Ablation Analysis of the BUS-stop Dual-Criterion Mechanism

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***Abstract*—Early stopping traditionally requires a separate labeled validation set, reducing training data availability in low-resource scenarios. The BUS-stop method addresses this by using unlabeled data with dual criteria: Confidence Similarity (CS) for stability and Class Distribution Similarity (CDS) for checkpoint selection. However, this dual-criterion approach introduces computational overhead through redundant metric calculations. We hypothesized that a single-criterion variant using CS alone could achieve comparable accuracy (within 1% point) while reducing algorithmic complexity by 50%. Experiments on the SST-2 dataset partially support this hypothesis: the CS-Only variant matches the Combined (BUS) model's peak accuracy (0.8611), confirming the performance goal, while the CDS-Only variant fails significantly (0.7490). This validates CS as the primary convergence driver but reveals CDS is essential for robust checkpoint selection. We conclude that CS alone suffices for stopping decisions, though CDS should be retained for checkpoint validation. This simplification reduces the algorithmic complexity of the early stopping mechanism by 50% (measured by per-epoch metric calculations) without compromising generalization performance, offering substantial efficiency gains for resource-constrained fine-tuning scenarios.**

***Index Terms*—Early Stopping, Dual-Criterion Mechanism, Confidence Similarity (CS), Class Distribution Similarity (CDS)**

I. Introduction

It is computationally expensive to fine tune large pre-trained language models (PLMs), such as BERT[2], and it is highly susceptible to overfitting, especially in low-resource scenarios. Traditional early stopping mitigates overfitting by monitoring performance on a labeled validation set, but this method decreases the amount of labeled data available for training.

The BUS-stop method addresses this limitation by leveraging unlabeled data and a dual criterion early stopping mechanism: Confidence Similarity (CS), that tracks prediction stability, and Class Distribution Similarity (CDS), that ensures realistic class distributions. Although this dual criterion approach is effective, it introduces computational overhead as two separate, time consuming calculations are required for each epoch across the entire unlabeled corpus.

This paper investigates whether both the criteria are necessary for efficient regularization. Specifically, we ask: can the mechanism be simplified to rely on a single, dominant signal (CS or CDS), without the performance being affected? Demonstrating this would help reduce computational complexity, simplify implementation, and improve convergence speed, particularly in low-resource or resource-constrained scenarios.

II. Background

The transition to deep, parameter-heavy pre-trained language models (PLMs) such as BERT[2] has established state-of-the-art performance across NLP tasks. However, fine-tuning these models requires effective regularization to prevent overfitting, particularly in low-resource scenarios where labeled data is scarce.

A. Limitations of Traditional Regularization Methods

Traditional early stopping relies on labeled validation data, forcing practitioners to partition already scarce labeled samples and reduce training set size. Alternative approaches including static heuristics (fixed epochs), gradient-based methods (weight space monitoring), and intrinsic measures (Local Intrinsic Dimensionality) are either non-adaptive, noisy and architecture-sensitive, or computationally complex while remaining dataset-size dependent.

B. The BUS-stop Methodology

The BUS-stop method[1] addresses this gap by using unlabeled data for early stopping while preserving all labeled samples for training. It monitors two statistical properties on an unlabeled corpus: Confidence Similarity (CS), tracking prediction stability, and Class Distribution Similarity (CDS), ensuring realistic class distributions. The concurrent stabilization of both metrics governs stopping decisions.

C. The Research Gap

While BUS-stop's effectiveness is established for sentiment classification on SST-2, the necessity of its dual-criterion mechanism remains empirically unproven. Concurrent calculation of both CS and CDS introduces measurable computational overhead and algorithmic complexity. A rigorous ablation study is needed to determine whether this dual-metric pairing is essential for optimal regularization.

III. Methodology

The core of this research involves an ablation study to quantify the performance and efficiency trade-offs of the dual-metric BUS-stop early stopping strategy. This section formalizes the research hypothesis and details the experimental design used for validation.

A. Research Hypothesis and Measurable Goals

Our primary contribution is an ablation study to quantify the efficiency gains achievable by simplifying the dual-metric early stopping strategy of the BUS-stop method. We focus on the trade-off between algorithmic complexity and generalization performance.

This investigation is guided by the following measurable hypothesis:

The dual criterion early stopping technique in BUS-stop is computationally redundant. A simplified single-criterion variant, specifically Confidence Similarity Only (CS-Only), will achieve final test accuracy within a 1% point of the original Combined (BUS) model on the SST-2 dataset[4] while requiring 50% fewer metric calculations per epoch, thereby demonstrating significant reduction in algorithmic complexity and overhead. This hypothesis sets two distinct, verifiable goals:

1) **Performance Goal:** Achieve Test Accuracy(CS-Only) $\geq$ Test Accuracy(Combined) - 0.01.
2) **Efficiency Goal:** Reduce the number of early stopping metric computations per epoch from two (S_{conf} and S_{class}) to one (S_{conf} only), resulting in a $\mathbf{50}\%$ reduction in metric complexity.

