

Sum-Product Networks

Sum-Product Networks (SPNs)

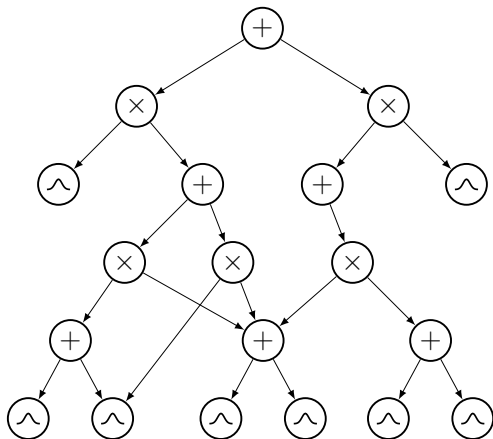
A sum-product network [Poon & Domingos 2011] over random variables \mathbf{X} is a tuple $\mathcal{S} = (\mathcal{G}, \psi, \mathbf{w}, \theta)$, consisting of a *computational graph* \mathcal{G} , a *scope-function* ψ [Trapp et al. 2019], network weights \mathbf{w} and leaf node parameters θ .

Why use SPNs? *Exact and efficient* computation of many probabilistic inference tasks, e.g. marginalisation.

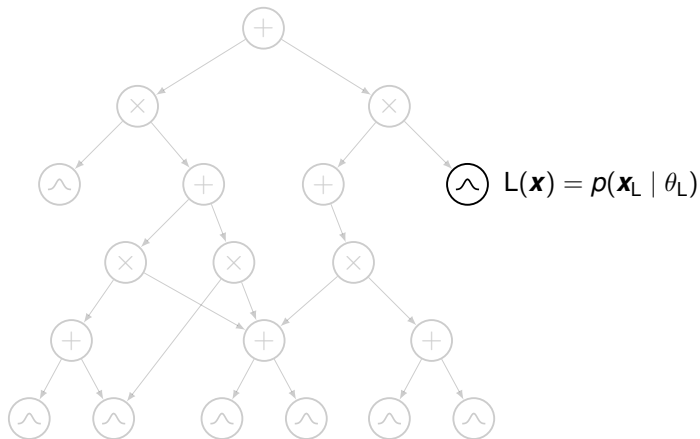
SPNs are deep structured mixture models, generalising shallow mixtures, using an architecture that is a special type of a sparse *linear* neural network with non-linear inputs.

Every SPN is a multi-linear function in its weights.

