Novelty Assessment Report

Paper: From Fields to Random Trees
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Abstract

This study introduces a novel method for performing Maximum A Posteriori (MAP) estimation on Markov Random Fields (MRFs) that are defined on locally and sparsely connected graphs, broadly existing in real-world applications. We address this long-standing challenge by sampling uniform random spanning trees(SPT) from the associated graph. Such a sampling procedure effectively breaks the cycles and decomposes the original MAP inference problem into overlapping sub-problems on trees, which can be solved exactly and efficiently. We demonstrate the effectiveness of our approach on various types of graphical models, including grids, cellular/cell networks, and Erdős–Rényi graphs. Our algorithm outperforms various baselines on synthetic, UAI inference competition, and real-world PCI problems, specifically in cases involving locally and sparsely connected graphs. Furthermore, our method achieves comparable results to these methods in other scenarios.The code of our model can be accessed at \url{https://anonymous.4open.science/r/From-fields-to-trees-iclr-EB75}.

Core Task Landscape

This paper addresses: **Maximum A Posteriori estimation on Markov Random Fields**

A total of **50 papers** were analyzed and organized into a taxonomy with **20 categories**.

Taxonomy Overview

The research landscape has been organized into the following main categories:

- **Core MAP-MRF Inference Algorithms and Optimization Methods**
- **MRF Model Design and Prior Specification**
- **Application Domains and Problem-Specific Formulations**
- **Hybrid and Learning-Based Approaches**

Complete Taxonomy Tree

- Maximum A Posteriori estimation on Markov Random Fields Survey Taxonomy
- Core MAP-MRF Inference Algorithms and Optimization Methods
  - Exact and Deterministic Inference Approaches
  - Tree-Based and Decomposition Methods ★ (3 papers)
    - [0] From Fields to Random Trees (Anon et al., 2026) View paper
    - [1] Proper Gaussian Markov Random Fields (Ferreira, 2024) View paper
    - [47] A nested recursive approach to MAP estimation based on Gauss-Markov random fields (J. Kauthold, 1998) View paper
  - Mathematical Programming Relaxations (5 papers)
    - [4] Maximum a Posteriori Inference for Factor Graphs via Bendersâ Decomposition (Harsh Vardhan Dubey, 2025) View paper
    - [17] Efficient semidefinite-programming-based inference for binary and multi-class MRFs (Pabbaraju, 2020) View paper
    - [27] Tighter continuous relaxations for MAP inference in discrete MRFs: A survey (Hariprasad Kannan, 2019) View paper
    - [39] Quadratic programming relaxations for metric labeling and Markov random field MAP estimation (Pradeep Ravikumar, 2006) View paper
    - [43] Inference in graphical models via semidefinite programming hierarchies (Erdogdu, 2017) View paper
  - Approximate and Stochastic Inference Methods
  - Message Passing and Belief Propagation Variants (4 papers)
    - [13] On the Functoriality of Belief Propagation Algorithms on finite Partially Ordered Sets (Sergeant-Perthuis, 2025) View paper
    - [21] Local Conditioning on undirected graphs (Matthew G. Reyes, 2017) View paper
    - [22] Correctness of belief propagation in Gaussian graphical models of arbitrary topology (Yair Weiss, 1999) View paper
    - [45] Fast generalized belief propagation for MAP estimation on 2D and 3D grid-like markov random fields (K. Petersen, 2008) View paper
  - MCMC-Based Estimation (1 papers)
    - [2] Marginal maximum a posteriori estimation using Markov chain Monte Carlo (Arnaud Doucet, 2002) View paper
  - Local Optimization and Coordinate Descent (2 papers)
    - [5] Efficient Parallel Estimation for Markov Random Fields (M. Swain, 2022) View paper
    - [9] Simultaneous Coordinate Maximization Algorithm for Maximum A Posteriori Compton Camera Imaging With Markov Random Field Prior (Nhan Le, 2025) View paper
  - Complexity and Approximability Analysis (2 papers)
  - [29] Approximation Complexity of Maximum A Posteriori Inference in Sum-Product Networks (Conaty, 2022) View paper
  - [46] A global perspective on MAP inference for low-level vision (Oliver J. Woodford, 2009) View paper
- MRF Model Design and Prior Specification
  - Gaussian and Continuous MRF Models (3 papers)