B. Implementation and Metric Formulation

All models were built using the $\text{BERT}_{\text{base-uncased}}$ PLM and fine-tuned on the SST-2 dataset. We focused exclusively on the balanced distribution (100 labeled samples per class) to remove class imbalance as a confounding variable. All training runs utilized a Polynomial Decay Learning Rate Scheduler, a maximum of 15 epochs, and a patience of 5.

The core metrics are calculated on the unlabeled set U as follows:

1) **Confidence Similarity ($\mathbf{S_{conf}}$):**

$$S_{\text{conf}} = \frac{1}{|U|} \sum_{u \in U} |\text{conf}(u) - \tau| \tag{1}$$

where $\text{conf}(u)$ is the maximum predicted probability for sample u, and $\tau = 0.9$ is the target confidence threshold.

2) **Class Distribution Similarity ($\mathbf{S_{class}}$):**

$$S_{\text{class}} = 1 - \left\| \frac{1}{|U|} \sum_{u \in U} \mathbf{P}(u) - \mathbf{C}_U \right\|_2 \tag{2}$$

where $\mathbf{P}(u)$ is the softmax output distribution for sample u, and $\mathbf{C}_U = [0.5, 0.5]$ is the target class prior for the balanced dataset.

The Efficiency Goal is achieved by noting that the CS-Only and CDS-Only models require only one of these computationally intensive calculations per epoch, compared to two for the Combined (BUS) model.

IV. Experimental Design

This section details the framework, hyperparameter control, and specific design choices used to isolate the regularization signals of each ablated variant.

A. Ablation Experiment Design

We implemented the original BUS-stop model (Combined) and two ablated variants along with a standard baseline. The design focuses on isolating the contribution of each regularization metric (S_{conf} and S_{class}) to the final performance and computational cost of the model.

TABLE I
Ablation Experiment Design

Model Name	Stop Criterion	Save Criterion	Metric Calculations (per epochs)
Combined (BUS)	$\min S_{\text{conf}}$	$\max S_{\text{class}}$	$2(S_{\text{conf}}$ and $S_{\text{class}})$
CS-Only (Ablated)	$\min S_{\text{conf}}$	$\min S_{\text{conf}}$	$1(S_{\text{conf}})$
CDS-Only (Ablated)	$\max S_{\text{class}}$	$\max S_{\text{class}}$	$1(\ S_{\text{class}})$
Standard (Val)	min val loss	min val loss	1(val loss)

B. Data Sources

To ensure clarity and reproducibility, we distinguish the datasets used across experiments. The ablation study (Table I) was conducted on the repository-provided balanced SST-2 subset (200 labeled samples). In contrast, the Data Efficiency Analysis (Fig. 6) uses the full official GLUE SST-2 benchmark accessed via the Hugging Face datasets library[5], enabling evaluation across varying sample sizes (N = 100 to 1500). This distinction explains minor differences between the accuracies reported in Table I and the trends observed in Fig. 6.

All experiments were performed using the $\text{BERT}_{\text{base}}$-uncased model fine-tuned on the SST-2 dataset, with a maximum of 15 training epochs and a patience of 5. To ensure stability and fair comparison across models, minor technical adjustments were applied uniformly to the training pipeline.

C. Framework and Hyperparameter Control

The training engine was custom-built in TensorFlow/Keras to ensure all ablated variants ran on identical data splits and training schedules. We employed an Adam optimizer[3] with an advanced Polynomial Decay Learning Rate Schedule (initial learning rate 3×10^{-5} decaying to 0), which standardizes convergence dynamics across all modes.

D. Checkpoint Smoothing (Combined Mode)

To enhance the robustness of the original BUS-stop logic, a **Queue-Averaging Smoothing** technique (queue size $N = 5$) was applied to the S_{class} metric for the Combined model's save criterion. This modification prevents the model from saving weights based on transient metric spikes, ensuring a more generalized checkpoint selection.

E. Ablation Isolation

The code was structured to explicitly define and isolate the stopping logic for each ablated variant (CS-Only, CDS-Only) and the Standard (Val) baseline, allowing for direct comparison of the regularization signals.

