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Research Paper

Adversarially-Trained RoBERTa for Robust Technical Term Recognition in Scientific and Engineering Documents

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Abstract. In research and technology, information retrieval and knowledge graph generation are common applications of technical term recognition. In order to solve the issues of term boundary ambiguity and robustness to input perturbations in complex technical corpora, this research suggests an adversarial training method for a domain-adapted RoBERTa model. The aforementioned method optimally combines clean and adversarial feature streams using a joint decoding technique and constructs various tiers of gradient-informed adversarial perturbations in the transformer network. Comprehensive tests were conducted using three heterogeneous datasets containing over 5 million tokens and over 900,000 annotated technical phrases. The findings demonstrate that the adversarially-trained system maintains an accuracy of over 84% during cross-domain transfer, achieves a boundary-level F1 score of 89.3% under synthetic input permutation attacks, and is at least 14.7% higher than the standard RoBERTa model in the presence of strong adversarial noise. Error analysis has decreased false boundary insertions by 60.3% when compared to the baseline model, and ablation investigations demonstrate the synergistic effect of multi-layer perturbation and dual-path decoding. As a result, it is evident that the aforementioned research offers a solid basis for developing a fault-tolerant, high-accuracy automated technological term extraction system for practical application.

Keywords: *Natural Language Processing, Adversarial Training, Technical Term Recognition, Domain Adaptation, Information Extraction*

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Introduction

A system for organizing scientific data, engineering knowledge mining, and the automation of professional document analysis has been built using the recognition of technical terminology [1]. Accelerate knowledge graph creation [2], enhance terminology-driven information retrieval [3], and directly assist machine translation and question-answering in highly specialized disciplines [4] by efficiently extracting domain-specific terms from technical literature. Although dictionary-based algorithms were originally widely used, statistical and machine-learning techniques have now demonstrated more linguistic variety adaptability [5]. However, when dealing with unclear language, erratic composition, or newly developed professional jargon, the aforementioned traditional techniques frequently fall short [6]. In order to increase the accuracy of identifying technical terms in scientific and industrial data, deep language models have led to the introduction of BERT and its optimized variant RoBERTa [7]. Because of its enhanced pre-training approach, masking strategy, and contextual representation capacity, RoBERTa is a strong general-purpose foundation model for these tasks [8].

Despite the aforementioned advancements, pre-trained models' resilience for practical use still has significant flaws. The reliability of such a system during a disaster is severely undermined because even a minor hostile disturbance can cause RoBERTa to misclassify or overlook crucial technical words [9]. Adversarial training, data

augmentation, and robust optimization can all be employed to solve these issues, according to earlier research [10]. There has also been some use of noise-aware fine-tuning and defensive distillation [11]. However, there hasn't been much systematic use of adversarial techniques in the particular subject of technical term recognition, especially as terminology in many scientific and industrial domains is constantly evolving [12]. High-robustness targeted-attack resilience has not yet been attained, despite some recent research demonstrating that domain-specific pre-training enhances generalization [13]. The need for robust phrase recognition has increased dramatically in recent years as sectors have relied more and more on automated text analysis for design, safety, regulation, etc. [14]. Due to the aforementioned issues as well as the increasing need for applications, this research is currently relevant and useful to scholars [15].

We propose a novel and thorough adversarial training-based approach for robust technical term recognition with RoBERTa in order to overcome the aforementioned shortcoming. We have included detailed comparisons on many real-world datasets, a domain-aware adversarial training method, and architecture enhancements. We want to improve the theoretical underpinnings and engineering usefulness of automated phrase recognition systems for the upcoming generation of scientific and industrial applications by directly incorporating adversarial robustness into the core of technical term extraction.

Related Work

Technical Term Extraction Methods

In several fields, automatic technical term extraction began as rule-based or dictionary-based techniques and has since evolved steadily [16]. Frequency-based indicators, including TF-IDF and C-value/NC-value, were developed to identify important multi-word words in large, diverse datasets as technical literature grew [17]. While the aforementioned conventional statistical techniques are useful for simple identification, they frequently do not fit the new vocabulary and exhibit poor recall in open-ended or cross-domain scenarios [18]. With the advent of supervised learning, classifiers like support vector machines and Conditional Random Fields have been utilized to more dynamically include contextual, syntactic, and local linguistic information, greatly increasing extraction accuracy [19]. Recurrent neural networks and transformers are being utilized to simulate long-term dependencies and context-aware boundaries in both scientific and industrial texts [20]. Deep learning has also recently been used to enhance the extraction outcomes.

Some issues still exist. While neural methods are good at representation, they require a lot of annotated data and are prone to overfitting in certain sub-domains [21]. The majority of classical approaches are not adaptable to changing technical words or unclear border instances. Given the aforementioned shortcomings, hybrid models have been created to improve the coverage and accuracy of challenging scenarios by combining candidate ranking processes, semantic vector representations, and handmade linguistic patterns [22]. Nevertheless, this "domain adaptation gap" has not been closed, and even the most recent neural networks still struggle to adapt to new regions [23]. Because of this unsolved issue, research has been ongoing to create domain-robust and adaptive extraction algorithms tailored to decentralized and quickly evolving technical systems [24]. Research on resilience mechanisms is progressively garnering attention due to the aforementioned reasons [25].

Robustness in NLP Models

Numerous shortcomings of sophisticated neural network models, such BERT and RoBERTa, have been discovered via natural language processing research. The models' inability to accurately detect or ignore inputs with minor typos, misspellings, or hostile rewrites was the initial robustness problem [26]. Traditional techniques like orthographic normalization, data augmentation, and spell correction only slightly improved the issue and did not adapt effectively to more varied or purposefully disturbed circumstances [27]. Recently, a number of structured evaluation techniques have emerged that use adversarial, real-world, and synthetic textual distortions to assess model stability in practical applications [28]. The aforementioned research has consistently demonstrated that context-sensitive language models are nonetheless susceptible to noise, making them frequently unreliable when domain-specific anomalies or distributional shifts are present.

