Learning Probabilistic Sentential Decision Diagrams Under Logic Constraints by Sampling and Averaging F

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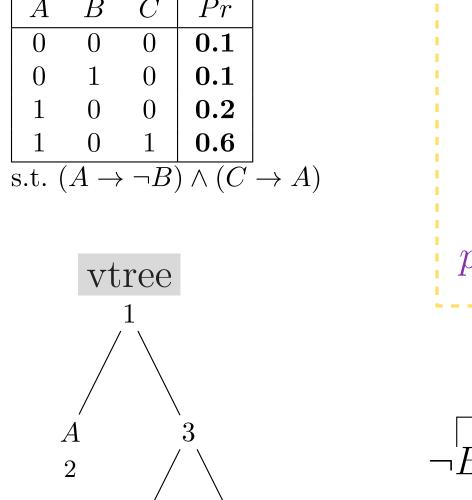


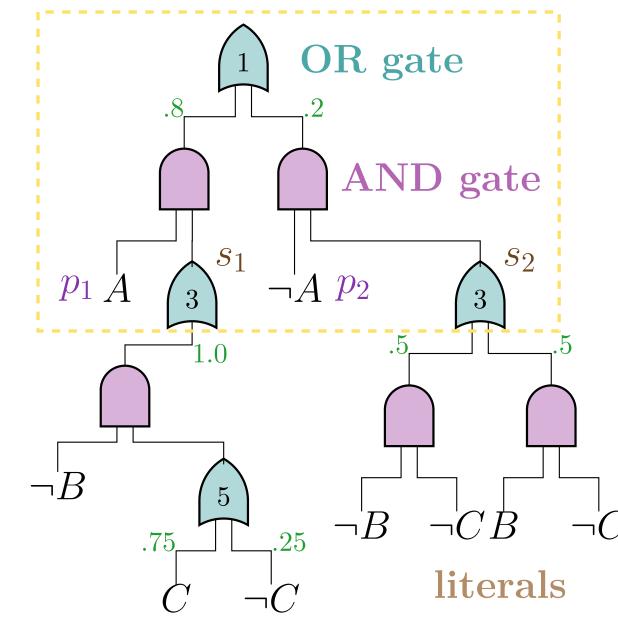
1. Motivation

Probabilistic Sentential Decision Diagrams (PSDDs):

- Structured Decomposable probabilistic circuits
- Encode certain knowledge as logic constraints
- Encode uncertain knowledge as probabilities
- Interpretable syntax
- Many inferences are exact and tractable:
 - Evidence

 - Marginals
 - MLE Parameter Learning
- - Most Probable Explanation
 - Expectations
 - KL-divergence





• PSDD circuit represents recursive decomposition of formula:

 $\bigvee (p_i \wedge s_i)$, where each prime p_i and $sub s_i$ are logical formulae

Existing PSDD learners:

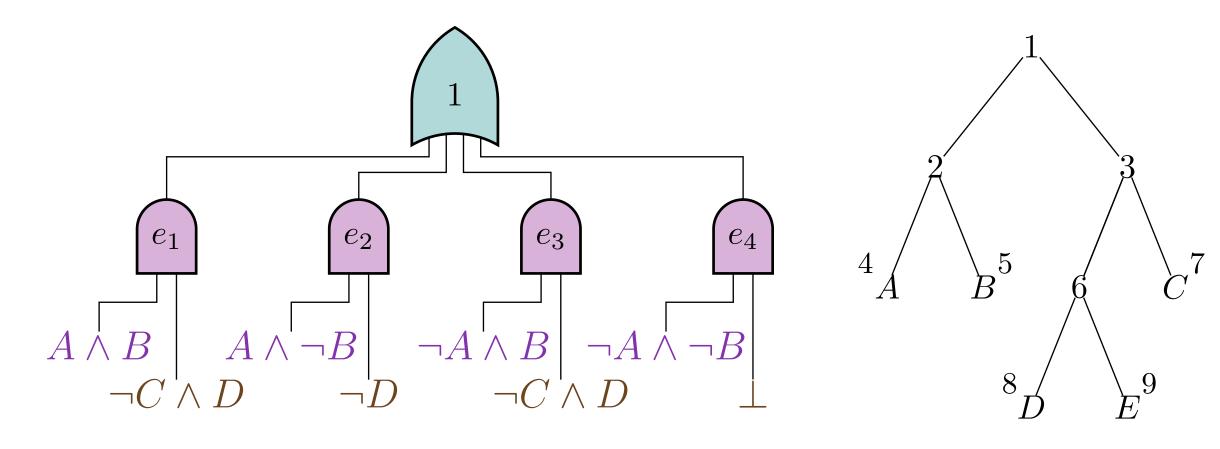
- require an initial PSDD encoding the support;
- scale poorly to complex formulae and/or high dimension.