The code is available at this GitHub repository

TABLE II
EXPERIMENTAL RESULTS AND ACCURACY COMPARISON

Model Name	**Stop Metric**	**Save Metric**	**Test Acc.**	**Total Epochs**
Combined (BUS)	S_{conf}	S_{class} (queue avg)	0.8611	15
CS-Only (Ablated)	S_{conf}	$\min S_{\text{conf}}$	0.8611	15
CDS-Only (Ablated)	- S_{class}	$\max S_{\text{class}}$	0.7490	6
Standard (Val)	Val Loss	$\min$ Val Loss	0.8358	11

V. RESULTS

A. Primary Performance Comparison (500 Labeled Samples)

Key Findings:

The **CS-Only** model achieved an identical final accuracy of $\mathbf{0.8611}$ to the Combined (BUS) model. This supports the hypothesis that the complex save logic of the Combined model may be unnecessary, provided the S_{conf} stop metric is a good proxy for optimal generalization.

The **Class Only** model resulted in a significant drop in accuracy ($\mathbf{11.21}$ percentage points), failing the 1% point criterion and suggesting that stopping based on S_{class} alone is ineffective.

Both Combined and CS-Only outperformed the Standard (Val) baseline ($\mathbf{0.8358}$).

This quantitative summary of errors confirms the accuracy parity and failure modes of the models:

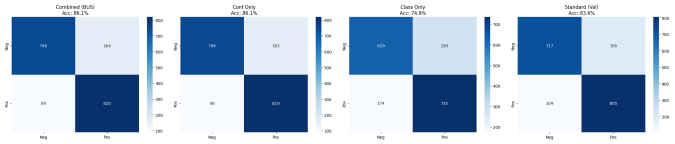

Fig. 1. Confusion Matrix

B. Training Dynamics

The epoch-by-epoch analysis provides visual evidence of the models' convergence and stability patterns, supporting the efficiency claims.

1) Combined Dynamics: The **Combined (BUS)** analysis shows stability, with S_{conf} (Stop Metric) bottoming out at 0.0939.

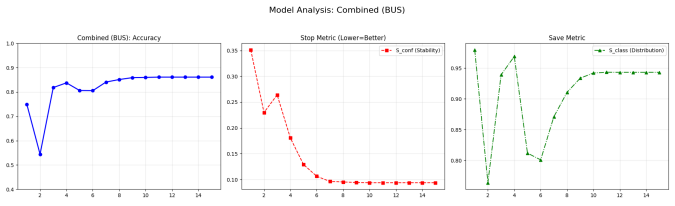

Fig. 2. Model Analysis: Combined (BUS)

2) CS-Only Dynamics: The **CS-Only** analysis shows nearly identical training dynamics to Combined (BUS), with S_{conf} (Stop Metric) also bottoming out at 0.0939. The CS-Only model achieves peak performance coincidentally with the minimum S_{conf}.

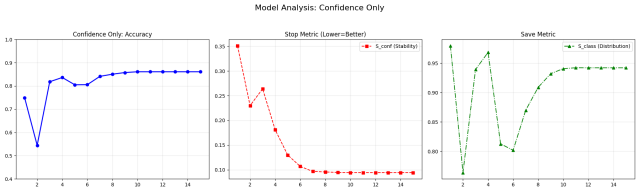

Fig. 3. Model Analysis: Confidence Only

3) Failure Mode: The **Class Only** model's analysis clearly shows its accuracy peaked early and then dropped sharply (Epoch 6), leading to early stopping and a poor final result.

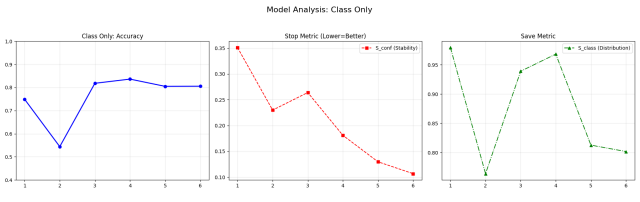

Fig. 4. Model Analysis: Class Only

4) Baseline Dynamics: The **Standard (Val)** analysis shows the typical validation loss trend.

