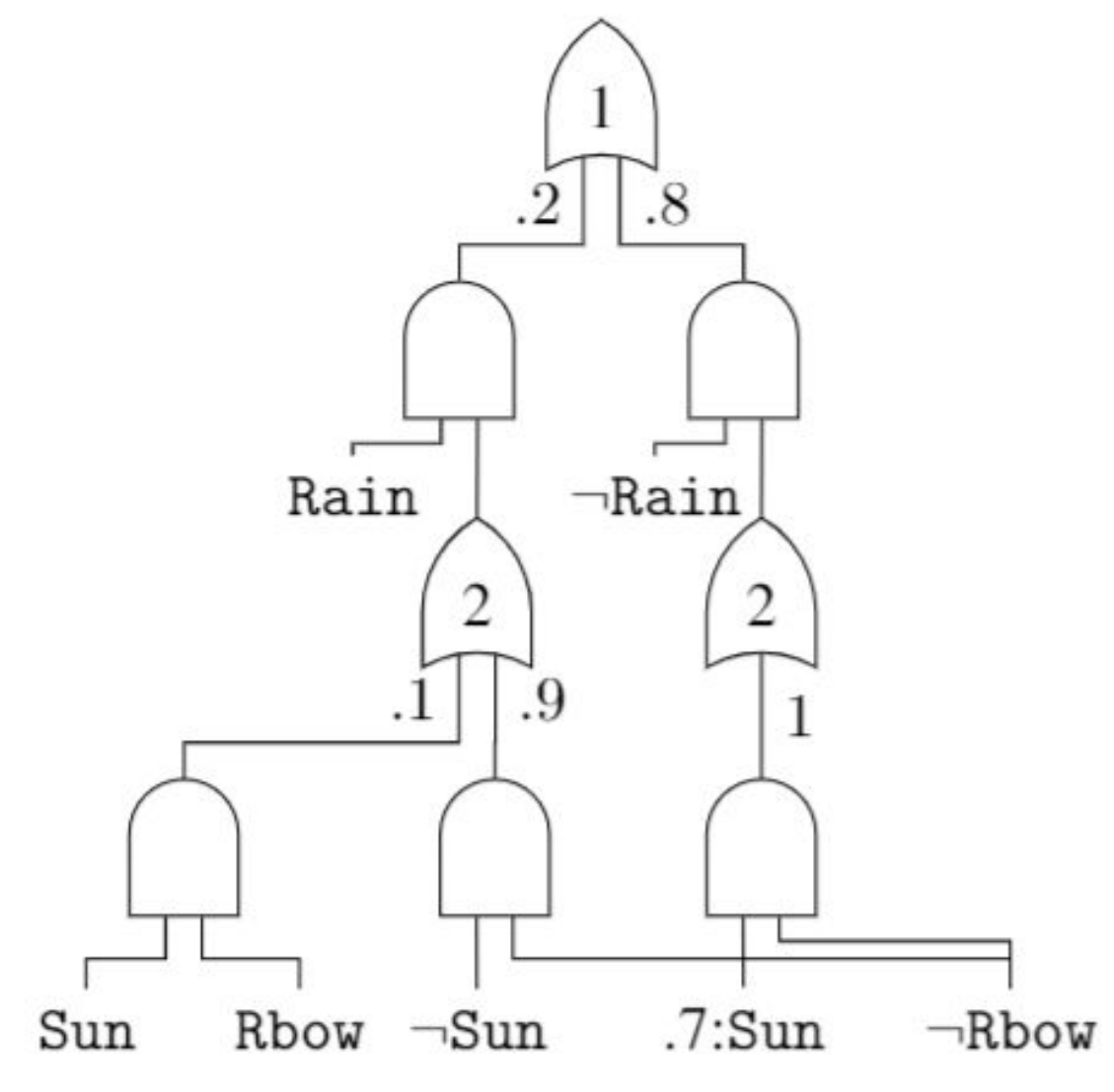


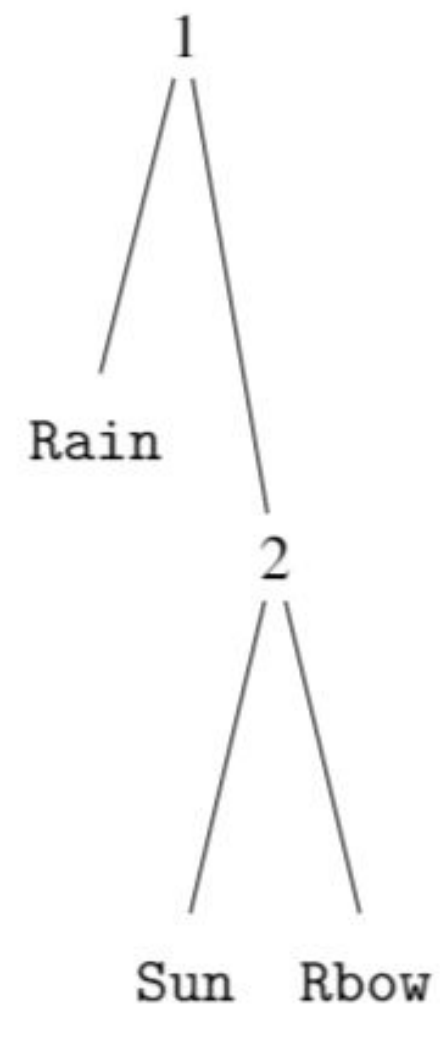
# IL-Strudel : Independence Based Learning of Structured-Decomposable Probabilistic Circuit Ensembles

Shreyas Kowshik, Yitao Liang, Guy Van den Broeck  
{shreyaskowshik@iitkgp.ac.in}, {yliang, guyvdb}@cs.ucla.edu

## INTRODUCTION



(a) PSDD



(b) Vtree

$$\begin{aligned} \Pr(\text{Rain}) &= 0.2, \\ \Pr(\text{Sun} \mid \text{Rain}) &= \begin{cases} 0.1 & \text{if Rain} \\ 