optimizer were set at 0.01 and 1e-8, respectively. Gradient accumulation steps were set at 1.

By fine-tuning the model with these hyperparameters, we sought to optimize its performance for zero-shot text classification, demonstrating its robustness in understanding textual entailment relationships across various genres. The logging and output directories were configured to ensure effective tracking and storage of results throughout the training process. The save_total_limit parameter was set to 2, allowing for the retention of two checkpoint models.

Although we used the default hyperparameters in order to get ideal results in order to preserve the purity of the evaluation.

B. Supervised learning

In our supervised learning approach, we explored and compared the performance of three distinct classification algorithms: Naive Bayes, Linear Support Vector Machine (Linear SVM), and Logistic Regression. The objective was to determine the optimal algorithm for achieving high accuracy in news article classification. This approach involved training these algorithms on the labeled training dataset and evaluating their performance on the test dataset.

For each algorithm, we tuned the specific parameters to optimize their performance in news article classification. The tuning process involved experimenting with different parameter combinations to find the settings that yielded the best results. For naive bayes, no significant hyperparameter tuning was performed for Naive Bayes, as it generally works well with its default settings for text classification tasks. For Linear Support Vector Machine, The Linear SVM was implemented using the SGDClassifier from Scikit-learn. Hyperparameters were set to optimize the model's performance, with key parameters including the choice of loss function ('hinge'), penalty ('l2'), learning rate ('alpha'), and maximum number of iterations ('max_iter'). For logistic regression, Logistic Regression hyperparameters, derived from scikit-learn's Logistic Regression model, included the number of jobs to run in parallel ('n_jobs') and the regularization strength ('C'). The tuning process focused on finding optimal values for these parameters.

C. Evaluation metrics

To comprehensively compare the performance and results of the Zero-Shot Classification and Supervised Learning approaches (utilizing Naive Bayes, Linear SVM, and Logistic Regression), we employed a set of key evaluation metrics, each offering unique insights into the models' effectiveness. Including Accuracy, Precision, Recall, F1 score, training & inference time and Resource utilization.

V. RESULTS

In this section, we present the findings of our comparative analysis between the Zero-Shot Classification and Supervised Learning approaches for news article classification.

Supervised Learning Results

Naive Bayes

Table 2

Performance Metrics for Naive Bayes Classification.

metric	value
accuracy	0.7930
macro precision	0.73
macro recall	0.61
macro f1 score	0.62
weighted precision	0.78
weighted recall	0.79
weighted f1 score	0.75

Linear Support Vector Machine (Linear SVM)

Table 3

Performance Metrics for Linear SVM Classification.

metric	value
accuracy	0.8563
macro precision	0.82
macro recall	0.78
macro f1 score	0.79
weighted precision	0.85
weighted recall	0.86
weighted f1 score	0.85

Logistic Regression

Table 4

Performance Metrics for Logistic Regression Classification.

metric	value
accuracy	0.8620
macro precision	0.81
macro recall	0.80
macro f1 score	0.81
weighted precision	0.86
weighted recall	0.86
weighted f1 score	0.86

The Logistic Regression model emerges as the best performer among the supervised learning models, demonstrating robust performance across all metrics. While Naive Bayes showed competitive results, its lower macro recall indicates potential limitations in capturing positive instances. Linear SVM performed well but slightly below Logistic Regression in overall metrics.

Surprisingly, Logistic Regression outperformed Linear Support Vector Machine (Linear SVM) n our experiment even with Linear SVM ability to create complex decision boundaries and its robustness to outliers. This unexpected result might be attributed to the specific characteristics of the dataset and the nature of the news articles. Linear SVM, while generally powerful, might not have captured intricate patterns present in the data as effectively as Logistic Regression.

Zero-Shot Classification Results

Table 5

Performance Metrics for Zero-Shot Classification.

metric	value
accuracy	0.7041
macro precision	0.72
macro recall	0.67
macro f1 score	0.67
weighted precision	0.79
weighted recall	0.70
weighted f1 score	0.73

Supervised vs. Zero-Shot Classification

Comparing Logistic Regression with the Zero-Shot Classification approach, we observe that the Logistic Regression model outperforms the Zero-Shot approach across most metrics.

Table 6

Performance Metrics comparison for Supervised vs Zero-shot Classification.

metric	logistic regression	zero-shot
accuracy	0.86	0.70
macro precision	0.81	0.72
macro recall	0.80	0.67
macro f1 score	0.81	0.67
weighted precision	0.86	0.79
weighted recall	0.86	0.70
weighted f1 score	0.86	0.73

The results indicate that, in our specific news article classification task, supervised learning, particularly Logistic Regression, outperforms the Zero-Shot Classification approach. The Logistic Regression model exhibits superior accuracy, precision, recall, and F1 scores, showcasing its effectiveness in classifying news articles.

Note: While these results provide valuable insights, it's essential to consider the specific characteristics of the dataset and task when choosing the most suitable approach for a given scenario. Additionally, the trade-off between model complexity and interpretability should be considered in real-world applications. The unexpected performance of Logistic Regression compared to Linear SVM emphasizes the importance of model selection based on task specifics.

VI. LIMITATIONS

The primary limitation of the supervised learning approach, particularly Logistic Regression, is the necessity for labeled data during the training phase. The process of manually labeling news articles for a diverse range of categories is inherently challenging and time-consuming. This introduces a potential source of bias and limits the scalability of the model to handle a broader range of classes.