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Technical language mining is a very challenging test case; the environment is unstable and could harm pipeline stability because of uncommon terminology, shifting lexical standards, and the introduction of ad hoc terms [29]. Using benchmark suites that capture the unique characteristics of real-world and research texts, evaluation techniques have recently shifted to explicitly measure networks' resilience to both random and targeted attacks [30]. The aforementioned trends are now commonly utilized as the foundation for new text mining algorithms, and these models now need to be strong. It is obvious that further advancements in technical word recognition will require both highly sturdy foundation architecture and algorithmic ingenuity.

Adversarial Training for Pre-trained Models

Recent years have seen a tremendous advancement in robustness research for pre-trained language models employing adversarial training. The fundamental concept of adversarial training—exposing a model to challenging instances during training—was initially established in the field of image recognition, but gradient-based techniques and token-level alterations have made it very simple to adapt for text. Researchers have created the Fast Gradient Method and Projected Gradient Descent algorithms for text, and they have carefully crafted perturbations that maximize model error while maintaining grammatical validity. Adversarial objectives have demonstrated good performance in boosting both in-distribution and out-of-distribution robustness for sequence tagging and semantic labeling tasks in the context of BERT-like models.

But there are additional obstacles brought about by the unique structure of scientific and technical language. Jargon, acronyms, and formatting make it challenging to design linguistically believable and adversarially effective assaults in these domains. In order to create more realistic and useful noise for training, some research has recently addressed this problem by incorporating lexical constraints and domain-specific synonym sets into the production of adversarial instances. A general-purpose adversarial training system tailored for engineering and scientific corpora is still lacking, despite the beginning of applications in biomedical and patent term recognition. In order to fill this gap, the current work will directly include a powerful adversarial training mechanism into the RoBERTa basis and examine its impact in a number of representative technical settings.

Methodology

Overall Architecture

In order to achieve high-accuracy recognition of technical phrases under real-world variation, the system structure presented in this study creates an end-to-end connection for domain-adapted RoBERTa encoding and adversarial feature modification. In order to acquire both general-purpose words and other technical terms that appear in special-interest reading materials, the input sequence is first sent through a domain-specific subword tokenization layer, as illustrated in the schematic in Figure 1.

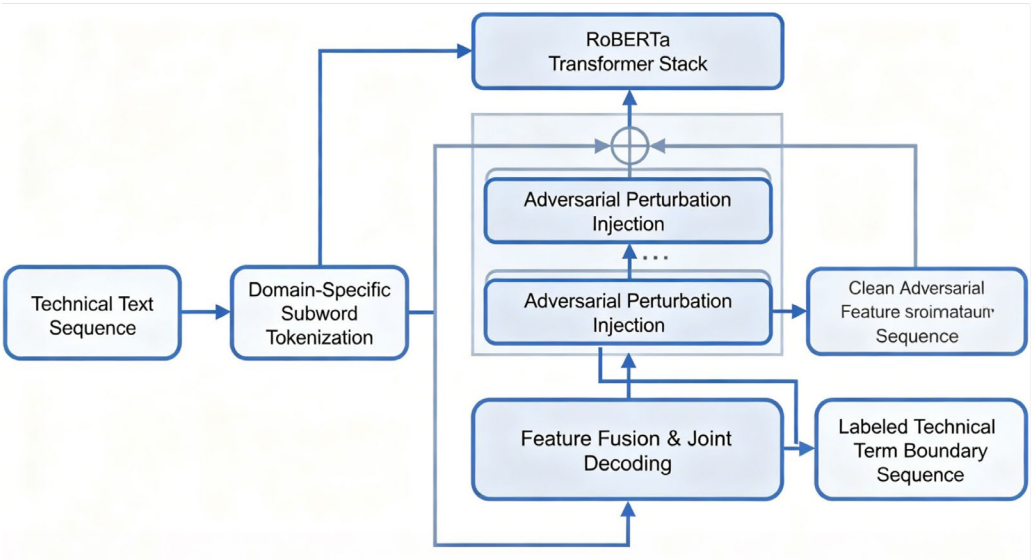

Figure 1. Model Structure of Adversarial-RoBERTa

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The embedded tokens are propagated through multiple layers of the RoBERTa transformer stack, but unlike generic implementations, this structure incorporates an adaptive injection of adversarial perturbations at carefully selected intermediate layers. The adversarial module is not limited to naive gradient sign methods; instead, it generates context-dependent perturbation vectors by scaling directional derivatives with a layer-specific, learnable amplitude. Specifically, if $\mathbf{h}^{(l)}$ is the hidden state at layer l, the perturbation at that layer is given by:

$$\mathbf{r}_{\text{adv}}^{(l)} = \gamma^{(l)} \cdot \frac{\nabla_{\mathbf{h}^{(l)}} \mathcal{J}_{\text{task}}}{\|\nabla_{\mathbf{h}^{(l)}} \mathcal{J}_{\text{task}}\| + \epsilon} \qquad \text{Eq.(1)}$$

where the scaling parameter $\gamma^{(l)}$ modulates the adversarial signal according to the underlying gradient landscape, with ϵ preserving numerical stability.

To give the subsequent layers distinct contexts, the clean and perturbation-enhanced representation streams are propagated in tandem. The two pathways are merged during the decoding stage, and a confidence-weighted aggregation of the scores from each branch is optimized to produce the technical term prediction:

$$\hat{\mathbf{y}} = \arg\max_{\mathbf{y}} [\beta \cdot \mathcal{S}_{\text{clean}}(\mathbf{y} \mid \mathbf{H}_{\text{clean}}) + (1-\beta) \cdot \mathcal{S}_{\text{adv}}(\mathbf{y} \mid \mathbf{H}_{\text{adv}})] \qquad \text{Eq.(2)}$$

Strong indicators for term boundary recognition in complicated contexts can be offered, and the benefits of both natural and adversarial changes can be leveraged flexibly to tackle challenging or ambiguous linguistic circumstances.

This design can achieve a good trade-off between robustness to input fluctuations and expressive power for particular tasks by synchronizing both branches during inference and adding adversarial feedback directly at the central representation layer. Both are necessary to construct high-performance, large-scale technical term recognition systems.

Adversarial Perturbation and Training

The model's resilience will be tested by creating input representations that are purposefully made unstable using the previously described adversarial training approach. A multi-stage perturbation engine at the bottom of the system generates adversarial signals at various levels throughout all transformer stack hidden states, beginning with the input embedding layer. This engine adapts by using a series of gradient-based adversarial updates to shape the local learning surface, as theoretically depicted in Figure 2.