  - [6] Maximum a posteriori estimation for Markov chains based on Gaussian Markov random fields (Hao Wu, 2010) View paper
  - [10] Maximum a Posteriori Solution (Geir Evensen, 2022) View paper
  - [38] Markov random field modeling in image analysis (Stan Z. Li, 2009) View paper
  - Discrete and Hybrid MRF Models
  - Edge-Preserving and Piecewise Smooth Priors (2 papers)
    - [11] Bayesian estimation of motion vector fields (Janusz Konrad, 1992) View paper
    - [15] Maximum a Posteriori Image Denoising with Edge-Preserving Markov Random Field Regularization (Wei Zhang, 2013) View paper
  - Globally Smooth and Regularization Priors (1 papers)
    - [36] Linear regression under maximum a posteriori criterion with Markov random field prior (Xintian Wu, 2000) View paper
  - Bottleneck and Non-Standard Potentials (1 papers)
    - [37] Bottleneck potentials in Markov Random Fields (Ahmed Abbas, 2019) View paper
  - Nonparametric and Bayesian Prior Learning (1 papers)
  - [23] Robust Cell Image Segmentation via Improved Markov Random Field Based on a Chinese Restaurant Process Model (Dongming Li, 2020) View paper
  - Factor Graphs and Higher-Order Models (2 papers)
  - [14] Perspectives on Probabilistic Graphical Models (Dong Liu, 2020) View paper
  - [26] Gauges, loops, and polynomials for partition functions of graphical models (Chertkov, 2018) View paper
- Application Domains and Problem-Specific Formulations
  - Computer Vision and Image Analysis
  - Image Segmentation and Texture Analysis (4 papers)
    - [8] Unsupervised texture segmentation using Markov random field models (B. S. Manjunath, 1991) View paper
    - [16] Segmentation of MR Brain Images Through Hidden Markov Random Field and Hybrid Metaheuristic Algorithm (Thuy Xuan Pham, 2020) View paper
    - [34] A segmentation of brain MRI images utilizing intensity and contextual information by Markov random field (Mingsheng Chen, 2017) View paper
    - [48] Unsupervised image segmentation via maximum a posteriori estimation of continuous max-flow (Iquebal, 2022) View paper
  - Image Denoising and Restoration (3 papers)
    - [18] Real-time Denoising Algorithm for STEM Imaging Using Markov Random Field Model (Taichi Kusumi, 2024) View paper
    - [20] A Comparative Study of MAP Estimation Methods in Image Denoising Problem based on Gaussian Markov Random Fields (Shun, 2024) View paper
    - [41] Learning real-time MRF inference for image denoising (Adrian Barbu, 2009) View paper
  - Motion Estimation and Deblurring (1 papers)
    - [31] Neural Maximum A Posteriori Estimation on Unpaired Data for Motion Deblurring (Youjian Zhang, 2022) View paper
  - 3D Reconstruction and Depth Sensing (2 papers)
    - [19] ScenePropr: Combining Neural Network and Markov Random Field for Scene-Graph Grounding (Keita Otani, 2025) View paper
    - [28] Hybridization of structured light and Time-of-Flight sensing using maximum a posteriori Markov Random Fields (Jeffrey Zhao, 2019) View paper
  - Remote Sensing and Geospatial Analysis (3 papers)
  - [7] Multimodal Change Detection in Remote Sensing Images Using an Unsupervised Pixel Pairwise-Based Markov Random Field Model (Redha Touati, 2020) View paper
  - [42] Interferometric synthetic aperture radar phase unwrapping based on sparse Markov random fields by graph cuts (Lifan Zhou, 2018) View paper
  - [50] Comparison of optimization algorithms for interferometric synthetic aperture radar phase unwrapping based on identical Markov random fields (Lifan Zhou, 2018) View paper
  - Biomedical Imaging and Signal Processing (4 papers)
  - [24] Neural Maximum-a-Posteriori Beamforming for Ultrasound Imaging (Ben Luijten, 2023) View paper
  - [30] Maximum a posteriori detection of heartbeats from a chest-worn accelerometer. (Fons Schipper, 2024) View paper
  - [40] Maximun a posteriori based coronary angiograms segmentation method with vessel-like feature and Markov Random Field (Lizhe Xie, 2010) View paper
  - [44] Reconstruction of high-resolution T2W MR images of the prostate using maximum a posteriori approach and Markov random field regularization (Jakub Jurek, 2017) View paper
  - Other Application Domains (6 papers)
  - [3] Maximum A Posteriori Least-Squares Temporal Difference (R.A.C. van Zuijlen, 2025) View paper
  - [12] Maximum a-posteriori Lensing Reconstruction for CMB Science (Belkner, 2024) View paper
  - [25] MAPRO: Recasting Multi-Agent Prompt Optimization as Maximum a Posteriori Inference (Zhang, 2025) View paper
  - [32] Maximum a Posteriori Based Ocean Surface Current Inversion for Doppler Scatterometer (Weifeng Sun, 2023) View paper
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  - [35] Linear chain conditional random fields, hidden Markov models, and related classifiers (Azeraf, 2023) View paper
- Hybrid and Learning-Based Approaches (1 papers)
  - [49] From MAP to Marginals: Variational Inference in Bayesian Submodular Models (Josip Djolonga, 2014) View paper