0.7 & \text{if } \neg\text{Rain} \end{cases} \\ \Pr(\text{Rbow} \mid \text{R}, \text{S}) &= \begin{cases} 1 & \text{if Rain} \wedge \text{Sun} \\ 0 & \text{otherwise} \end{cases} \end{aligned}$$

(c) Equivalent distribution

**PSDD** : Circuit representation of a Probability Distribution over boolean random variables

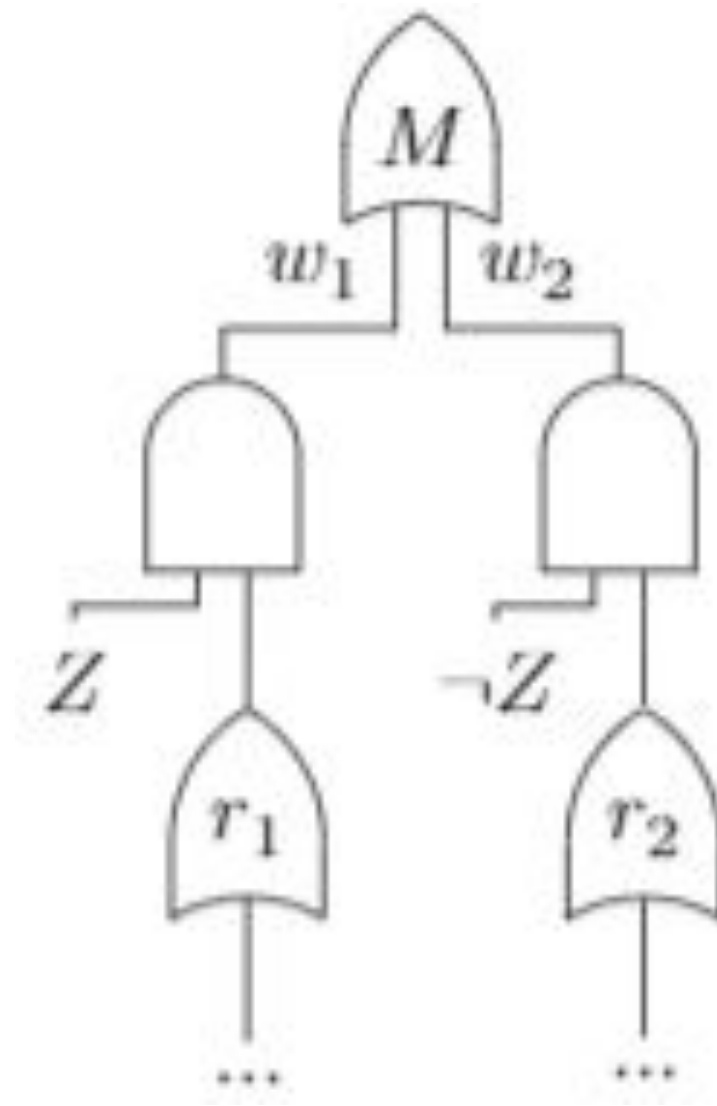
**Structured Decomposability** : Encoded distribution factorizes according to a given vtree