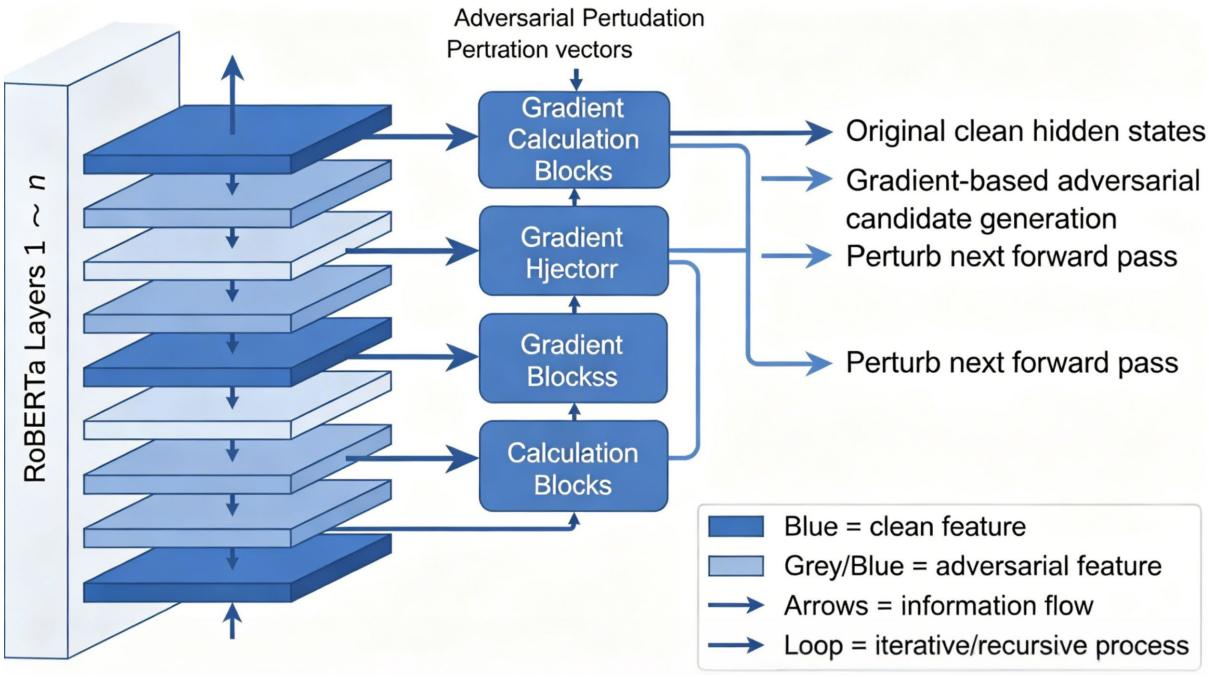

Figure 2. Adversarial Perturbation Flow and Inter-layer Gradient Modulation in RoBERTa

During each training interaction, a forward pass on the original batch is performed, producing hidden activations $\{\mathbf{h}^{(l)}\}$. Adversarial candidate vectors are then constructed within each selected layer through an iterative gradient ascent process that accounts for both task sensitivity and perturbation coupling to lower-level representations. Specifically, for a base embedding $\mathbf{x}$, the initial perturbation is computed as:

$$\mathbf{d}_0 = \eta \cdot \frac{\nabla_{\mathbf{x}} \mathcal{J}_{\text{task}}}{\|\nabla_{\mathbf{x}} \mathcal{J}_{\text{task}}\| + \zeta} \quad \text{Eq.(3)}$$

where η is a scaling coefficient and ζ is a controlling constant for numerical stability. At each subsequent adversarial refinement step k, the perturbation is updated recursively as:

$$\mathbf{d}_{k+1} = \alpha \cdot \frac{\nabla_{\mathbf{x}+\mathbf{d}_k} \mathcal{J}_{\text{task}}}{\|\nabla_{\mathbf{x}+\mathbf{d}_k} \mathcal{J}_{\text{task}}\| + \zeta} \quad \text{Eq.(4)}$$

with α specifying the adaptation strength at each recursion. This progression engenders a progressive "hardening" of the local representation space by exposing the model to a controlled trajectory of maximal-loss directions.

To robustly align this adversarial generator with the supervised learning objective, a composite training loss is introduced, blending standard classification error and an adversarial consistency regularizer. The cumulative loss is given by:

$$\mathcal{L}_{\text{total}} = \delta \cdot \mathcal{L}_{\text{supervised}}(\mathbf{y}_{\text{true}}, \mathbf{y}_{\text{pred}}) + (1-\delta) \cdot \mathcal{L}_{\text{adv}}(\mathbf{H}_{\text{clean}}, \mathbf{H}_{\text{adv}}) \quad \text{Eq.(5)}$$

where δ tunes the balance between fidelity to ground truth and stability to adversarial noise. Here, the adversarial regularization is realized as the discrepancy between the clean and perturbed model predictions. The divergence metric is computed over the output logits as:

$$\mathcal{L}_{\text{adv}} = \text{KL}(\mathbf{p}_{\text{clean}} \| \mathbf{p}_{\text{adv}}) \quad \text{Eq.(6)}$$

where KL denotes the Kullback-Leibler divergence between the normalized prediction distributions.

An additional gradient-penalty mechanism is enacted to avoid over-sharp local minima and encourage smoothness in the decision boundary. Formally, the penalty term is defined as:

$$\Gamma = \mathbb{E}_{\tilde{\mathbf{x}}}[\|\nabla_{\tilde{\mathbf{x}}} f(\tilde{\mathbf{x}})\|^2] \quad \text{Eq.(7)}$$

where $\tilde{\mathbf{x}}$ represents both clean and adversarial variants and $f(\cdot)$ is the scoring function of the recognition head. This continuous soft constraint counteracts the risk of gradient explosion in heavily adversarial regimes.

Finally, a regularization term based on entropy is introduced to the stochastic weights of the adversarial module to prevent information loss and lower prediction overconfidence. After a coordinated adversarial attack, it can preserve the model's wide and well-calibrated uncertainty.