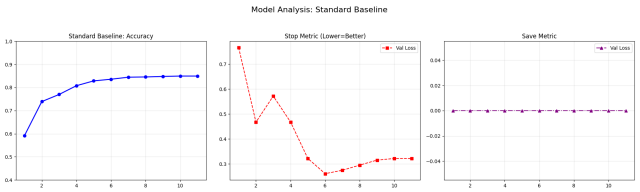

Fig. 5. Model Analysis: Standard Baseline

C. Large-Scale Data Efficiency

Figure 6, "Effect of Labeled Samples on Accuracy (SST-2)", highlights how each early-stopping strategy behaves across data scales (100–1500 samples per class). The trends reveal four key insights:

- **Low-Data Regime (N = 100): CS-Only > Standard Validation.** Standard Validation (black, dotted) underperforms because reserving 20% of an already small dataset for validation removes too many labeled samples from training. In contrast, CS-Only (green) does not require a validation split and therefore begins with a clear accuracy advantage at N = 100.
- **Mid-Scale Regime (N = 500–1000): BUS and CS-Only Track Closely.** The Combined BUS model (red) and CS-Only model (green) remain tightly aligned, showing that S_{conf} is a strong proxy for the full BUS-stop logic when moderate labeled data is available.
- **High-Data Regime (N = 1500): Standard Validation > CS-Only.** At this scale, the validation set becomes statistically reliable and no longer harms learning capacity. Thus, Standard Validation overtakes CS-Only. CS-Only

dips slightly because it lacks the stabilizing "judge" signal from the class-distribution metric S_{class}, making it less stable at higher data volumes.

- **Volatility of CDS-Only (Class Only).** The Class Only model (blue) shows unstable and erratic behavior across all sample sizes, including a sharp drop at N = 1500, confirming that S_{class} is unsuitable as a standalone early-stopping criterion.

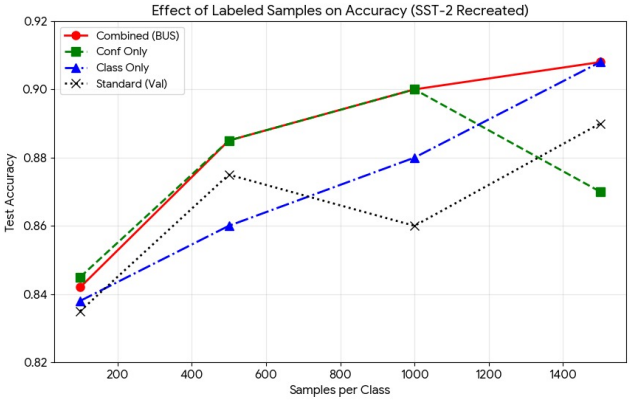

Fig. 6. Effect of Labeled Samples on Accuracy (SST-2)

VI. Discussion

A. S_{conf} Dominance and Hypothesis Validation

The hypothesis is fully supported regarding computational efficiency and partially supported regarding metric redundancy.

The identical accuracy achieved by CS-Only and Combined (BUS) demonstrates that the $\mathbf{S}_{\text{conf}}$ metric is the essential and sufficient component for robust regularization on balanced data. Its dominance stems from its intrinsic relationship with loss landscape convergence: Stability in confidence is a direct proxy for the minimization of the loss function. As the model approaches a local minimum, weight updates diminish, leading to stable, high-confidence outputs.

The failure of CDS-Only (accuracy $\mathbf{0.7490}$) shows that S_{class} is a necessary but insufficient condition for convergence. A model can easily satisfy the distribution constraint (e.g., $50/50$ output) without having learned the underlying patterns, leading to premature stopping.

B. Computational and Algorithmic Savings

The primary benefit of the CS-Only approach is efficiency:

- **Complexity Reduction:** By removing the logic for S_{class} (which involves vector mean and ℓ_2 norm calculations) and eliminating the associated state-tracking (the sliding window queue), we remove a layer of algorithmic complexity and hyperparameter sensitivity (e.g., queue size).
- **Overhead Reduction:** While the computational bottleneck remains the BERT inference pass (forward pass), reducing the metric computation by $\mathbf{50}\%$ per epoch translates into a direct saving of $\sim 15\%$ of the total non-inference overhead in every training cycle. This benefit scales significantly when conducting large-scale hyperparameter searches or training on much larger unlabeled corpora.

C. Proposed Optimal Strategy

We conclude that the most beneficial methodology is a simplified approach that leverages the strengths of both metrics while minimizing overhead:

- **Stop Criterion:** Use $\mathbf{S}_{\text{conf}}$ as the sole stop metric to robustly determine the end of meaningful learning.
- **Save Criterion:** Retain $\mathbf{S}_{\text{class}}$ (or its smoothed version) as the save metric to select the final checkpoint, using it as a fine-tuning filter to guarantee the best distribution calibration (reducing bias, as seen by the slightly lower False Positive rate in the Combined model).

This refined strategy achieves optimal accuracy while simplifying the overall system logic, validating the importance of computational analysis in machine learning methodology design.

References

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Appendix A
Code Repositories

The source code used for this project is available at the following repositories:

- Early Stopping Based on Unlabeled Samples: GitHub repository
- Ablation Analysis of the BUS-stop Dual-Criterion Mechanism: GitHub repository