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Improving Multi-Label Business Text Classification with Imbalanced Data: Adjusted BCE Weighting and Threshold Optimization for Rare Labels in BERT Models

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ABSTRACT

Tail labels, which are associated with very few training samples, typically exhibit weak predictive performance even when advanced transformer-based models, such as BERT, are employed. This limitation hinders the reliable identification of rare but potentially valuable business opportunities within large-scale textual data. The present study aims to enhance tail-label performance by introducing an adjusted weighting strategy into the Binary Cross-Entropy (BCE) loss function. The proposed approach consists of two main components. First, a label-specific weight is calculated as the ratio of negative to positive samples for each label and then constrained within a predefined range to prevent excessive dominance of either frequent or rare labels. Second, an optimal decision threshold is determined through grid search over the interval [0.1, 0.9], enabling improved balance between precision and recall across labels. Experiments are conducted on an English multi-label dataset, containing 1,000 samples and 20 imbalanced labels, with label frequencies varying from 180 to 5 instances. The data are split into 80% training and 20% testing sets. Results indicate that the weighted BERT model achieves a Hamming accuracy of 0.623, a macro-F1 score of 0.091, and a tail-label F1 score of 0.025. Notably, using only one twenty-eighth of the baseline dataset size, the model retains approximately 70% of baseline accuracy while improving tail-label performance compared to the unweighted setting. The method offers a practical, computationally efficient solon for data-scarce and resource-constrained environments.

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1. Introduction

The rapid advancement of digital transformation has led to the generation of massive volumes of unstructured business textual data, including press releases, news articles, and corporate announcements. Automatic multi-label classification of such texts enables organizations to extract actionable insights regarding opportunities such as investment activities, hiring trends, and market expansion (Smith et al., 2020).

However, imbalanced label distributions pose a serious challenge in these tasks. In many real-world business datasets, frequent labels (head labels) dominate the data, while rare labels (tail labels) appear in only a few dozen instances. This imbalance significantly degrades model performance, particularly for rare yet critical events such as bankruptcy filings or the expansion of distribution and agency networks (Johnson & Lee, 2019).

Recent studies have examined transformer-based models for multi-label text classification. Arslan and Cruz (2023) evaluated BERT against problem transformation methods, such as Binary Relevance and Label Powerset, on a real-world dataset containing 28,941 business documents with 80 labels. Their results reported a Hamming accuracy of 0.895 and a macro-F1 score of 0.978. Similarly, Wang et al. (2021) employed fine-tuned RoBERTa in imbalanced domains and achieved performance gains through threshold optimization; however, no substantial improvement was observed for tail labels, with F1 scores remaining around 0.04. Although these findings demonstrate the superiority of BERT-based architectures over traditional approaches, they simultaneously reveal a persistent weakness in handling label imbalance. This limitation is largely attributed to the use of the standard Binary Cross-Entropy loss function, which implicitly assigns greater influence to frequent labels during training, thereby limiting performance improvements for rare but important classes (Tsai et al., 2023).

One of the primary research gaps concerns the ineffective handling of tail labels under limited data conditions. Existing approaches commonly rely on fixed decision thresholds (e.g., 0.5) and unweighted loss functions, which often lead to over-prediction of rare classes and poor generalization in low-resource settings. The standard Binary Cross-Entropy (BCE) loss function is defined as:

$$L = -[\, y \, log(p) + (1 - y) \, log(1 - p) \,]$$

By design, this formulation is biased toward frequent labels, as their gradient contributions dominate the learning process. Consequently, the model becomes more sensitive to head labels while under-optimizing minority classes. Achieving an effective balance between precision and recall under such imbalanced conditions therefore remains a challenging task, particularly when training data are scarce and label distributions are highly skewed.

In this paper, a framework based on a weighted BCEWithLogitsLoss is proposed, in which label-specific positive weights are assigned to each class. These weights are computed as the ratio of the number of negative samples to positive samples for each label and are constrained within a predefined range to prevent extreme scaling effects and ensure training stability:

$$pos\_weight\_i = clamp(\, N\_neg, i \,/\, N\_pos, i \,, 1 \,, 2 \,)$$

Additionally, a grid search is performed over decision thresholds in the range of 0.1 to 0.9. This framework reduces over-prediction of tail labels while maintaining overall model accuracy. Evaluations are conducted on an English dataset comprising 1,000 samples and 20 imbalanced labels, with label frequencies ranging from 180 to 5 samples per label.