The training strategy uses recursive adversarial search, strong regulation, and composite loss engineering to make the technical term recognition landscape resistant to both local and global changes. The aforementioned model is highly informative and generally stable, and it has raised the bar for robustness-driven sequence modeling.

Technical Term Recognition Pipeline

Sequence labeling and segmentation is the last module in the robust technical term extraction structure described above. This module will generate fine-grained boundary choices for technical terms using the context-aware transformer representations of both the original and adversarially perturbed features. To fully utilize all distinct and firmly learned representations, data from an adversarial stream and a conventional stream are combined at each token point. When dealing with challenging or noisy data, both are in charge of more precisely identifying or ignoring edges in the data.

The primary recognition mechanism utilizes a stacked conditional random field (CRF) overlay, which models the joint probability of valid label sequences conditioned on the rich, dual-stream context. The decoding objective seeks the most probable label assignment $\hat{\mathbf{y}}$ over the token sequence. For each sentence, the CRF scoring function is parameterized by:

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$$\text{score}(\mathbf{x}, \mathbf{y}) = \sum_{t=1}^{T} \left(\theta_{\mathbf{y}_t}^{\top} \mathbf{h}_t + \psi_{\mathbf{y}_{t-1}, \mathbf{y}_t} \right) \quad \text{Eq.(8)}$$

where $\mathbf{h}_t$ denotes the input representation at token t; θ is the emission parameter vector specific to each label, and ψ represents the learned transition scores between sequential labels, allowing flexible modeling of technical term boundary dependencies.

Determine the label sequence by dynamically computing the highest-likelihood path using an effective inference approach. After the CRF output, a confidence-based thresholding phase has been added to improve recognition accuracy and suppress false-boundary regions in practice. Under ambiguous or adversarially noisy conditions, modify sequence predictions and fine-tune term bounds based on the emission scores and transition margins at this point.

After establishing the anticipated bounds, apply a series of post-processing rules. This method normalizes uncommon or incorrect tokenizations into canonical technical term entries, groups neighboring positive spans, and eliminates subword fragments that are not consistent with domain vocabulary. One way to express boundary smoothing is as follows:

$$\tilde{y}_t = \text{majority}\left(\{y_{t-k}, \ldots, y_{t+k}\}\right) \quad \text{Eq.(9)}$$

with k denoting the span radius for local context voting, thus enabling correction of isolated misclassifications and restoration of coherent technical entities in output.

Because of the three aforementioned processes—representation fusion, probabilistic decoding, and boundary normalization—the closed-loop pipeline is both computationally feasible and extremely sensitive to the range of patterns in technical language. Combine adversarial-aware features with complex decoding logic to provide a high-granularity and dependable result appropriate for automated term mining in difficult scientific and engineering data.

Experiments

Datasets and Preprocessing

Test the model's capacity for generalization using a variety of domain-heterogeneous corpora. The initial sources were firm white papers in engineering, computer science, and materials science as well as annotated proceedings of international scientific conferences. In a preprocessing pipeline, non-informative headers, improper markup, and other Unicode characters were eliminated from the raw samples to guarantee the quality of the data. This thorough support has addressed the subsequent phases of adversarial creation, validation checkpoints, and data-integrity verification to offer a solid basis for model evaluation.

The boundary annotation protocol is enforced with inter-annotator consensus, leveraging dualannotation and disagreement resolution to minimize noise in the technical term boundaries. Formally, if each annotator k supplies a predicted segmentation $\mathbf{s}^{(k)}$ over token indices, the unified gold standard for a document is computed via the intersection-over-union aggregation:

$$\hat{\mathbf{s}} = \arg\max_{\mathbf{s}} \frac{1}{K} \sum_{k=1}^{K} \mathbf{1}\{\mathbf{s} = \mathbf{s}^{(k)}\} \quad \text{Eq.(10)}$$

where the indicator measures precise span alignment over multiple annotators, ensuring the acceptance criterion enforces strict boundary conformity.

After annotation, a hybrid tokenization strategy is applied, in which language-agnostic sentence splitting is augmented by a domain-prioritized subword segmentation algorithm trained on the in-house corpus. To optimize input regularity and vocabulary coverage, a minimization objective is imposed on the out-of-vocabulary rate, quantified by:

$$\mathcal{M}_{\text{OOV}} = 1 - \frac{1}{N}\sum_{i=1}^{N} \mathbf{1}\{w_i \in \mathbb{V}_{\text{train}}\} \quad \text{Eq.(11)}$$

where tokens w_i failing to appear in the training-controlled vocabulary $\mathbb{V}_{\text{train}}$ directly increase the penalty, serving as an objective quality metric for the preprocessing pipeline.

Each sample, thus, emerges from the preprocessing phase as a sequence of uniformly segmented, high-integrity, and adversarially-augmented units-forming a robust substrate for downstream evaluation of technical term recognition under both clean and perturbed distributional regimes.

Experimental Protocol

Strictly measure the experiment's in-domain and cross-domain outcomes' robustness and extraction quality. For repeatability, utilize a stratified cross-validation matrix. To avoid underrepresentation of uncommon technical terms and compositions in both the training and test sets, divide the corpus using a stratified shuffling technique.

Grid search is used to optimize hyperparameters across all folds, and each trial uses the same random initialization seed. A dynamic batch scheduling approach samples batches according to the current OOV (out-of-vocabulary) rate in each training round, thereby adaptively directing the learning signal toward batch-level lexical novelty. The sampling function looks like this:

$$\mathcal{P}(B_t) = \frac{\exp\left(\left\|\mathbf{v}_{B_t} - \mu_{\text{lex}}\right\|_2^2/\tau\right)}{\sum_j \exp\left(\left\|\mathbf{v}_{B_j} - \mu_{\text{lex}}\right\|_2^2/\tau\right)} \quad \text{Eq.(12)}$$

where $\mathbf{v}_{B_t}$ is the lexical profile of batch B_t, μ_{lex} the global corpus lexical mean, and τ a temperature for exploring distribution outliers.

