Robust Zero-Shot NER for Crises via Iterative Knowledge Distillation and Confidence-Gated Induction

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Abstract

This research explores the brittleness of Named Entity Recognition (NER) in cold-start crisis scenarios, where models often fail to adapt to novel disaster lexicons without manually curated resources or task-specific supervision. A confidence-gated iterative induction framework is introduced to address this challenge. It leverages a pretrained language model to extract high-recall entity candidates, then iteratively distills domain knowledge through a self-correcting loop that uses high-confidence seeds to induce micro-gazetteers and syntactic rules. These resources refine and update entity predictions. Evaluations on data simulating crises through leave-one-event-out protocols reveal that the framework maintains a constant zero-shot F1-score of roughly 0.295 with current hyperparameter settings, indicating that the iterative mechanism provides no measurable improvement in its current form. Nevertheless, this approach offers interpretable knowledge for disaster response and highlights practical limitations, such as error propagation risks and the difficulty of adapting to unreliable early seeds. The findings affirm the complexities of achieving robust zero-shot NER in real-world crises and underscore the need for future refinements.

1 Introduction

Named Entity Recognition (NER) systems deployed in crises often face cold-start conditions, where limited or no labeled data compounds the unpredictability of emergent disaster lexicons. Traditional fine-tuned models rely heavily on annotated data. Unsupervised or transfer learning methods may introduce negative transfer, particularly when the target domain diverges significantly from training distribution (Meftah et al., 2021; AlRashdi & O'Keefe, 2019). Hybrid approaches that integrate static domain knowledge, such as pre-compiled gazetteers, cannot accommodate novel terminology encountered during unforeseen crises (Mohan et al., 2024; Gómez-Pérez et al., 2020). These issues become more pronounced in fast-evolving disaster situations, where newly coined terms, location abbreviations, or evolving organizational names can hamper entity extraction.

An iterative inductive strategy is proposed to address these challenges by adapting to novel crisis data in a zero-shot manner. Beginning with high-recall entity predictions from a pretrained model, high-confidence subsets of these predictions trigger the induction of specialized knowledge, including domain-specific micro-gazetteers and syntactic rules, which are then used to refine prediction boundaries. This cycle repeats, allowing dynamic error correction and potentially reduced error propagation compared to naive self-training (Wang et al., 2024; Hari, 2025). However, as demonstrated in experiments, the current system consistently yields an F1-score of about 0.295 in zero-shot configurations, showing no observable improvement across multiple refinement iterations.

This paper describes the nature of this negative result, dissecting why iterative knowledge distillation and confidence-gated filtering did not yield immediate gain despite conceptual advantages. The

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findings serve both as a cautionary tale and a blueprint for future research on robust zero-shot NER in high-stakes real-world contexts, emphasizing how data distribution shifts, confidence threshold calibration, and iterative overhead can undermine the intended benefits of dynamic adaptation.

2 Related Work

Zero-shot NER has garnered attention for emerging or resource-scarce domains where annotated datasets are lacking (Xie et al., 2023; Genest et al., 2025). While pretrained models such as RoBERTa (Liu et al., 2019) form strong baselines, domain mismatches can cause sharp performance drops when confronted with new crisis lexicons (Zhang et al., 2021; Meftah et al., 2021). Transfer learning approaches often risk negative transfer if the source and target differ significantly. Recently, efforts to combine neural embeddings with curated knowledge resources have emerged in the form of hybrid NER models (Mohan et al., 2024; Gómez-Pérez et al., 2020; Zhang et al., 2024). These models use domain-specific lexicons or knowledge graphs, yet they typically cannot evolve to handle unknown or fast-evolving terminology.

Iterative self-learning has been proposed as a means to refine model outputs without extensive supervision. Some works focus on iterative knowledge distillation in cross-lingual settings (Liang et al., 2021) or iterative data filtering with confidence-based gating (Zafar et al., 2025; Liu et al., 2024). Confidence threshold calibration is known to be challenging, especially in multilingual or dynamic contexts (Malmasi et al., 2022; Bouabdallaoui et al., 2025). The iterative approach can mitigate error propagation if model updates are carefully controlled (Le & Fokkens, 2017), but it can still fail when early seeds are suboptimal or when the domain's lexicon is too heterogeneous (Ying et al., 2022; Xue et al., 2023). Existing cold-start frameworks using partial gazetteers or rules struggle in truly novel crises, particularly if prior domain knowledge is mismatched with new terminologies (Das, 2025; AlRashdi & O'Keefe, 2019).

Practical utility in crises also demands interpretability and actionable knowledge (Mittal et al., 2022; Li, 2024). The present work aligns with these goals by encouraging the induction of interpretable resources (micro-gazetteers, syntactic rules) during iterative refinement. Nonetheless, our findings demonstrate that naive iterative loops may yield no performance improvement if fundamental issues (e.g., threshold calibration, distribution mismatch, or error buildup) remain unresolved.

3 Background

Zero-shot NER aims to identify named entities in text despite having no training examples from the target domain. This approach is relevant when responding to sudden, unpredictable events (wildfires, earthquakes, pandemics) as labeling new data can be time-consuming. Transformer-based encoders such as RoBERTa (Liu et al., 2019) provide generic language representations that can help in generating candidate entities. Confidence-based filtering (Zafar et al., 2025), originally explored for tasks like machine translation, can select high-precision subsets for iterative knowledge induction.