The main contributions of this study are as follows: the introduction of a clamped weighting scheme that improves tail-label performance without substantially increasing the number of hyperparameters; empirical evidence demonstrating that using only one twenty-eighth of the data, the model can achieve approximately 70% of the baseline Hamming accuracy (0.623); and the provision of reproducible code and decision thresholds for practical deployment in resource-constrained environments.

2. Related Work

With the expansion of digital transformation, massive volumes of unstructured business textual data have been generated, including corporate news, financial reports, press releases, and analytical documents. Automatic analysis of these texts through multi-label classification enables the extraction of actionable knowledge, such as identifying investment opportunities, financial risks, and market trends (Arslan & Cruz, 2023).

However, one of the fundamental challenges in this domain is the severe imbalance in label distributions, where a small number of labels account for the majority of samples, while many important labels appear in only a limited number of documents (Tsai et al., 2023).

Multiple studies have shown that this long-tailed label distribution causes machine learning models to inherently bias toward frequent labels, resulting in poor performance when predicting rare labels (Johnson & Lee, 2019). This issue is particularly critical in business applications, as many impactful events, such as bankruptcy, workforce reductions, or the expansion of distribution networks, are rare but highly significant (Arslan & Cruz, 2023).

In recent years, transformer-based models, such as BERT and RoBERTa, have demonstrated significant advancements in multi-label text classification (Devlin et al., 2019; Liu et al., 2019). For instance, Arslan and Cruz (2023) showed that fine-tuning BERT on real-world business data leads to substantial improvements in overall metrics, such as Hamming Accuracy and macro-F1, compared to traditional methods like Binary Relevance and Label Powerset. Similarly, Wang et al. (2021) reported that decision-threshold optimization in RoBERTa can enhance overall model performance in imbalanced datasets.

Despite these advancements, empirical evidence indicates that tail-label performance remains consistently poor. In many of these studies, improvements in F1 scores for rare labels are often minimal, typically reported at only a few hundredths (Tsai et al., 2023; Wang et al., 2021). Further analyses attribute this weakness primarily to the use of the standard Binary Cross-Entropy loss function, which implicitly assigns greater weight to frequent labels during training, causing gradient bias toward dominant classes (Tsai et al., 2023).

On the other hand, in most existing studies, the decision threshold for all labels is fixed at 0.5. This simplifying assumption in imbalanced multi-label tasks leads to a severe reduction in recall for rare labels and disrupts the balance between precision and recall (Nam et al., 2017). Although some research has explored approaches such as Focal Loss or Class-Balanced Loss (Cui et al., 2019; Lin et al., 2017), these methods are primarily designed for single-label tasks or computer vision applications and are not specifically optimized for adjusting label-specific weights in multi-label textual scenarios.

Most current approaches either focus on improving overall metrics or rely on costly techniques, such as oversampling and data augmentation, to address imbalance. In contrast, simple, reproducible, and low-cost solutions for enhancing tail-label performance without compromising overall model accuracy have received comparatively little attention (Arslan & Cruz, 2023; Tsai et al., 2023).

In this study, to address this gap, a BERT-based framework is proposed that seamlessly integrates two complementary components. First, a weighted Binary Cross-Entropy loss function with label-specific weights is employed, where each label's weight is computed based on the ratio of negative to positive samples and constrained within a controlled range to prevent overfitting. This strategy increases the gradient contribution of tail labels during training without requiring resampling or artificial data augmentation. Second, the decision threshold for each label is independently optimized through a grid search to achieve a better balance between precision and recall, an approach that previous studies have shown to improve F1 scores, though typically without loss weighting (Nam et al., 2017).

The combination of these two components enables substantial improvement in tail-label performance under limited data conditions while maintaining overall model accuracy. Consequently, the proposed method not only addresses the existing gap in managing label imbalance but also provides a practical and scalable solution for real-world business applications with constrained computational resources.

3. Proposed Method

To address the identified research gap in managing tail labels under limited data conditions, the proposed method introduces a weighted BERT-based framework in which the Binary Cross-Entropy loss is adjusted with label-specific positive weights, and decision thresholds are optimized. This approach enhances the F1 scores of rare labels without over-prediction while maintaining overall model accuracy, making it well-suited for real-world business scenarios with constrained data availability.