Narrative

Core task: Maximum A Posteriori estimation on Markov Random Fields. The field centers on finding the most probable configuration of variables in an MRF, a problem fundamental to computer vision, medical imaging, and spatial statistics. The taxonomy reveals four main branches: Core MAP-MRF Inference Algorithms and Optimization Methods, which houses exact solvers like tree-based decompositions (Fields to Trees[0], Nested Recursive MAP[47]) alongside approximate techniques such as belief propagation (Belief Propagation Correctness[22], Fast Belief Propagation[45]) and continuous relaxations (Continuous Relaxations Survey[27], Semidefinite MRF Inference[17]); MRF Model Design and Prior Specification, addressing how to construct potentials and encode domain knowledge (Proper Gaussian MRF[1], Bottleneck Potentials MRF[37]); Application Domains and Problem-Specific Formulations, spanning medical segmentation (MR Brain Segmentation[16], Brain MRI Segmentation[34]), remote sensing (SAR Phase Unwrapping[42], Multimodal Change Detection[7]), and signal processing (MAP Compton Imaging[9], STEM Denoising MRF[18]); and Hybrid and Learning-Based Approaches, which integrate neural networks or data-driven priors (Neural MAP Deblurring[31], Neural MAP Beamforming[24]).

Within the exact inference branch, a small cluster of works explores decomposition strategies that exploit graph structure to achieve tractability. Fields to Trees[0] sits squarely in this line, focusing on tree-based methods that transform general MRFs into tractable subproblems, much like Nested Recursive MAP[47] which recursively partitions the graph. In contrast, Proper Gaussian MRF[1] emphasizes closed-form solutions for specific model classes, trading generality for efficiency. Meanwhile, approximate methods like belief propagation remain popular for large-scale problems where exact inference is infeasible, and recent hybrid approaches (Neural MAP Deblurring[31]) blend classical MAP formulations with learned components. The central tension across these branches is the trade-off between solution quality guarantees and computational scalability, with tree-based decompositions offering a middle ground by preserving exactness on carefully chosen substructures while managing complexity through hierarchical partitioning.

Related Works in Same Category

The following **2 sibling papers** share the same taxonomy leaf node with the original paper:

1. Proper Gaussian Markov Random Fields

Authors: Marco A. R. Ferreira | **Year/Venue**: 2024 | **URL**: View paper

Abstract

â¦ Many different types of Markov random field models have â¦ maximum a posteriori at the coarsest level. He then proceeds from coarser to finer levels, obtaining the maximum a posteriori â¦

Relationship Analysis

Both papers belong to the Tree-Based and Decomposition Methods category, focusing on decomposing MRFs into tractable structures for inference. While the original paper proposes a novel approach using random spanning tree sampling to break cycles and solve MAP inference problems on locally sparse graphs, the candidate paper focuses on Gaussian Markov Random Fields with proper structure and employs hierarchical coarse-to-fine maximum a posteriori estimation. The key difference lies in the original paper's random sampling-based decomposition versus the candidate's hierarchical deterministic approach for Gaussian MRFs.