**Context-Specific-Independences** : PSDDs capture structure in data by inducing different types of CSIs

**Proposition 1.** (Prime-Sub Independence) *For a PSDD rooted at  $r$ , for every decision node  $n$  with prime and sub variables  $X$  and  $Y$  and their every element  $(p, s)^2$ :*

$$\begin{aligned} & \Pr_r(\mathbf{xy} \mid [p] \wedge [s] \wedge \gamma_n) \\ &= \Pr_n(\mathbf{xy} \mid [p] \wedge [s]) = \Pr_n(\mathbf{x} \mid [p] \wedge [s]) \cdot \Pr_n(\mathbf{y} \mid [p] \wedge [s]) \\ &= \Pr_r(\mathbf{x} \mid [p] \wedge [s] \wedge \gamma_n) \cdot \Pr_r(\mathbf{y} \mid [p] \wedge [s] \wedge \gamma_n) \end{aligned}$$

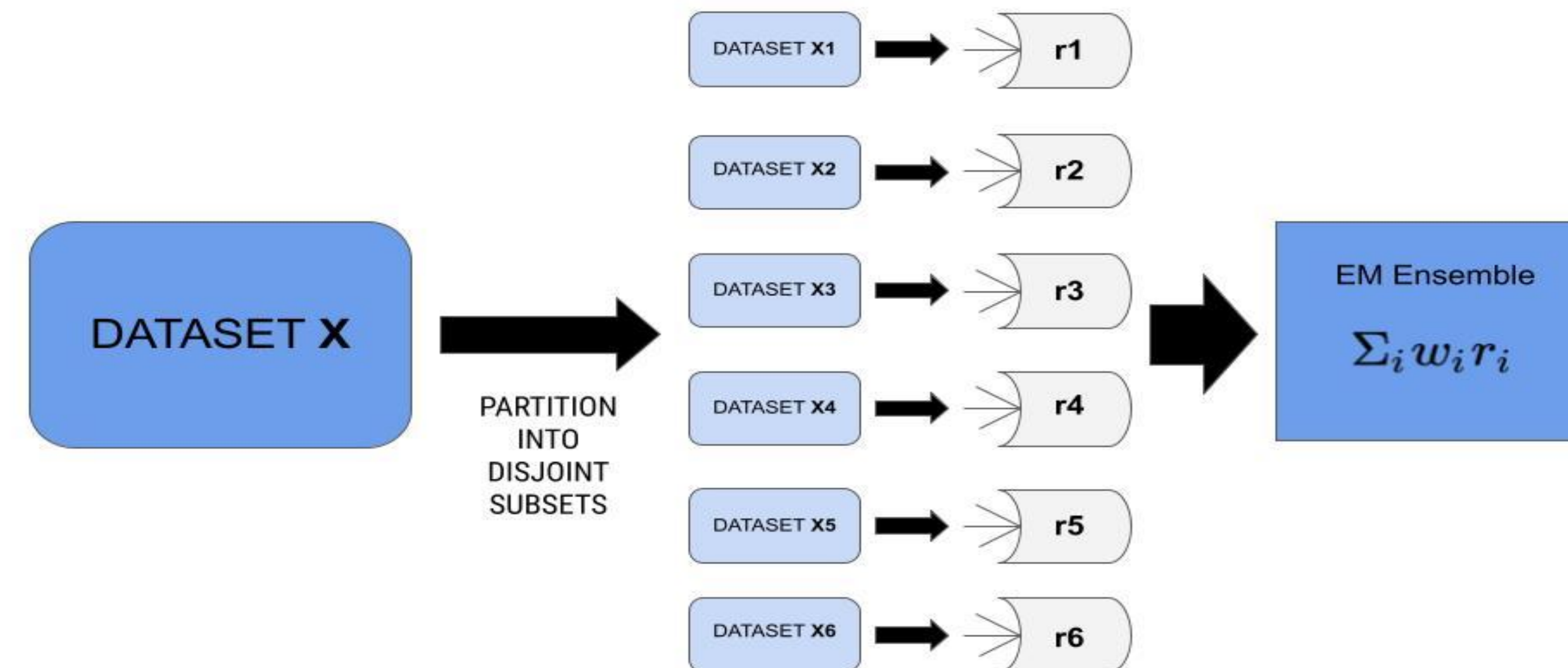
## ENSEMBLE LEARNING



- **Ensemble of PSDDs** : Represented as a single PSDD with latent variable at root
- For fixed component structures, parameter learning done using **Soft-EM Algorithm**
- Highly sensitive to **Initialization**



### WHAT IS A STRONG INITIALIZATION STRATEGY FOR EM ENSEMBLES?



**Approach** : Partition dataset into disjoint sets. Train a component structure on each subset. Use these as initialization to EM ensemble.

**How to partition?** : Find maximal subsets such that prime-sub-independence satisfied approximately at component root level (measured by pairwise-mutual-information)

**Optimization Problem** : Finding maximal partitions can be cast as a discrete optimization problem.

$$\begin{aligned} & \text{Max}_{\mathcal{B} \in [0,1]^N} \mathbb{1}(\mathcal{B}) \\ & \text{subject to : } \mathcal{F}(\mathbf{X}[\mathcal{B}]) \leq \mathcal{T} \end{aligned}$$