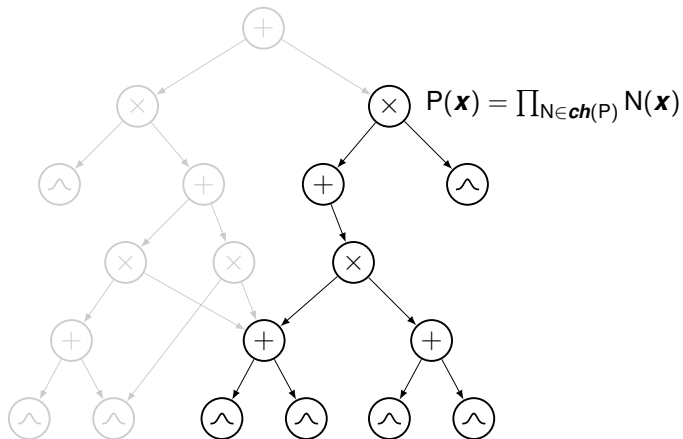
Computational Graph: \mathcal{G}



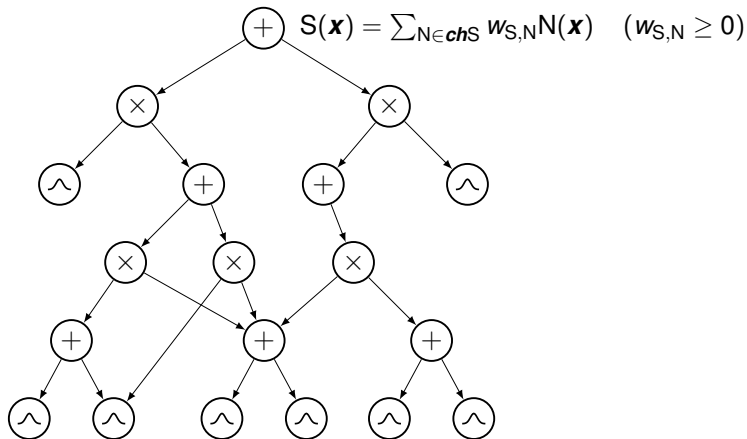
Computational Graph: \mathcal{G}



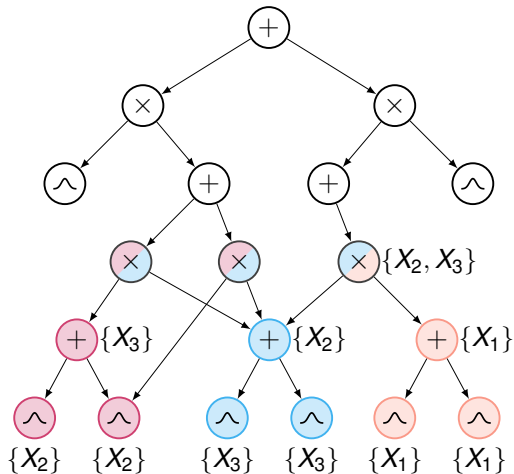
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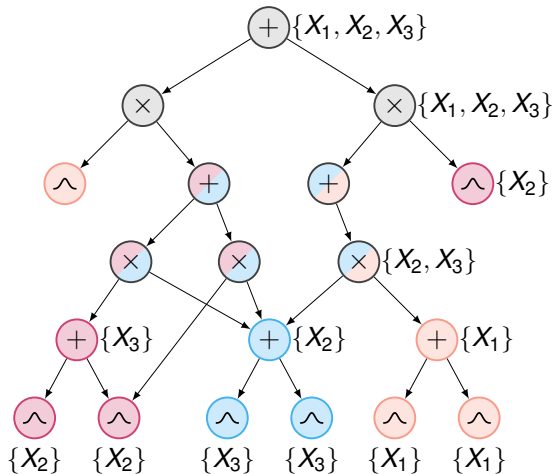
Computational Graph: \mathcal{G}



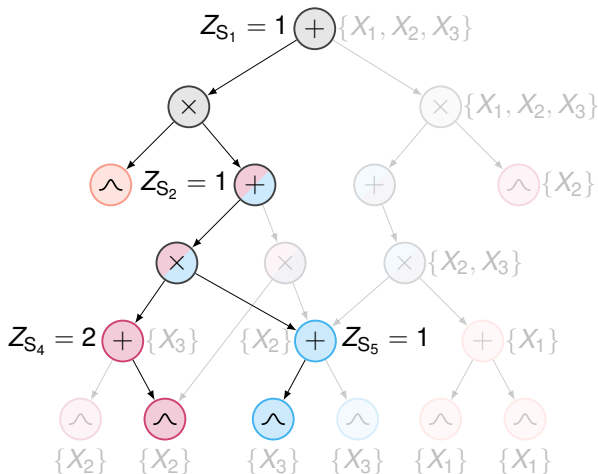
Scope Function: $\psi: \mathbf{N} \mapsto \mathcal{P}(\mathbf{X})$



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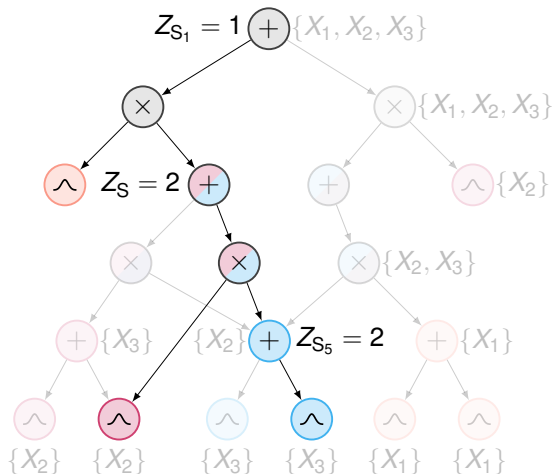