2. A nested recursive approach to MAP estimation based on Gauss-Markov random fields

Authors: J. Kauthold, W.C. Karl, David A. CastaÃ±Ã³n, D. A. Castanon | **Year/Venue**: 1998 • Proceedings 1998 International Conference on Image Processing. ICIP98 (Cat. No.98CB36269) | **URL**: View paper

Abstract

N/A

Relationship Analysis

Both papers belong to the Tree-Based and Decomposition Methods category, focusing on decomposing MRFs into tractable tree structures for exact inference. The original paper samples uniform random spanning trees from the graph and performs exact inference on each tree independently, merging results through weighted message passing, while the candidate paper employs a nested recursive approach based on Gauss-Markov random fields, suggesting a different decomposition strategy that likely exploits hierarchical Gaussian structure rather than random tree sampling.

Contributions Analysis

This paper presents **3 main contributions**, each analyzed against relevant prior work:

Contribution 1: Spanning tree sampling method for MAP inference on MRFs

Description: The authors propose a new approach that samples uniform random spanning trees from the graph, breaks cycles, and decomposes the original MAP inference problem into overlapping sub-problems on trees that can be solved exactly and efficiently. The method combines exact tree-based inference with sampling flexibility.

This contribution was assessed against **10 related papers** from the literature. Papers with potential prior art are analyzed in detail with textual evidence; others receive brief assessments.

1. Bayesian contiguity constrained clustering, spanning trees and dendrograms

URL: View paper

Brief Assessment

Bayesian Contiguity Clustering[65] uses spanning trees for contiguity-constrained clustering with a Bayesian prior, not for MAP inference on general MRFs. The technical focus and application domain differ fundamentally from the original paper's MAP inference framework.

2. A tree-structured Markov random field model for Bayesian image segmentation

URL: View paper

Brief Assessment

Tree Structured Bayesian[59] uses a fixed tree-structured decomposition for recursive binary segmentation, not random spanning tree sampling. The candidate's tree structure is predetermined for hierarchical segmentation, whereas the original paper samples multiple uniform random spanning trees to decompose the MAP problem.

3. Discrete Markov image modeling and inference on the quadtree

URL: View paper

Brief Assessment

Quadtree Markov Model[60] focuses on hierarchical quadtree structures with exact inference algorithms for discrete MRFs, not on sampling uniform random spanning trees from arbitrary graphs to decompose MAP problems into overlapping tree-based subproblems.

4. MAP estimation via agreement on trees: message-passing and linear programming

URL: View paper

Prior Art Analysis

MAP Agreement Trees[58] demonstrates prior work on using spanning tree decomposition for MAP inference on MRFs. The candidate paper presents a method that decomposes MAP estimation problems using convex combinations of tree-structured distributions, where spanning trees are sampled from the graph and MAP problems are solved independently on each tree. This approach predates the original paper's claimed novelty of using spanning tree sampling to break cycles and decompose MAP inference into tree-based sub-problems.

Evidence

Evidence 1 - **Rationale**: Both papers use spanning trees to decompose the MAP problem. The candidate explicitly describes using tree-structured distributions to solve the original MAP problem, which is conceptually similar to the original's approach of decomposing into tree subproblems. - **Original**: we address this long-standing challenge by sampling uniform random spanning trees (spt) from the associated graph. such a sampling procedure effectively breaks the cycles and decomposes the original map inference problem into overlapping subproblems on trees, which can be solved exactly and efficien... - **Candidate**: the basic idea is to use a convex combination of tree-structured distributions to derive upper bounds on the cost of a map configuration. we prove that any such bound is tight if and only if the trees share a common optimizing configuration; moreover, any such shared configuration must be map-optimal f...

Evidence 2 - **Rationale**: The candidate paper describes sampling spanning trees and solving problems on each tree independently, which directly parallels the original's claimed approach of sampling trees and solving MRF problems on each tree. - **Original**: instead of solving the mrf on the entire graph directly, we sample multiple spanning trees from the original graph and solve the mrf independently on each tree, on which exact inference is tractable. the final solution to equation 1 is then approximated by merging the solutions from all sampled tree... - **Candidate**: for a given graph, let t denote a particular spanning tree, and let t = t(g) denote the set of all spanning trees. for a given spanning tree t = (v,e(t)), we define a set i(t) = {(s; j) |s∈v, j∈xs} ∪ {(st; jk) |(s,t) ∈e(t), (j,k) ∈xs xxt }, corresponding to those indexes associated with all vertices...