## RESULTS

Datasets	IL-Strudel	Strudel-EM	EM-LearnPSDD
NLTCS	<b>-6.03</b>	-6.07	-6.03
MSNBC	<b>-6.04</b>	-6.04	-6.04
KDD	<b>-2.12</b>	-2.14	-2.12
Plants	-13.30	<b>-13.22</b>	-13.79
Audio	<b>-40.22</b>	-41.2	-41.98
Jester	<b>-52.95</b>	-54.24	-53.47
Netflix	<b>-56.99</b>	-57.93	-58.41
Accidents	-29.86	<b>-29.05</b>	-33.64
Retail	-10.84	-10.83	<b>-10.81</b>
Pumsb-Star	-25.55	<b>-24.39</b>	-33.67
DNA	<b>-86.93</b>	-87.15	-92.67
Kosarek	<b>-10.61</b>	-10.7	-10.81
MSWeb	-9.78	<b>-9.74</b>	-9.97
Book	<b>-34.12</b>	-34.49	-34.97
EachMovie	<b>-51.92</b>	-53.72	-58.01
WebKB	<b>-152.79</b>	-154.83	-161.09
Reuters-52	<b>-85.60</b>	-86.35	-89.61
20NewsGrp.	<b>-152.24</b>	-153.87	-161.09
BBC	-253.46	-256.53	<b>-253.19</b>
AD	<b>-15.23</b>	-16.52	-31.78

- IL-Strudel beats Strudel-EM on 14/20 datasets
- Better results on the larger datasets
- More the number of variables, better the potential to capture rich CSIs.

## CONCLUSION

**Summary** : Initial component structures trained on disjoint sub-supports with prime-sub independence holding at component root levels is a better EM initialization strategy

**Future work** : Explore incorporation of vtree in ensemble learning setup. Use of more robust independence measures than pairwise-mutual-information.