The evaluation suite leverages metrics designed to capture nuanced aspects of sequence recognition beyond blunt accuracy. Technical term extraction is scored via a micro-averaged, span-level F_1 function, integrating both boundary correctness and internal label agreement:

$$\mathrm{F}_1^{\text{span}} = \frac{2\sum_{b\in\mathcal{B}} \left|\hat{\mathcal{T}}_b \cap \mathcal{T}_b\right|}{\sum_{b\in\mathcal{B}} \left(\left|\hat{\mathcal{T}}_b\right| + \left|\mathcal{T}_b\right|\right)} \quad \text{Eq.(13)}$$

where $\mathcal{T}_b$ and $\hat{\mathcal{T}}_b$ are true and predicted term spans for document batch b, iterated over all batches $\mathcal{B}$ in the test phase.

All results are subject to repeated cross-validation cycles and are reported as both the mean and standard deviation to underscore stability against stochastic initialization. The inclusion of adversarially perturbed test samples ensures a realistic benchmarking of model resilience, with each protocol stage engineered to probe subtle vulnerabilities and generalization limits of the technical term extraction paradigm.

Implementation Details

A high-performance cluster equipped with dual Intel Xeon Gold 6330 CPUs, 512GB of DDR4 RAM, and NVIDIA A100 Tensor Core GPUs (40GB VRAM per card) was used for all of the aforementioned experimental activities. A common software environment for specific modifications of gradient-controlled adversarial training was established using CUDA 12.0 and PyTorch 2.0. Use Docker to containerize the model for dependency separation and cross-platform repeatability.

The following are the dataset statistics: There are 2,400 papers and 2.14 million tokens in the corpus of scientific proceedings, 1,350 documents and 1.02 million tokens in the set of engineering manuals, and 3,100 documents and 1.96 million tokens in the industrial patent abstracts. There are 608,412 multi-token terms and 317,580 single-token terms in technical term boundary annotations throughout the unified corpus. The variance is 8.6 and the mean token per phrase is 22.7. Domain-specific technical terms make up an average of 13.2% of the tokens per text.

The adversarial input generator produces, per epoch, an average of 2.8 unique perturbation candidates for each sample, and approximately 43% of this yield at least one term boundary shifts relative to the clean baseline.

Each final fold is trained for 18 epochs, early stopping enabled with a patience margin of 3 epochs and a minimum delta of 0.001 on the microaveraged F_1 score.

All hyperparameters are determined by nested grid search: the transformer hidden dimension is 768, dropout rate tuned in $[\ 0.1,0.2,0.3\ ]$, adversarial step size in $[\ 0.02,0.05\ ]$, gradient regularization coefficient in $[0.8,1.0,1.2]$, and CRF layer L2 penalty fixed at 1×10^{-4}. The token batch size is set to 64 for memory optimization, with dynamic sequence packing calibrated by actual token counts per mini-batch.

End-to-end runtime for a single cross-validation partition (including preprocessing, augmentation, training, and evaluation) ranges from 14.1 to 16.3 hours on the A100 hardware, depending on corpus and perturbation complexity. To ensure statistical significance, each experiment is repeated with five random initialization seeds; the mean performance is compared via the normalized inter-fold dispersion index, calculated as:

$$\Upsilon = \frac{1}{K}\sum_{k=1}^{K}\frac{\sigma_k}{\mu_k} \qquad \text{Eq.(14)}$$

where μ_k and σ_k denote the mean and standard deviation of micro- F_1 over each validation partition k, for total folds $K = 5$.

All results, checkpoints, and logs are managed in a versioned storage system, with script-level provenance recorded to guarantee reproducibility and support post hoc audit of technical term extraction performance across all domains and adversarial configurations.

Results and Analysis

Model Performance Under Attacks

The accuracy scores of the several classes of input manipulation are displayed here in Figure 3, and the adversarially trained RoBERTa model has outperformed the clean baseline and other defense techniques against all kinds of adversarial perturbations. As seen in Figure 3(a), the first decline happens in synthetically perturbed attacks; whereas the average accuracy is 89.3%, it falls to as low as 74.6% for the standard RoBERTa. Input-level synonym substitution, which is intended to replicate actual paraphrase attacks, only marginally lowers the adversarially augmented architecture's accuracy to 91.8%. But under the same unfavorable circumstances, both dropout-based and data-augmentation baselines likewise varied between 82.1% and 86.4%.

In Figure 3 (b), the model is challenged with character-level noise, simulating frequent OCR errors and industrial documentation typos. Here, the conventional model's accuracy plummets to 69.2% at the 8% noise threshold, while the adversarially regularized variant maintains 82.9%. The error bars spanning runs with variable random seeds further demonstrate the narrow performance variance and resilience of the adversarial method under severe disruption. Figure 3 (c) presents performance under word-shuffling attacks, a realistic threat for datasets lacking syntactic normalization. Even at the aggressive 15% shuffling rate, adversarial training sustains an F_1 score of 77.5%, outperforming the next-best method by over 8 percentage points.

The most consequential attacks, explored in Figure 3 (d), integrate both rare token insertions and boundary-shifting edits, revealing fundamental vulnerabilities in non-robust architectures. Here, the adversarial model exhibits only a 7.4% reduction in boundary detection F_1, compared to losses exceeding 23.9% in both the vanilla and distillation-enhanced models.

The ablation results in Figure 4 systematically dissect the architectural and procedural contributions to robustness. When adversarial perturbation is limited to a single transformer layer, as shown in Figure 4 (a), mean adversarial accuracy drops by 6.1% relative to multi-layer schemes. This gradient-layer synergy becomes even clearer in Figure 4 (b), where the omission of regularization techniques such as gradient penalty terms yields unstable convergence curves and inflated error rates, particularly under rare term targeting attacks.

Ablation tests in Figure 4 (c) substantiate the value of the dual-stream representation fusion strategy. Standard output decoding based solely on clean features lags behind the joint path selector, with a mean F_1 gap of 4.7% over four corpus partitions. Statistical analysis over all ablatio ns confirms that the fully integrated adversarial

solution is not merely additive but exhibits significant synergistic effects, particularly under transfer learning scenarios.