This Work: How to effectively learn PSDDs s.t. complex formula?

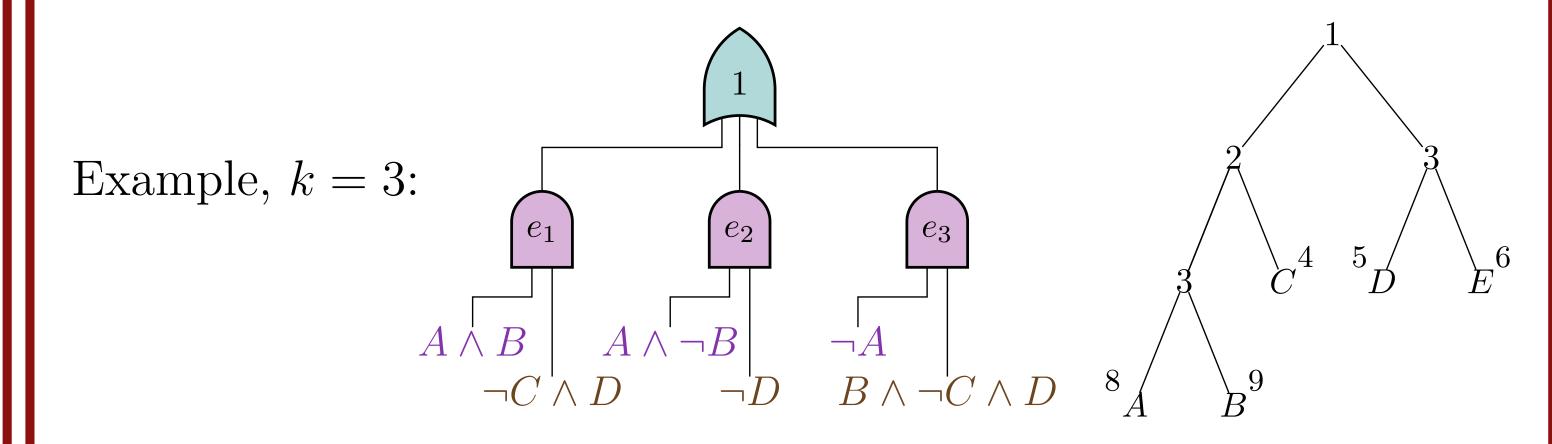
2. SamplePSDD

• Common assumption: primes p_i are conjunctions of literals.

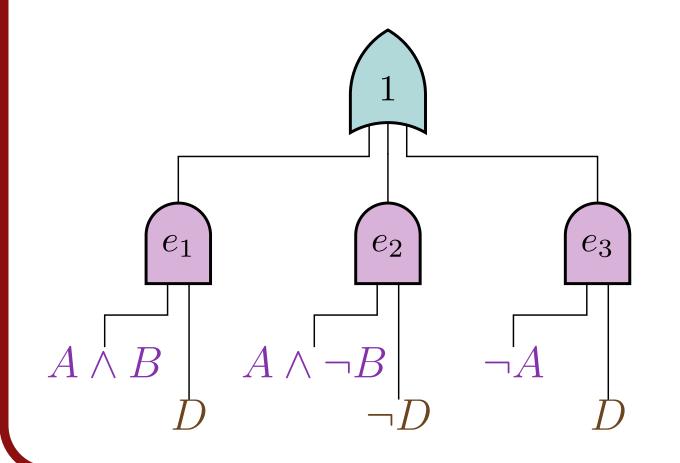
$$\phi(A,B,C,D) = (A \land \neg B \land \neg D) \lor (B \land \neg C \land D)$$

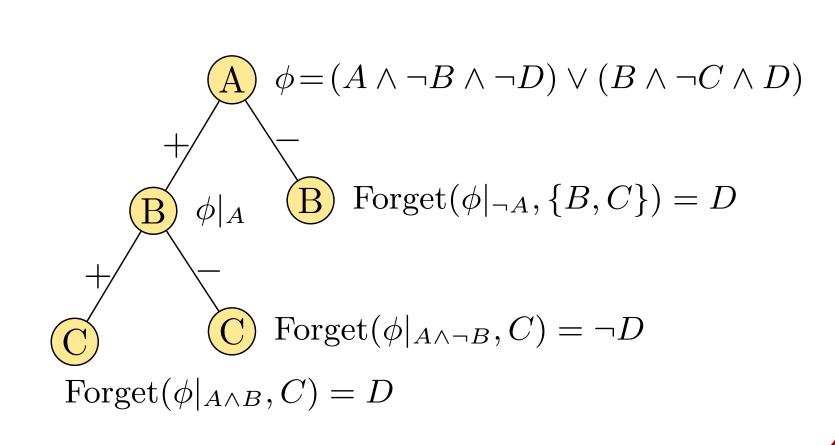


- **Problem:** size of circuit is exponential in the size of p_i
- **Solution:** randomly sample a bounded number (k) of p_i
- But: this violates structure decomposability



