



From Exact to Anytime Solutions for Marginal MAP

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Introduction

Marginal MAP

- Mode of probability distribution after marginalizing subset of variables
- Complexity Class: NP^{PP} Complete
 - MPE (NP-Complete) : optimizing over max variables
 - PR (#P-Complete) : evaluating full instantiation

Application to Probabilistic Planning

Marginal MAP query returns optimal probabilistic conformant plan*

* "Applying Search Based Probabilistic Inference Algorithms to Probabilistic Conformant Planning: Preliminary Results", 2016 ISAIM



Earlier Works on Marginal MAP Inference



[Maua, De Campos 2012] Factor-set elimination algorithm

Motivation

Best First Schemes avoid evaluating summation sub problems, but they requires enormous amount of memory \rightarrow Turn to anytime approach



Probabilistic Graphical Models

A graphical model (X, D, F)

- $X = \{X_1, \dots, X_n\}$ variables
- $D=\{D_1, \dots, D_n\}$ domains
- $F = \{f_1, \dots, f_m\}$ functions
- Operators
 - Combination (product)
 - Elimination (max/sum)
- **T**asks
 - Probability of Evidence (PR) $Pr(e) = \sum_{X_s} \prod_j f_j(X_s, e)$
 - Most Probable Explanation (MPE) $\mathbf{x}_{MPE} = argmax_{\mathbf{x}} \prod_{j} f_{j}(\mathbf{x})$
 - Marginal MAP (Maximum A Posteriori)

 $\mathbf{x}_{MMAP} = argmax_{\mathbf{x}_m \in X_M} \sum_{\mathbf{x}_s \in X_s} \prod_j f_j(\mathbf{x}_m, \mathbf{x}_s)$



All these tasks are NP-hard Exploit problem structure (primal graph)



AND/OR Search Space for MMAP





Anytime AND/OR Search for MMAP

Anytime AOBB (BRAOBB)





(UB) Upper Bound = best solution so far

Prune node n if current best solution is better than optimistic evaluation at n

Problem decomposition rejects anytime performance of AOBB Rotate through sub-problems



Anytime AND/OR Search for MMAP

Weighted Best First Search



Expand Nodes with best heuristic evaluation value f(n)

Weighted Best First

Initialize w While w >= 1 Inflate heuristic by w AOBF (sub-optimal solution within w) optionally Revise traversed search space reduce w

- Weighted Restarting AOBF (WAOBF)
- Weighted Restarting RBFAOO (WRBFAOO)
- Weighted Repairing AOBF (WRAOBF)



Experiment Setup

Benchmark Instances

Domain	# instances			
GRID	75			
PEDIGREE	50			
PROMEDAS	50			

Problem instances are modified from PASCAL2 Probabilistic Inference Challenge Data Set (http://www.cs.huji.ac.il/project/PASCAL/)

Algorithm Parameters

Algorithm	Parameters	Memory
Weighted Mini Bucket Heuristic	i-bound from 2 to 20	-
BRAOBB	Rotation Limit 1000	Max 24 GB
WAOBF/ WRAOBF /WRBFAOO	Starting Weight 64	Max 24 GB, Cache 4 GB

Performance Measures

Responsiveness, Quality Score



Performance Regimes

		Overall		Pedigree		Promedas	
AND/OR Search for MMAP		Resp.	Quality	Resp.	Quality	Resp.	Quality
Exact	AOBB	89%	339%	84%	342%	86%	405%
	AOBF	50%	208%	42%	158%	42%	258%
	RBFAOO	58%	90%	42%	95%	42%	132%
Anytime	WAOBF	82%	365%	88%	442%	54%	266%
	WRBFAOO	86%	394%	90%	440%	60%	305%
	WRAOBF	82%	339%	88%	364%	54%	261%
	BRAOBB	86%	365%	58%	259%	94%	473%

- Summarized from 1 hour time bound,
- Responsiveness: WMB-MM(18), Quality Score: WMB-MM(12) heuristic
- WRBFAOO is the overall best performed algorithm
- BRAOBB is the second best performer, but the best at PROMEDAS DOMAIN



WRBFAOO vs. BRAOBB

Closer look at individual problem instances







Conclusion

Improvement from Exact to Anytime

- Anytime Best-First approach
 - Recovers responsiveness close to Depth-First schemes
 - Provide high quality solutions

Future Work

- Better Search Strategy
 - Memory issue with hard problems (Ws > 10, Wc > 200)
- Integrate approximation for summation problems
 - From exact to approximation