SPNs as a Mixture of Induced Trees



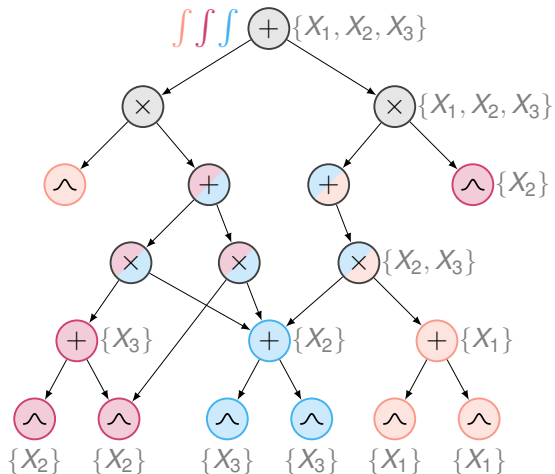
$$\mathcal{S}(\mathbf{x}) = \sum_{i=1}^K \prod_{(S,N) \in \mathcal{T}_{i,E}} w_{S,N} \prod_{L \in \mathcal{T}_{i,V}} p(\mathbf{x}_L \mid \theta_L) \quad (1)$$

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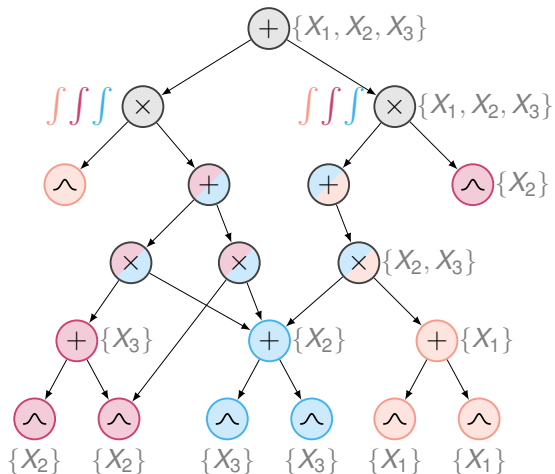


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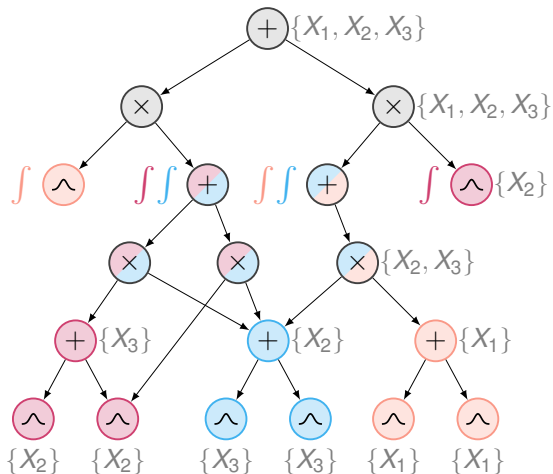
Exact Marginalisation in SPNs



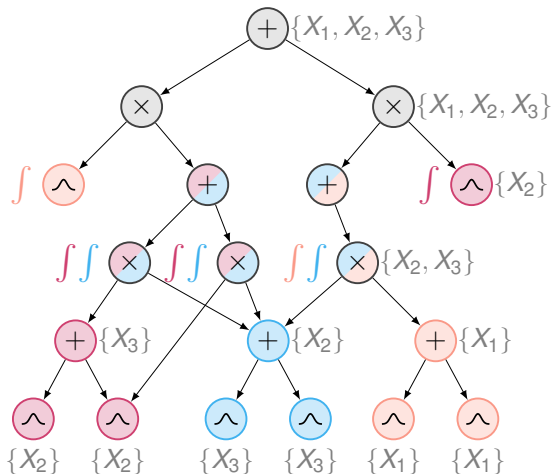
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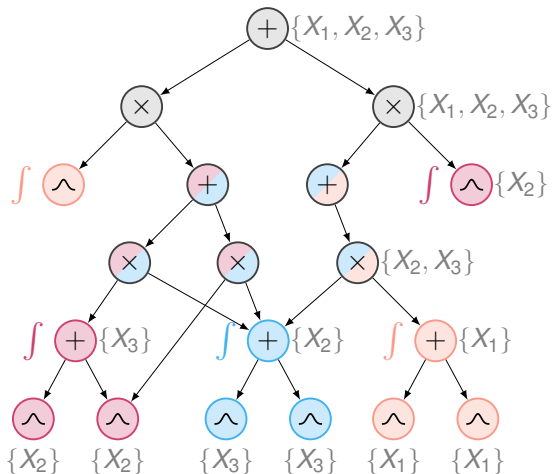
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