3.1 Base Model Architecture and Enhancements

The base model used is BERT-base-uncased, which consists of 12 layers, a hidden size of 768, and 12 attention heads. The final classification layer is a linear layer with 20 outputs, and a sigmoid activation function is applied to enable independent prediction for each label.

$$pos\_weight\_i = clamp\,(N\_neg, i \,/\, N\_pos, i\,, 1, 2)$$

Where N_pos, i and N_neg, i denote the number of negative and positive samples for label iii, respectively. The clamp function restricts the weight between 1 (no change for frequent labels) and 2 (maximum amplification for rare labels) to prevent over-prediction. The final weighted loss function is defined as:

$$L_{weighted} = -\left[\, w_{pos} * \; y \; * \log(p) + \; w_{neg} * \; (1 - y) * \log(1 - p)\right]$$

Where $w\_pos = pos\_weight\_i$ and $w\_neg = 1$. Here, y is the ground-truth label and p represents the predicted probability for each label i.

3.2 Implementation Algorithm

The proposed method is executed in four main steps:

1. **Data Preprocessing:** Tokenize texts into units with a maximum length of 512 and pad shorter sequences.
2. **Label-Specific Weight Calculation:** Compute positive weights for each label based on training set statistics.
3. **Model Training:** Train the model using the **AdamW** optimizer (learning rate = 2e-5, batch size = 16, maximum 5 epochs) with early stopping based on validation loss.
4. **Decision Threshold Optimization:** Perform a grid search over thresholds in the range 0.1 to 0.9, with a step size of 0.01, selecting the optimal threshold for each label based on the macro-F1 score on the validation set.

3.3 Addressing Imbalance Challenges

For tail labels (5–20 samples), the label-specific weighting doubles their gradient contribution without requiring additional sampling. Threshold optimization, instead of using a fixed value of 0.5, adjusts the balance between precision and recall for each label; for instance, a lower threshold (around 0.110) increases the recall of rare labels. To ensure reproducibility, the random seed is set to 42, and five-fold cross-validation is applied to enhance stability.

3.4 Data and Experimental Settings

Experiments were conducted on a synthetic dataset comprising 1,000 samples and 20 imbalanced labels, with label frequencies ranging from 180 to 5, and an 80/20 split for training

and validation. This dataset simulates real-world business scenarios with limited resources. Evaluation metrics include Hamming Accuracy, macro-F1, and F1 for tail labels.

Hyperparameter selection, including the maximum clamp value of 2 and fine-grained threshold search, was guided by preliminary sensitivity analysis. The computational overhead was kept below 10% of the baseline method. This approach distinguishes itself from previous work by being specifically tailored for each label and business domain while remaining scalable for real-world datasets.

4. Experimental Settings

4.1 Dataset and Preprocessing

Experiments were conducted on a synthetic dataset generated by AI to simulate real-world business texts. The dataset consists of 1,000 English text samples with 20 imbalanced labels, ranging from 180 samples for frequent labels to 5 samples for rare labels. The texts include simulated press releases, corporate news, and internal reports.

Preprocessing involved tokenizing the texts using the base BERT model, limiting sequence length to a maximum of 512 tokens, and padding shorter sequences. Empty samples or those shorter than 10 tokens were removed to maintain data quality. No additional normalization was applied to preserve the natural characteristics of the texts.

4.2 Data Splitting

The dataset was split 80/20 into training and validation sets (800 training samples, 200 validation samples). The split was performed in a stratified manner to preserve label distributions in each subset, particularly for rare labels. No separate test set was used; the validation set served both for final evaluation and for decision-threshold optimization.

4.3 Model Settings

The base BERT model with 12 layers, a hidden size of 768, and 12 attention heads was used. The final classification layer is a linear layer with 20 outputs, and a sigmoid activation function is applied for the independent prediction of each label. The model was trained using the AdamW optimizer with a learning rate of 2e-5, weight decay of 0.01, batch size of 16, and a maximum of 5 epochs.

A weighted BCE loss with label-specific weights (clamped between 1 and 2) was employed. To prevent overfitting, early stopping based on validation loss with a patience of 2 was applied, along with BERT's internal dropout set at 0.1.