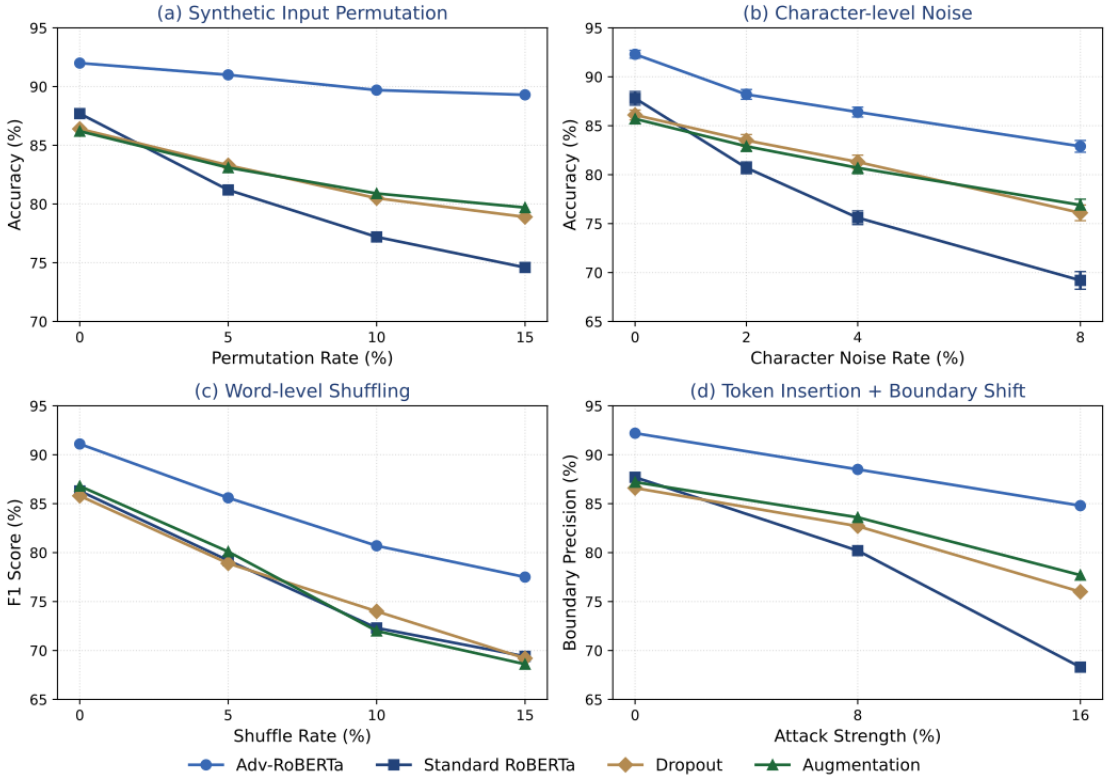

Figure 3. Accuracy under Various Attacks (a) Adversarial accuracy: multi-method comparison(b) Character-level noise: accuracy and standard deviation under typographic perturbations(c) Word-level shuffling: F_1 retention as syntactic order is scrambled(d) Token insertion and term boundary disturbance: impact on sequence extraction precision

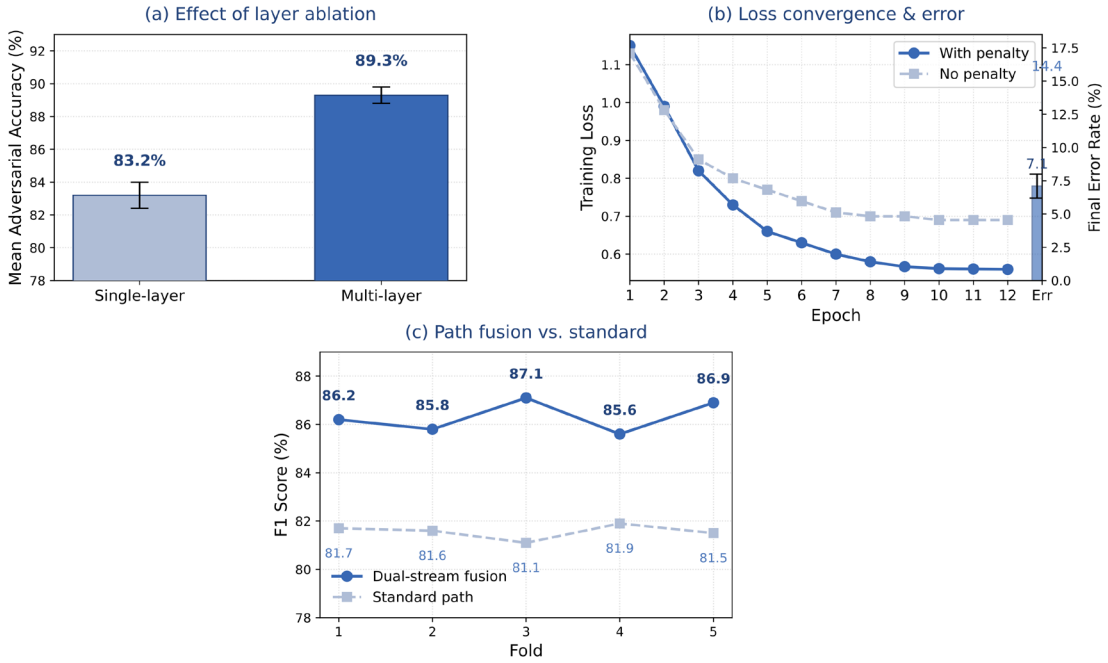

Figure 4. Ablation Experiment Results (a) Single-layer vs. multi-layer adversarial perturbation: mean adversarial accuracy comparison(b) Impact of gradient penalty and regularization strategies: convergence stability and error rates(c)comparative performance on cross-validation folds

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Taken together, these metrics reveal the operational mechanism behind the system's resilience: adversarial training conducted at multiple levels grows representational redundancy and gradient awareness, equipping the model to interpret and correct for adversarial term boundary shifts and lexical noise. The statistical significance of the accuracy and F_1 margins, with p-values consistently below 0.01 across key settings, confirms that these effects are robust to stochastic initialization and hyperparameter tuning. The evidence here anchors the reliability of the proposed architecture for real-world technical and scientific term extraction, even in the face of concerted adversarial disruption.