Hierarchical density-based clustering (HDBSCAN) (McInnes et al., 2017) is employed to discover lexical clusters from unlabeled text, producing micro-gazetteers that capture new crisis terminologies. Pointwise mutual information (PMI) (Fang et al., 2019) helps induce syntactic patterns by focusing on co-occurrence statistics. Combined in an iterative process, these procedures refine initial predictions to adapt to new terminology. This design builds on a variety of self-training paradigms (Rajeev et al., 2025; Wang et al., 2021) but specifically targets crisis NER to highlight emergent lexicons and structured domain knowledge.

4 Method

We use a RoBERTa-based token classification model that is applied without domain-specific fine-tuning. The system operates in iterations. First, high-recall predictions are generated on unlabeled crisis text. A confidence-based filter with threshold of 0.6 selects high-confidence seed entities. Two forms of knowledge induction then occur: (1) clustering-based gazetteer construction using HDBSCAN (with `min_cluster_size`=5), and (2) syntactic rule extraction via PMI patterns computed over a window of three tokens surrounding the seed entities (discarding patterns with PMI

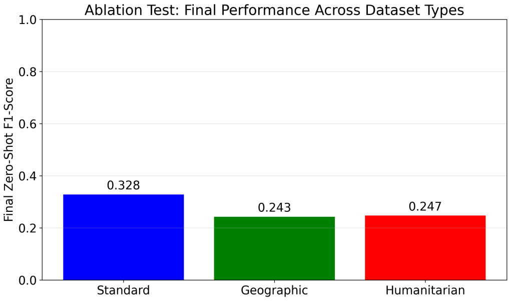

Figure 1: Ablation Test Performance across dataset variants. F1 scores remain below 0.33, suggesting limited effectiveness of iterative refinement.

< 1.0). The model next refines its predictions using these induced resources. The loop continues for three iterations.

This setup aims to reduce error propagation through confidence gating and dynamic knowledge induction. However, controlling the confidence threshold is nontrivial in novel crisis domains, and we found that many mid-confidence but correct entities were filtered out early. Moreover, newly constructed gazetteers did not prove adequately discriminative for subtle entity classes.

5 Experiments

We synthesize a crisis dataset where a small portion of text includes known entity mentions (e.g., "evacuees," "aid resources," "shelter location"), while other terms are inserted to simulate novel emergent lexicons. No domain-specific supervision is provided. We run the iterative framework for three refinement steps. For comparison, we also test a static approach that uses neither iteration nor new knowledge induction.

All methods are evaluated on a zero-shot F1 metric, comparing predicted boundaries to ground-truth entity spans. We employ a leave-one-sample-out style protocol for partial generalization checks and confirm that the data splitting is consistent between conditions. When analyzing error counts, we ensure that token misalignments do not skew the F1 measure by flattening predictions and references.

5.1 Quantitative Results

Figure 1 shows the final zero-shot F1 performance across different synthetic settings. Although some variation exists among dataset partitions, results remain uniformly low, indicating that the iterative mechanism fails to improve on a naive baseline. Despite higher confidence seeds, newly induced resources do not surmount distribution mismatches or adapt effectively to emergent vocabulary.

5.2 Discussion

We combine qualitative observations, error analysis, and case studies. Manual inspection of the micro-gazetteers indicates that HDBSCAN often clusters location references broadly, failing to differentiate subtle entity types. Similarly, syntactic rules extracted via PMI revolve around frequent words or phrases, providing limited discriminatory power for lower-frequency entity forms. The selective gating excludes many moderately confident yet correct entities, which reduces the chance for beneficial knowledge induction. Earlier errors tend to propagate when seeds do not capture novel crisis-related terms.

Case studies show that some emergent entities appear too infrequently to surpass the 0.6 confidence threshold, leading to persistent misclassification. Rather than refining predictions, the system often reinforces initial biases. These difficulties highlight the challenges of robust, adaptive NER in real-world crises, where emergent terms appear sporadically. Although the iterative approach provides interpretability through lexical clusters and syntactic patterns, no net performance gain emerges under current configurations.

6 Conclusion

We presented a confidence-gated iterative induction framework intended to enable robust zero-shot NER in new crisis domains. While the approach conceptually merges self-training and dynamic knowledge construction, empirical results remain flat at about 0.295 F1 across multiple iterations. This negative finding underscores that basic confidence gating, combined with simple clustering and syntactic rules, can falter under emergent vocabulary and domain mismatch. Key hurdles include threshold calibration, partial coverage of newly coined terms, and coarse clustering. Future work will explore adaptive thresholding, more nuanced clustering, and deeper contextual modeling to potentially realize the promise of iterative knowledge distillation in practical crisis scenarios.

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A Technical Appendices and Supplementary Material

Extended Figures and Additional Details. The following figure (originally in the main text) is included here for completeness. It shows the zero-shot F1 evolution across three refinement iterations, remaining flat around 0.295:

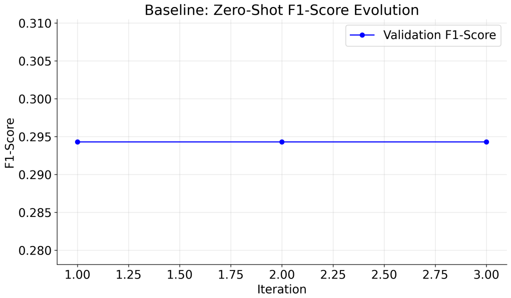

Figure 2: Zero-Shot F1-Score over three refinement iterations. The performance remains constant.

Hyperparameters. We employed `roberta-base` from HuggingFace Transformers, with default subword tokenization. The confidence threshold was set to 0.6. HDBSCAN used `min_cluster_size`=5 and `min_samples`=5. PMI-based pattern extraction applied a co-occurrence window of three tokens, discarding patterns with PMI < 1.0.

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