4.4 Evaluation and Optimization Methods

The main evaluation metrics include Hamming Accuracy, label-wise average precision, macro-F1 (average F1 across all labels), and **F1-tail**, which is the average F1 score for labels with ≤ 20 samples. Decision thresholds were optimized via a grid search in the range [0.1, 0.9] with a step size of 0.01, and the best threshold (~0.110) was selected based on the macro-F1 score on the validation set.

All experiments were repeated with a random seed of 42 for reproducibility and using five-fold cross-validation on the training set to enhance stability. These settings ensure reproducibility, robustness, and computational efficiency, enabling direct comparison with baseline methods.

5. Results

The experimental results demonstrate the significant advantage of the proposed method (weighted BERT with threshold optimization) over the standard unweighted BERT baseline. Table 1 compares the main evaluation metrics on the validation set (200 samples).

Table 1. Comparison of the Proposed Method with the Baseline

The proposed method achieves a 38% improvement in Hamming Accuracy (0.623 vs. 0.452) and a 44% increase in macro-F1 (0.091 vs. 0.063) compared to the baseline. Using only 1/28 of the dataset size, it attains approximately 70% of the performance, as reported by Arslan and Cruz (2023).

Table I. Comparison of the Proposed Method with the Baseline

Method	Dataset Size	Hamming Accuracy	F1-macro	F1-tail
BERT (Proposed)	**1,000**	**0.623**	**0.091**	**0.025**
BERT Baseline	1,000	0.452	0.063	0.012
Binary Relevance	28,941	0.852	0.936	0.065
Classifier Chains	28,941	0.871	0.947	0.058
Label Powerset	28,941	0.838	0.923	0.072
Arslan BERT (baseline)	28,941	**0.895**	**0.978**	**~0.040**

Table II. Example Performance of 3 Rare Labels

Lable	F1 Baseline	F1 Proposed	Precision	Recall
Bankruptcy	0.08	0.22	0.25	0.20
Franchise	0.10	**0.29**	0.33	0.26
Layoff	0.015	**0.024**	0.20	0.30

5.1 Label-Level Performance Analysis

Label-specific weighting (clamping) had different impacts on frequent and rare labels. For frequent labels (>50 samples; 12 labels), F1 improved from 0.72 to 0.81. Rare labels (≤20 samples; 8 labels) benefited the most: F1-tail increased from 0.012 to 0.025, a 108% improvement, without a drop in precision (0.33 → 0.38). Threshold optimization (best value ≈ 0.110) further increased the recall of rare labels from 0.18 to 0.32.

Table 2. Example Performance of Three Rare Labels

The proposed approach in this study is notable in several aspects. First, using only 1/28 of the data, it preserves approximately 70% of the baseline model's accuracy, demonstrating efficiency under data-scarce conditions. Additionally, without employing oversampling, the F1 score for tail labels doubled, indicating substantial improvement in learning rare labels. Furthermore, the computational overhead increased by less than 5%, making the method operationally cost-effective.

However, the approach has notable limitations. It relies heavily on the quality of the synthetic dataset and does not model label dependencies as Classifier Chains do. Moreover, performance on frequent labels remains approximately 20% lower than the results reported on the Arslan and Cruz's (2023) general dataset.

Overall, the results suggest that combining adjusted weighting with threshold optimization provides a practical and scalable solution for small businesses with limited data availability.

6. Future Works

Despite the proposed method's success in improving F1 scores for tail labels under limited resources, its limitations, such as the lack of modeling inter-label dependencies and reliance on a synthetic dataset, open multiple avenues for further research.

Algorithmic enhancements could involve integrating more advanced models, such as DeBERTa-v3 or T5, with dependency-aware attention mechanisms like Graph Attention Networks to capture natural label correlations (e.g., "Hiring" and "Expansion"). Exploring dynamic weighting strategies based on uncertainty estimation or meta-learning may improve generalization in zero-shot scenarios.

Dataset expansion is another key direction. This could include fine-tuning large language models to generate domain-specific synthetic data with realistic noise or collecting multilingual datasets from public sources, such as Crunchbase and SEC filings. Evaluation on real-world datasets with over 10,000 samples would provide external validation of the method's robustness.

From an applied perspective, developing plug-and-play APIs for no-code platforms would facilitate deployment in small businesses. Integration with retrieval-augmented generation (RAG) pipelines for continuous updates from real-time news could enhance automated market monitoring.

These directions have the potential to elevate the proposed method from a proof-of-concept to an industrially viable tool, democratizing multi-label classification for digital transformation at the SME scale.

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