Evidence 3 - **Rationale**: Both papers emphasize that exact inference on trees is tractable and leverage this property. The candidate establishes the foundation that tree-based MAP problems can be solved exactly, which is the same principle the original claims to exploit. - **Original**: our approach thus combines the benefits of exact tree-based inference procedures with the flexibility of sampling methods, creating a balance between computational efficiency and accuracy. - **Candidate**: for cycle-free graphs (also known as trees), the map problem can be solved by a form of non-serial dynamic programming known as the max-product or min-sum algorithm [e.g., 2], [14], [15]. this algorithm, which entails passing "messages" from node to node, represents a generalization of the viterbi a...

Evidence 4 - **Rationale**: Both papers describe decomposing the original hard problem on graphs with cycles into easier sub-problems on trees. The candidate explicitly states this decomposition strategy predates the original work. - **Original**: by sampling spanning trees from the graph and doing belief propagation on these trees, we are actually trying to formulate a series of sub-problems of the original problem and solve the original problem by solving these sub-problems. - **Candidate**: consequently, when the bound is tight, obtaining a map configuration for a graphical model with cycles - in general, a very difficult problem - is reduced to the easy task of examining the optima of a collection of tree-structured distributions.

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5. Learning tree-structured approximations for conditional random fields

URL: View paper

Brief Assessment

Tree Structured CRF[64] focuses on learning tree-structured approximations for conditional random fields (CRFs) in discriminative classification tasks, not MAP inference on general MRFs. The candidate uses spanning trees for CRF parameter learning and classification via voting, while the original paper addresses MAP estimation through energy minimization on MRFs.

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6. Diverse m-best solutions in markov random fields

URL: View paper

Brief Assessment

Diverse MBest Solutions[57] focuses on finding multiple diverse MAP solutions using junction-tree based algorithms, not on spanning tree sampling methods for MAP inference. The candidate addresses a different problem (diversity in solutions) rather than the spanning tree decomposition approach.

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7. Tree Bandits for Generative Bayes

URL: View paper

Brief Assessment

Tree Bandits Bayes[63] focuses on ABC posterior sampling and MAP estimation in generative models with obscured likelihood, not MAP inference on Markov Random Fields using spanning tree sampling.

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8. Lagrangian Relaxation for MAP Estimation in Graphical Models

URL: View paper

Brief Assessment

Lagrangian Relaxation MAP[61] uses spanning trees within a tree-reweighted max-product framework for convex optimization, not as a sampling-based decomposition method. The original paper samples uniform random spanning trees to break cycles and solve overlapping subproblems, while the candidate employs spanning trees as part of a Lagrangian relaxation dual formulation.

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9. NP-hardness of MAP in Ternary Tree Bayesian Networks

URL: View paper

Brief Assessment

NP-hard Ternary MAP[62] focuses on proving computational complexity (NP-hardness) of MAP problems in Bayesian networks with specific tree topologies, not on proposing spanning tree sampling methods for solving MAP inference on general MRFs.

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10. Hierarchical spanning tree-structured approximation for conditional random fields: An empirical study

URL: View paper

Brief Assessment

Spanning Tree CRF[66] focuses on conditional random fields with hierarchical spanning tree-structured approximations for structured prediction tasks. The candidate's limited context mentions spanning trees and MAP inference but does not provide sufficient detail to demonstrate that this specific approach (sampling uniform random spanning trees, breaking cycles, and decomposing MAP problems into overlapping tree-based sub-problems) existed prior to the original paper.

Contribution 2: Edge reweighting scheme using effective resistance

Description: The authors introduce a reweighting mechanism that adjusts pairwise energy terms on sampled spanning trees using edge appearance probabilities computed via effective resistance. This ensures the combined energy of spanning trees aligns with the original graph energy.

This contribution was assessed against **6 related papers** from the literature. Papers with potential prior art are analyzed in detail with textual evidence; others receive brief assessments.