With respect to zero-shot learning, while offering flexibility, the approach may face challenges in grasping the nuanced semantics of certain classes, especially those significantly differing from the training data. The model's capacity to accurately classify news articles into novel categories relies on its ability to generalize semantic understanding, which may be constrained. Additionally, there is an external knowledge dependence in zero-shot classification, often relying on external knowledge sources to infer the meaning of unseen classes. The effectiveness of the approach is contingent on the availability and relevance of such knowledge. In scenarios where comprehensive external knowledge is lacking or outdated, the model's performance may be compromised. The performance of zero-shot approaches can vary significantly across different tasks and datasets. While it provides adaptability, the model's effectiveness is contingent on the inherent characteristics of the data, and it may not consistently outperform traditional supervised learning methods. Zero-shot approaches often rely on high-quality pre-trained models. The success of the approach is heavily influenced by the capabilities and

generalization power of these models. In scenarios where suitable pre-trained models are not available or lack relevance to the task at hand, the performance may be suboptimal.
Furthermore, general considerations should be noted. The limitations discussed are task-specific, and the challenges and constraints identified may vary based on the nature of the news article classification task and the characteristics of the dataset used. Both supervised and zero-shot approaches may inherit biases present in the training data, potentially leading to biased predictions. Both supervised and zero-shot approaches may inherit biases present in the training data, potentially leading to biased predictions. Ethical considerations should be taken into account to address any unintended consequences or perpetuation of biases in the classification results.

Furthermore, the limitations discussed are based on standard evaluation metrics such as accuracy, precision, recall, and F1 score. However, these metrics might not fully capture the real-world implications of the model's performance. Considering additional evaluation measures is crucial for a more comprehensive assessment.

VII. ADDRESSING THE LIMITATIONS

Supervised learning, although effective, requires a large amount of labeled data for training. This can be time-consuming and costly, especially when dealing with multiple classes and domains. Additionally, supervised learning models may struggle with classifying unseen or out-of-domain data accurately.

On the other hand, zero-shot learning faces its own limitations. One drawback is that zero-shot classifiers often rely on predefined class descriptions or attributes, which may not be available or accurate for all classes. This can lead to reduced performance when classifying new or unseen classes. Zero-shot classifiers also tend to have lower accuracy compared to supervised learning models.

Recognizing the challenges posed by traditional zero-shot classification, researchers have explored innovative methods to bolster its accuracy. One notable solution is presented in the paper 'Zero-Shot Text Classification with Self-Training' by Ariel Gera, Alon Halfon, Eyal Shnarch, and Yotam. This paper proposes a solution to improve zero-shot classification results through self-training. The authors of this paper propose a novel approach through self-training to enhance the performance of zero-shot classification. Self-training involves fine-tuning the zero-shot classifier on its most confident predictions and then retraining the model on a limited number of instances from each class.

According to Gera et al. (2022), self-training is based on the idea that incorporating additional data, even if it is limited in quantity, can significantly improve the accuracy of zero-shot classification models. The authors demonstrate that by fine-tuning the classifier on the most confident predictions, the model can effectively learn from its own mistakes and improve its classification performance.
To implement self-training, the authors suggest selecting a subset of instances from each class based on the highest confidence scores assigned by the zero-shot classifier. These instances are then added to the training set, and the model is retrained using this augmented data. By iteratively repeating this process, the model gradually improves its classification accuracy.

The effectiveness of self-training in enhancing zero-shot text classification is demonstrated through experiments conducted by Gera et al. (2022). Their comparative analysis showcases the significant improvement in accuracy achieved by the self-training approach, thereby reducing the error rate and enhancing overall classification performance.

In conclusion, the self-training approach proposed by Gera et al. offers a promising solution to address the limitation of lower accuracy in zero-shot text classification. By fine-tuning the classifier on confident predictions and incorporating a limited number of instances from each class, the model can learn from its own mistakes and significantly improve its classification performance.

VIII. CONCLUSION

Our research aimed to compare supervised learning and zero-shot classification in multiclass text classification. Through our investigation, we gained insights into their strengths, limitations, and innovative strategies.
Supervised learning, known for its ability to extract knowledge from labeled data, showed high accuracy in classifying news articles. However, it relies heavily on labeled datasets, posing scalability issues and struggling with data outside its training scope.

Zero-shot classification, which predicts class labels without specific training, appears promising. Yet, it faces challenges in accurately understanding complex meanings and depends greatly on predefined class attributes, affecting its accuracy with new or unfamiliar classes.

Gera et al.'s work on 'Zero-Shot Text Classification with Self-Training' introduced an innovative approach. Their concept of self-training within zero-shot learning aims to refine classifiers iteratively by fine-tuning models based on confident predictions and integrating limited instances from each class, potentially improving accuracy.

Our research also recognized challenges in both methodologies. Supervised learning deals with labeling demands and adaptability, while zero-shot classification struggles with semantic understanding and reliance on external knowledge. Nevertheless, Gera's self-training technique offers a promising path to enhance zero-shot classification accuracy.

Ethical concerns, such as biases inherited from training data, are critical in both supervised and zero-shot approaches and require careful evaluation and mitigation strategies. These considerations extend beyond our study, urging caution in advancing machine learning boundaries.

Our paper highlighted the evolving nature of machine learning, showcasing possibilities and challenges. The convergence of structured supervised learning and innovative zero-shot classification enriches progress. Gera's team’s self-training presents an opportunity for improved zero-shot classification accuracy.

As machine learning evolves, our study serves as a guide for informed decisions. Balancing innovation and limitations, a combination of methodologies and strategies aims to advance text interpretation accuracy and adaptability in machines.

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XI. APPENDIX

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