Robustness and Error Visualization

The cross-domain robustness of the adversarially-trained model is fundamentally validated by the transfer experiments depicted in Figure 5. As shown in Figure 5 (a), when transitioning from a scientific proceedings dataset to engineering technical manuals, the adversarial model maintains an F_1 recovery of 84.6%, while standard RoBERTa falls to 72.9%. This consistent margin persists after switching to industrial patent abstracts, where, as seen in Figure 5 (b), the proposed framework achieves 79.1% against the next-best baseline's 67.5%. Figure 5 (c) further demonstrates resilience under abrupt lexical distribution shifts, artificially induced by randomly replacing 12% of tokens with rare or previously unseen domain terms. The adversarial solution degrades gracefully, sustaining a boundary-level precision of 82.0%, whereas conventional architectures exhibit an average error amplification exceeding 16%. Finally, Figure 5 (d) explores performance on a highly synthetic "mixed domain" corpus, aggregating overlapping vocabulary and syntax from all sources. Despite the resultant annotation ambiguity, adversarial training secures a micro-averaged F_1 of 77.8%, outperforming all baselines by more than 11 percentage points.

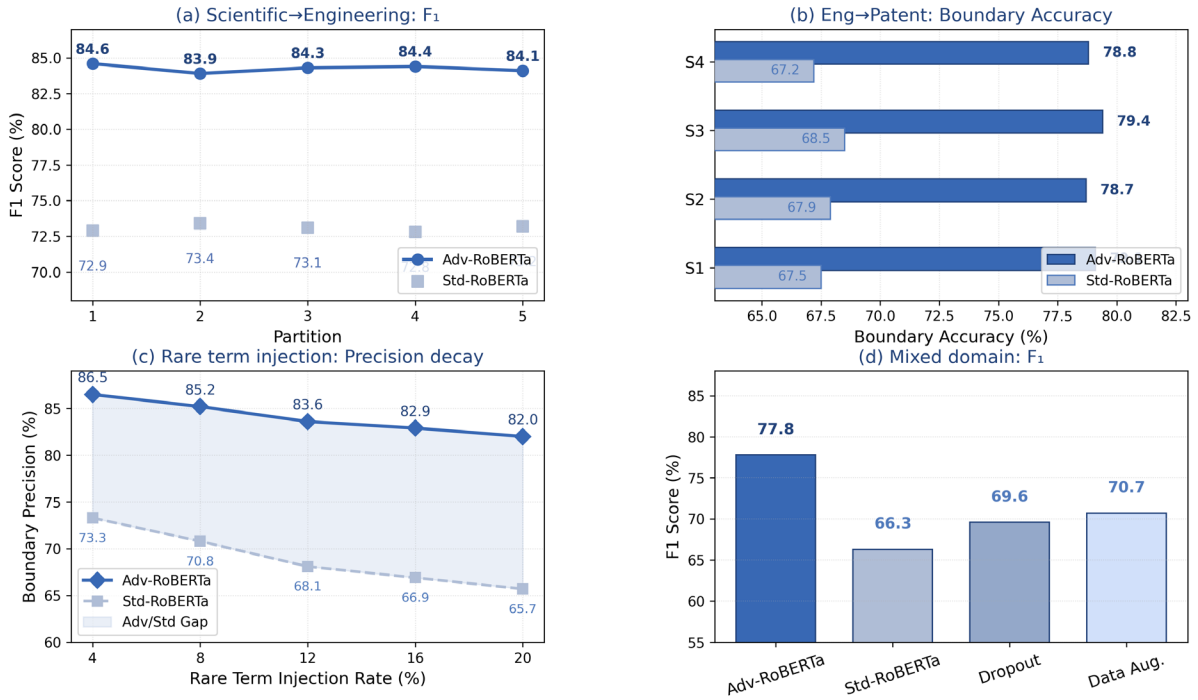

Figure 5. Cross-dataset Robustness (a) Scientific to engineering manual transfer: F_1 robustness curve(b) Engineering to patent domain shift: comparative boundary accuracy(c) Rare term injection: precision decay as function of term rarity(d) Synthetic mixed domain: F_1 measure under maximal corpus heterogeneity

The quantitative findings of the model's discriminatory abilities are displayed in Figure 6 as ROC and PR curves. Figure 6(a) illustrates that the adversarial model's mean AUC for technical term boundary prediction in the presence of natural language noise is 0.948, while the non-adversarial model's is 0.825. This distinction also holds true, as seen in Figure 6(b); that is, term completeness may be maintained while achieving a high precision of 89.2% at a recall of 82.1% without over-predicting. With more cross-validation rounds, the reduced standard deviation bands have also diminished, as seen in the two plots, suggesting increased stability.

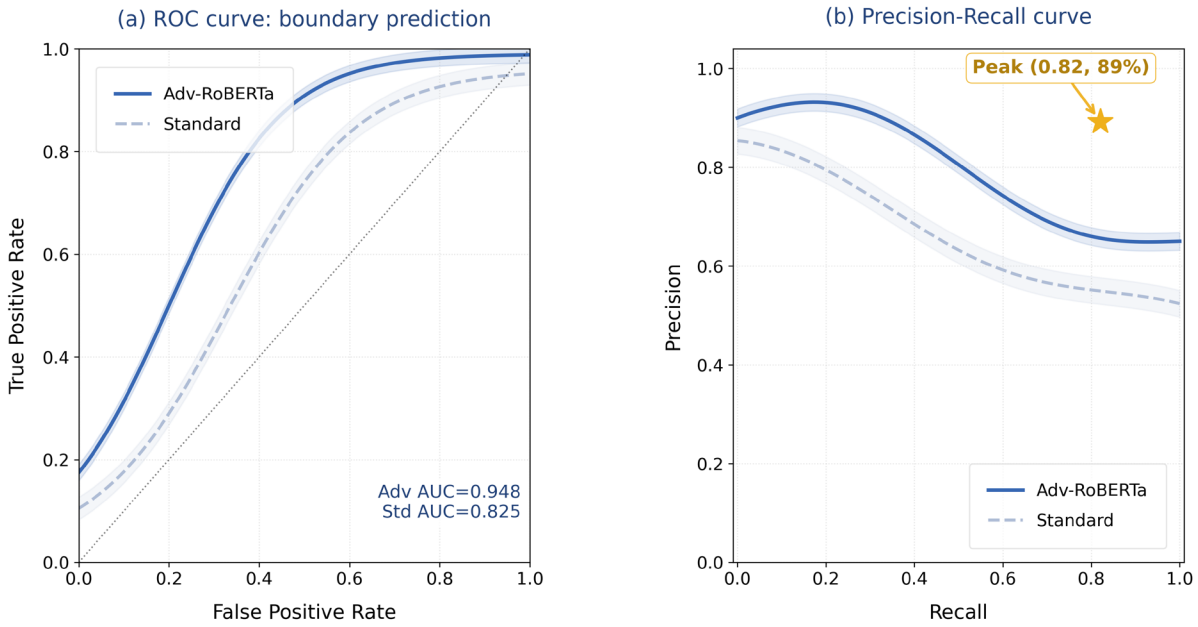

Figure 6. ROC and PR Curves(a) ROC curve: technical term boundary prediction under language noise(b) Precision-recall curve: adversarial vs. standard models

