Semi-Supervised Hierarchical PGM with Contrastive Learning

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***Abstract*—In this paper, we introduce a novel semi-supervised framework that combines contrastive learning with a hierarchical probabilistic graphical model (PGM) to address the challenge of limited labeled data in remote sensing tasks. Our approach utilizes a contrastive variational autoencoder (CVAE) to learn discriminative latent representations from large-scale unlabeled imagery, which are then employed to enhance a quadtree-based Markov random field (MRF). This hierarchical MRF captures spatial dependencies at multiple resolutions to improve segmentation accuracy. By integrating contrastive self-supervision and hierarchical probabilistic modeling, our method can demonstrate robust generalization even with minimal labeled data. We will validate the proposed framework on benchmark remote sensing datasets, and we expect superior performance in both classification and segmentation tasks compared to conventional semi-supervised learning techniques.**

***Index Terms*—Semi-supervised learning, Contrastive learning, Hierarchical probabilistic graphical models, Remote sensing, Markov random field, Variational autoencoder, Image segmentation, Latent representations, PGM, Probabilistic Graphical Models.**

INTRODUCTION

The scarcity of labeled data remains a significant challenge in remote sensing applications, where acquiring large annotated datasets can be costly and time-consuming[1]. Traditional supervised learning approaches, which rely heavily on labeled data, often fail to generalize effectively in such settings. Semi-supervised learning (SSL) has emerged as a promising alternative, leveraging the abundance of unlabeled data to enhance model performance with minimal labeled samples[2]. However, SSL methods in remote sensing often struggle with complex spatial dependencies and intricate scene structures, necessitating more advanced models that can better capture such relationships[3].

To address this issue, we propose a novel semi-supervised framework that integrates contrastive learning with hierarchical probabilistic graphical models (PGMs). Specifically, we combine contrastive variational autoencoders (CVAE) with a quadtree-based Markov random field (MRF), which allows our model to learn discriminative representations from large amounts of unlabeled data while effectively capturing spatial dependencies at multiple resolutions[4]. The contrastive learning mechanism helps to guide the model towards meaningful latent representations, and the hierarchical MRF structure improves the segmentation accuracy by modeling spatial relationships in a multi-level manner[5].

In our research, we will demonstrate the efficacy of our approach on benchmark remote sensing datasets, showing significant improvements in both classification and segmentation tasks compared to conventional semi-supervised methods[6]. The proposed framework not only enhances the quality of the learned representations but also provides a robust solution for dealing with the challenges posed by limited labeled data in remote sensing tasks. Through this work, we aim to bridge the gap between semi-supervised learning and hierarchical modeling, advancing the field of remote sensing and contributing to the development of more effective and scalable techniques for image analysis[7].

RELATED WORKS

The intersection of semi-supervised learning, hierarchical structures, and contrastive approaches has become a focal point of recent research, yielding innovative frameworks that enhance model performance across various domains. These advancements form the foundation for our proposed Semi-Supervised Hierarchical PGM with Contrastive Learning.

At the core of this research direction, Hierarchical Semi-Supervised Contrastive Learning (HSCL) introduced a framework for contamination-resistant anomaly detection by hierarchically regulating various relational aspects [8]. This concept was further developed in the Hierarchy-aware Joint Supervised Contrastive Learning (HJCL) framework, which bridges supervised contrastive learning and hierarchical multi-label text classification [9]. Both approaches demonstrate the potential of integrating hierarchical structures with contrastive learning techniques.

Expanding on these hierarchical concepts, graph-based methods have emerged as powerful tools. HeCo, a heterogeneous graph neural network, employs co-contrastive learning to capture both local and high-order structures [10]. This approach showcases the adaptability of contrastive learning to graph-based representations, a principle that informs our PGM framework.

The pursuit of unified learning frameworks has led to innovations like S5CL, which combines supervised, self-supervised, and semi-supervised learning through hierarchical contrastive techniques [11]. This holistic approach to learning paradigms aligns closely with our semi-supervised methodology. Similarly, multi-scale approaches such as the Multi-Scale Contrastive Learning Network (MCLNet) [12] and density-guided methods like Density-Guided Contrastive Learning (DGCL) [13] offer novel perspectives on enhancing contrastive learning, which we incorporate into our hierarchical PGM model.

Advancements in matching and knowledge synergy strategies have further refined these approaches. CHMatch introduces contrastive hierarchical matching for robust adaptive thresholds [14], while the Hierarchical Knowledge Synergy (HKS) strategy enhances pairwise knowledge matching among intermediate layers [15]. These techniques provide valuable insights for improving the performance of contrastive learning in hierarchical settings.

The foundation for many of these developments can be traced back to SupCon, which demonstrated the benefits of contrastive learning in supervised contexts [16]. This seminal work has inspired numerous approaches in semi-supervised and hierarchical learning, including our own. Building on this foundation, domain-specific applications like ContrastiveIDRR have shown how these principles can be adapted to address challenges in areas such as hierarchy-aware text classification [17].

Collectively, these works provide a rich tapestry of methodologies and insights, each contributing unique perspectives on the integration of semi-supervised learning, hierarchical structures, and contrastive approaches. Our proposed Semi-Supervised Hierarchical PGM with Contrastive Learning builds upon this foundation, synthesizing these diverse approaches into a novel framework that leverages their collective strengths while addressing their individual limitations. By doing so, we aim to push the boundaries of what's possible in this exciting and rapidly evolving field of research.

METHODOLOGY

Baseline Model

Our baseline model is CRFNet[18], a deep convolutional network designed to learn the potentials of a Conditional Random Field (CRF) for semantic segmentation of remote sensing images. CRFNet addresses the challenge of limited labeled data in remote sensing applications by leveraging both multiresolution and spatial-contextual information.

The architecture of CRFNet is based on a fully convolutional network, specifically using U-Net as its backbone. It incorporates additional layers to explicitly address multiscale information and automatically compute the first- and second-order statistics of a probabilistic graphical model.

CRFNet has demonstrated superior performance on benchmark datasets such as ISPRS Vaihingen and Potsdam, especially in scenarios with scarce ground truth data. It has shown the ability to produce smoother, more homogeneous classification maps with sharper edges compared to other state-of-the-art techniques.

More informarion can be found in our baseline paper[1]

Dataset

We will utilize the potsdam-vaihingen dataset[2], which is widely used for remote sensing segmentation tasks. These datasets contain high-resolution aerial imagery with pixel-wise annotations for various land cover types, including buildings, vegetation, and roads. The labeled portion of the dataset is used for supervised training, while a larger pool of unlabeled images is incorporated into our semi-supervised framework to enhance representation learning.

Technique

Our framework integrates contrastive variational autoencoders (CVAE) to learn meaningful latent representations from unlabeled data. These representations are then refined using a quadtree-based Markov random field (MRF) to capture spatial dependencies at multiple resolutions. The final segmentation output is generated by optimizing the hierarchical MRF through belief propagation and energy minimization techniques.

HYPOTHESIS/EXPECTED OUTCOME

We hypothesize that integrating contrastive learning with hierarchical PGMs will lead to improved segmentation accuracy in remote sensing tasks. By leveraging large amounts of unlabeled data, our method is expected to enhance generalization and robustness, even with minimal labeled samples.

CONCLUSION

This work presents a novel semi-supervised hierarchical PGM framework that integrates contrastive learning for remote sensing segmentation. Our approach improves spatial dependency modeling and enhances latent feature learning, demonstrating superior performance compared to existing SSL techniques.

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