New solution: relax logical constraints ϕ





3. Experiments

Evaluation: we sample 30 PSDDs and use 5 ensemble strategies:

- Likelihood weighting (LLW)
- Uniform weights,
- Expectation Maximization (EM)
- Stacking.
- Bayesian Model Combination;

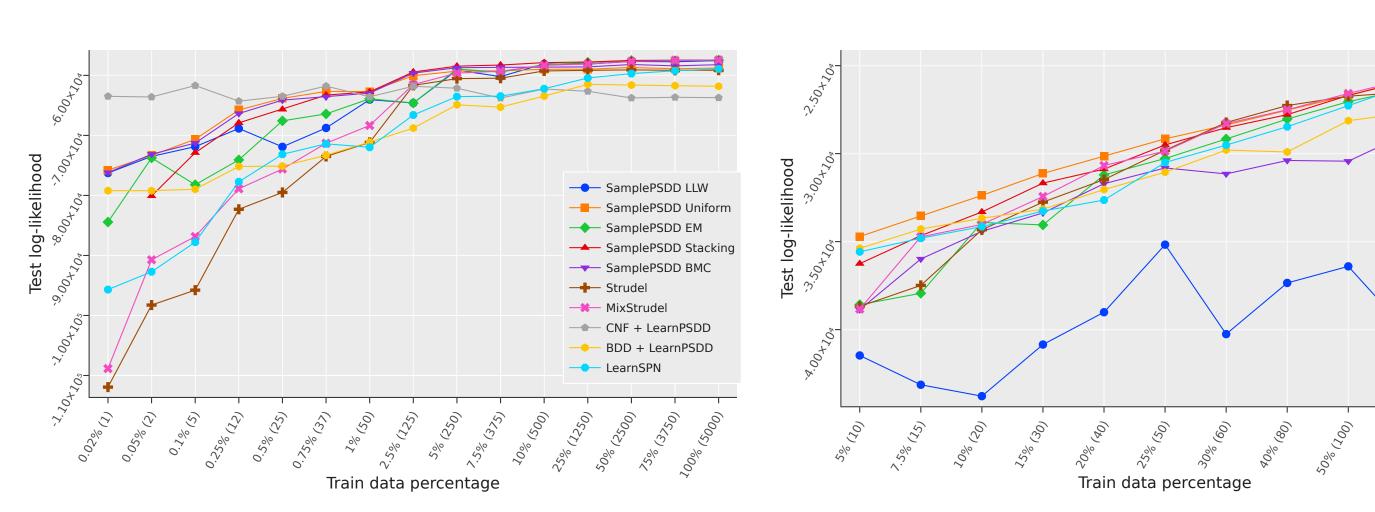
comparing with STRUDEL, LEARNPSDD and LEARNSPN.

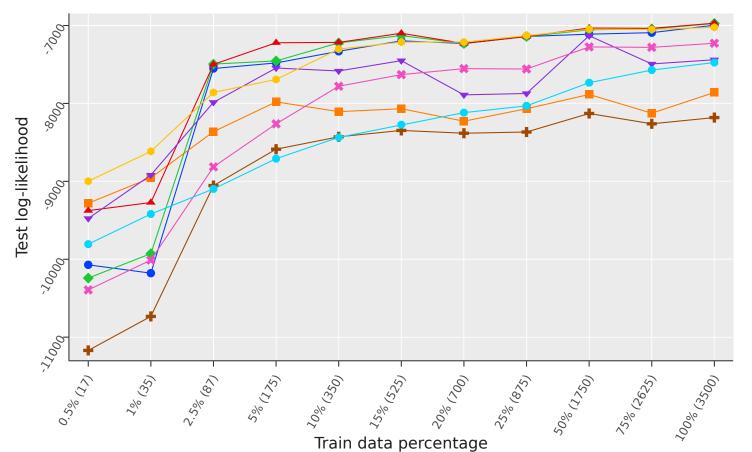
Datasets: we evaluate with 5 data + knowledge as logic constraints:

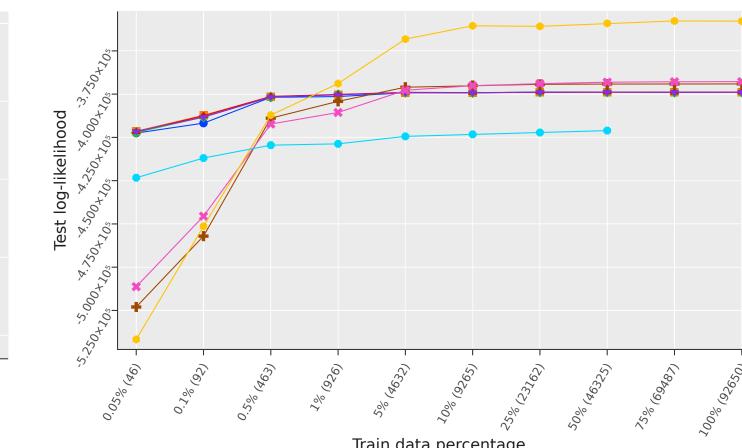
Dataset	#vars	#train	ϕ 's size
LED	14	5000	23
LED + Images	157	700	39899
Sushi Ranking	100	3500	17413
Sushi Top 5	10	3500	37
Dota 2 Games	227	92650	1308

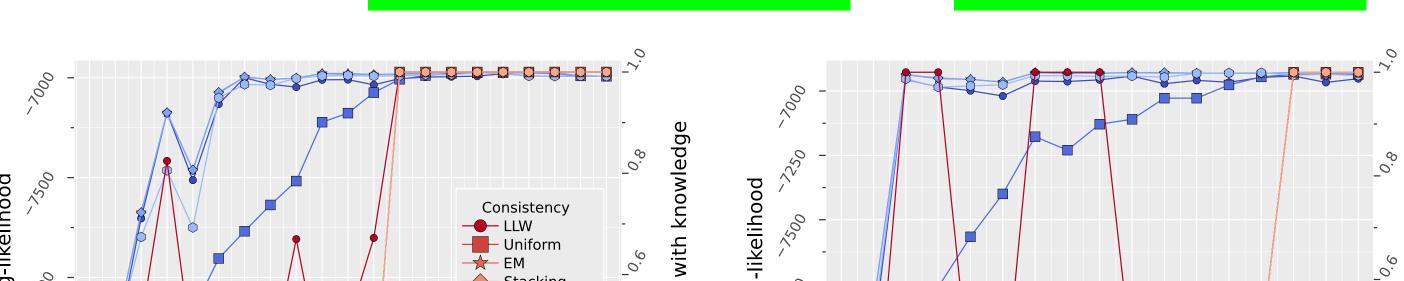
Our approach fares better with fewer data, yet

remains competitive under lots of data

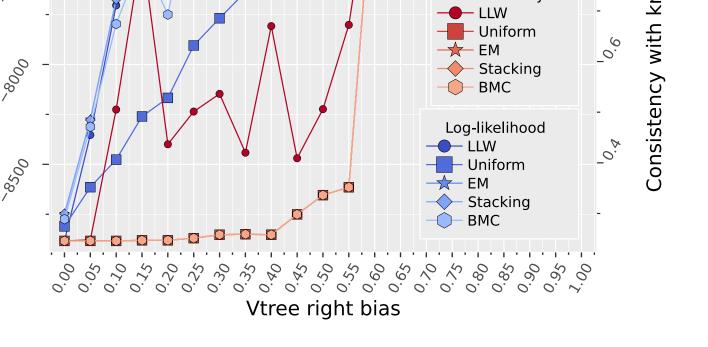


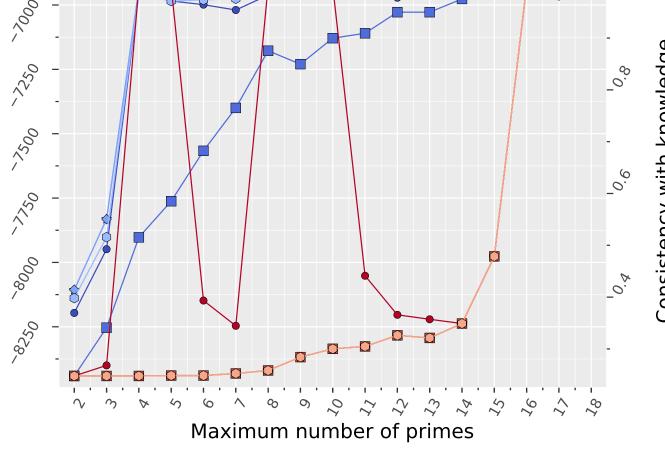






Samples perform better with higher k's and right-leaning vtrees ...





...but at a **cost** to complexity.