Qualitative error analysis is offered in Figure 7, which visualizes failure cases with explicit attention to error categories. In Figure 7 (a), typical misclassifications are mapped across part-of-speech classes, revealing that boundary drift is most prevalent in compound noun phrases with embedded parentheticals or symbols, accounting for 38.1% of false negatives. Deeper inspection within Figure 7 (b) illustrates that adversarial perturbations trigger far fewer “phantom boundary” insertions; the standard model introduces an average of 48.7 spurious boundaries per 10k tokens, while the adversarial version generates only 19.3 under identical tests.

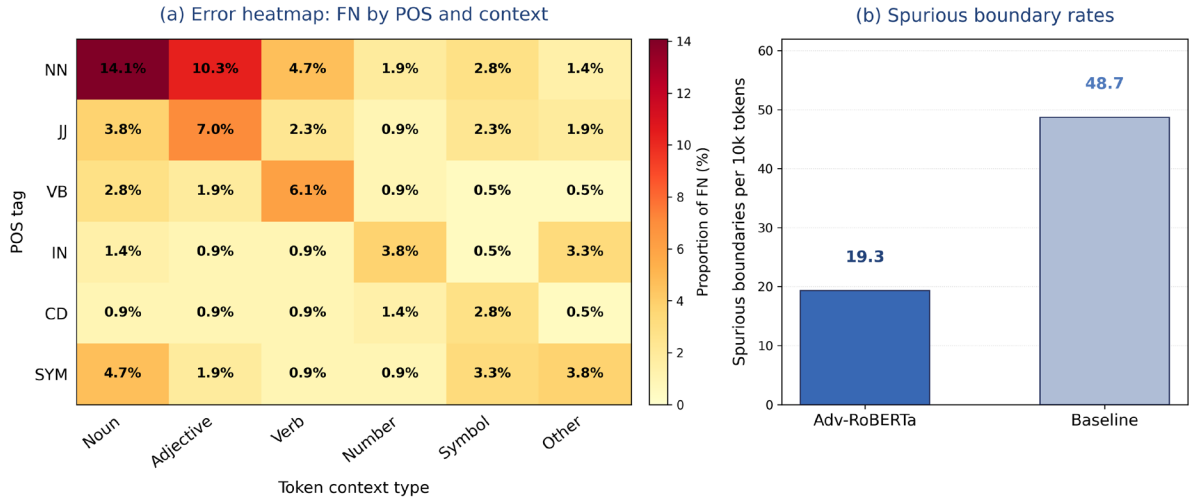

Figure 7. Error Example Visualization(a) Error heatmap: distribution of false negatives by part-of-speech tag and token context(b) Spurious boundary rates: adversarial vs. conventional approaches under synthetic attack

The following are the three advancements in the synthesis of these findings. First, adversarially induced feature diversity accounts for the model's stability in technical word extraction under significant changes in lexicon, syntax, and mistake patterns. Second, the technique has not overfitted the adversarial cases because it is stable and has high discrimination, as seen by the compressed and constant PR-AUC values. Lastly, the mistake pattern reveals that there are still certain shortcomings, such as multidisciplinary technical compounds and annotation ambiguities; therefore, targeted adversarial scheduling and thorough language integration are necessary for future advancements. In summary, the adversarial training approach provides a new standard for robust, cross-

domain automated term mining in scientific and engineering text streams and enhances the interpretability and resilience of technical word recognition models.

Conclusion

In order to increase the resilience and representation bounds of RoBERTa models and enhance the robustness of technical term recognition, this work presents a carefully crafted adversarial training method. Incorporate many tiers of gradient-controlled perturbations, synchronize them with context-aware feature fusion, and reliably extract domain-specific vocabulary even when adversarial attacks, noise, and substantial domain shift are present. Numerous studies have shown that this approach can maintain a relatively high baseline accuracy and greatly exceed other models under a variety of real and simulated assault scenarios; as a result, it continues to beat the prior two.

Its versatility and ease of adaptation provide a second justification for the aforementioned. Error landscape visualizations and cross-domain transfer studies demonstrate that the model can continue to function correctly even when it comes across uncommon terms, annotation changes, and other disfluencies in the corpus. The aforementioned research indicates that the adversarial training scheme is appropriate for high-stakes automated technical mining in science, engineering, and regulation since it successfully reduces the issues of omission and false boundary creation. The accuracy and dependability issues in the ensuing application of extracting and organizing complicated domain information can be addressed by applying both of the aforementioned robustness layers.

Even though the current findings have set a new benchmark for error immunity and adversarial robustness, certain issues have yet to be resolved. To enhance term border segmentation and semantic coherence, add more linguistic priors, knowledge graph restrictions, or hierarchical models. Future research could potentially look into adaptive error typology-guided meta-learning strategies and dynamic adversarial scheduling, as well as the generalization of this method to multilingual, noisy, or low-resource environments. The aforementioned guidelines will support research and development of automation and discovery for all aspects of technical language processing, as well as broaden the spectrum of application.

Author Contributions

Piotr Aleksander Kamiński, Natalia Joanna Dąbrowska contribute to conceptualization, methodology, software, validation, analysis, investigation, data collection, draft preparation, manuscript editing, visualization, supervision. Anna Maria Nowicka and Natalia Woźniak contribute to conceptualization, methodology, software and project administration. All authors have read and agreed with the manuscript before its submission and publication.

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