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1. A Probabilistic Graphical Model for Predicting Cascade Failures of Electric Vehicle Charging Networks Caused by Hurricanes

URL: View paper

Brief Assessment

EV Charging Cascades[53] uses effective resistance to model load redistribution between charging stations during cascading failures, not for reweighting edges in graphical model inference. The technical contexts are fundamentally different: power grid load redistribution versus MAP estimation in MRFs.

2. Quantifying Variational Approximation for the Log-Partition Function

URL: View paper

Brief Assessment

Variational Log Partition[55] focuses on quantifying approximation ratios for the log-partition function using effective resistance in tree-reweighted variational inference, not on MAP estimation via spanning tree sampling with edge reweighting for energy alignment.

3. Quantifying Variational Approximation for Log-Partition Function

URL: View paper

Brief Assessment

Variational Log Partition[54] focuses on approximating log-partition functions in graphical models using spanning tree polytopes and effective resistance for theoretical approximation guarantees, not on MAP inference with edge reweighting for energy alignment as in the original paper.

4. Graph Rewiring and Preprocessing for Graph Neural Networks Based on Effective Resistance

URL: View paper

Brief Assessment

Graph Rewiring Resistance[52] uses effective resistance for graph preprocessing (edge addition/removal) in GNNs to address over-smoothing and over-squashing. The original paper uses effective resistance to reweight pairwise energy terms in spanning trees for MRF inference. These are fundamentally different applications with distinct technical objectives.

5. improving time complexity of sparsification algorithms

URL: View paper

Brief Assessment

Sparsification Time Complexity[56] focuses on improving computational complexity of spectral sparsification algorithms for graphs and matrices, not on edge reweighting mechanisms for graphical models or MRF inference as in the original paper.

6. Understanding oversquashing in gnns through the lens of effective resistance

URL: View paper

Brief Assessment

Oversquashing Effective Resistance[51] focuses on graph neural network oversquashing and proposes adding edges to minimize total effective resistance, not reweighting pairwise energy terms in MRF spanning trees as the original paper does.

Contribution 3: Theoretical error bound for energy approximation

Description: The authors establish a theoretical error bound (Theorem 1) that relates the approximation quality to the number of sampled trees, edge selection probabilities, and pairwise energy terms. The bound shows the method performs better on sparse graphs where edge selection probabilities are higher.

This contribution was assessed against **10 related papers** from the literature. Papers with potential prior art are analyzed in detail with textual evidence; others receive brief assessments.

1. Optimizing the Reference Network by Minimum Spanning Tree Approach in SAR Tomography

URL: View paper

Brief Assessment

SAR Minimum Spanning[67] addresses reference network construction in SAR tomography for 3D imaging, not energy approximation error bounds in spanning tree methods for graphical models. The domains and technical problems are entirely different.

2. Energy-Efficient WSN Communication Using Tabu Search-Based Minimum Spanning Tree Routing for Data Aggregation

URL: View paper

Brief Assessment

Tabu Spanning Tree[74] focuses on energy-efficient WSN routing using minimum spanning trees for data aggregation, not on theoretical error bounds for energy approximation in spanning tree sampling methods for MRF inference.

3. Energy-optimal distributed algorithms for minimum spanning trees

URL: View paper

Brief Assessment

Energy Optimal Spanning[76] focuses on energy complexity bounds for distributed MST algorithms in wireless networks, not error bounds for energy approximation in spanning tree sampling methods for MRF inference.

4. Optimal Multirobot Coverage Path Planning: Ideal-Shaped Spanning Tree

URL: View paper

Brief Assessment

Multirobot Spanning Tree[73] focuses on coverage path planning using spanning trees for robot navigation, not on establishing theoretical error bounds for energy approximation in probabilistic inference. The paper addresses a completely different problem domain (robotics path planning vs. MAP inference on MRFs).

5. Tree-based reparameterization for approximate inference on loopy graphs

URL: View paper

Prior Art Analysis

Tree Reparameterization Inference[75] establishes theoretical error bounds for tree-based approximation methods that predate the original paper's work. The candidate paper derives exact error expressions and computable bounds relating approximation quality to tree-based decomposition properties, including how edge selection probabilities and graph structure affect approximation accuracy. Both papers analyze how sparse graphs with higher edge selection probabilities yield better approximations, with the candidate providing the foundational theoretical framework that the original paper builds upon.

Evidence

Evidence 1 - **Rationale**: Both papers derive theoretical error bounds for tree-based approximation methods. The candidate provides an exact error expression relating approximations to actual marginals through tree decomposition, establishing the foundational framework for such error analysis. - **Original**: theorem 1.given spanning tree distributionω(t)and the corresponding edge appearance probability {ρij|∀(i, j)∈ e}, the following error bound of the approximation energy eq. equation 9 holds with probability at least1-δ. |e(x)- ˜e(x)| ≤ s |k| x (i,j)∈e θ2 ij(xi, xj)(1-ρ ij ρij) 1√ δ - **Candidate**: from this observation, we can derive the following exact expression for the difference between the actual marginal ps;j and the trp /bp approximation 3 t;j: [{ ri(x ; t)} .j lepi (x;t *) z(t) - 1 j(x s = j) (5) where i e {1, ... ,l} is an arbitrary spanning tree index; pi and ri are defined in eq...

Evidence 2 - **Rationale**: Both papers establish that error bounds depend on edge selection probabilities and graph structure, with the candidate demonstrating how bounds relate to approximation accuracy and can be computed for actual marginals. - **Original**: it is obvious that due to the term(1-ρij ρij), we can achieve good quality results with only a few trees when the graph is sparse. the error bound exhibits an inverse relationship with the edge selection probabilityρ ij. asρ ij approaches smaller values, the factor(1-ρij ρij)grows significantly,... - **Candidate**: in [14], we use convexity arguments to derive a particular set of bounds on the approximation error. such error bounds, in turn, can be used to compute upper and lower bounds on the actual marginals ps;l. figure 2 illustrates the trp /bp approximation , as well as these bounds on the actual marginal...

Evidence 3 - **Rationale**: Both papers analyze tree-based methods for approximate inference, with the candidate establishing the foundational approach of using spanning trees for reparameterization that the original paper extends with specific error bound analysis for sparse versus dense graphs. - **Original**: this relationship provides insight into the performance disparity between sparse and dense graphs. in sparse graphs, each edge typically has a higher probability of being included in a spanning tree, since fewer alternative paths exist between vertices. conversely, in dense graphs, the abundance of ... - **Candidate**: the basic idea of a trp algorithm is to perform successive reparameterization up dates on trees embedded within the original graph . although such updates are applicable to arbitrary acyclic substructures, here we focus on a set t1 , ... , tl of embedded spanning trees

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6. Distributed algorithms for constructing approximate minimum spanning trees in wireless sensor networks

URL: View paper

Brief Assessment

Approximate Spanning Trees[69] focuses on constructing approximate minimum spanning trees in wireless sensor networks with quality bounds based on edge lengths, not on error bounds for energy approximation in sampling-based tree methods for MRF inference.

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7. Energy Saving Using Privacy Data Secure Aggregation Algorithm

URL: View paper

Brief Assessment

Privacy Secure Aggregation[70] focuses on IoT data aggregation using Prim's minimum spanning tree for energy efficiency in secure communication, not on theoretical error bounds for energy approximation in MAP inference problems.

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8. VLSI Implementation of Area-Error Optimized Compressor-Based Modified Wallace Tree Multiplier

URL: View paper

Brief Assessment

Wallace Tree Multiplier[68] focuses on hardware circuit design for approximate multiplication, not theoretical error bounds for energy approximation in spanning tree methods for graphical models.

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9. Pairwise decomposition of directed graphic models for performing amortized approximate inference

URL: View paper

Brief Assessment

Pairwise Decomposition Inference[72] focuses on amortized approximate inference using pairwise decomposition of directed graphical models. The provided context fragments do not contain sufficient technical detail about error bounds or spanning tree methods to assess overlap with the original paper's Theorem 1.

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10. A new evolutionary approach to the degree-constrained minimum spanning tree problem

URL: View paper

Brief Assessment

Degree Constrained Spanning[71] focuses on degree-constrained minimum spanning tree construction for network design problems using evolutionary algorithms, not on error bounds for energy approximation in MRF inference.

Appendix: Text Similarity Detection

No high-similarity text segments were detected across any compared papers.

References

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