# mm 40 60 80 100 120 140 160 180 200 220 240 260 280 300 320 340 360 380 400 420 440 460 480 500 520 540 560 580 60 400 Market Strengthening Sum-Product Network Structure Learning

University of Bari "Aldo Moro", Italy



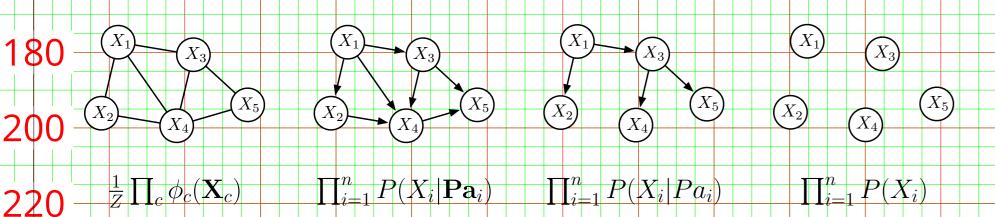
Department of Computer Science

Antonio Vergari, Nicola Di Mauro and Floriana Esposito

{firstname.lastname@uniba.it}

#### Sum-Product Networks and Tractable Models

Tractable inference on Probabilistic Graphical Models (PGMs) is at a 1 de off with model expressiveness.



240

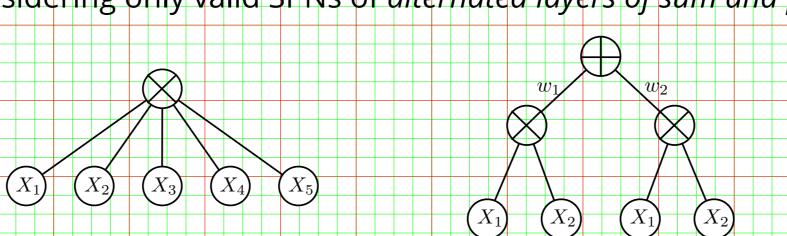
260

280

Compiling the partition function of a pdf into a deep architecture of sum and product nodes.

Product nodes define factorizations over independent vars, sum nodes mixtures. Leaves are tractable univariate distributions. Products over nodes with different scopes (decomposability) and sums over nodes with same scopes (completeness) guarantee modeling a pdf (validity).

Considering only valid SPNs of alternated layers of sum and products.



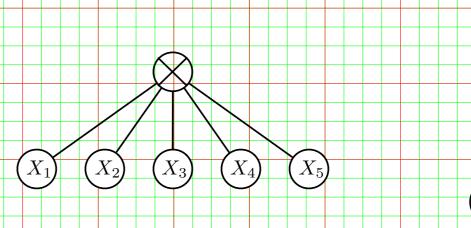
#### Compiling the partition function of a pdf into a deep architecture of sum and product nodes.

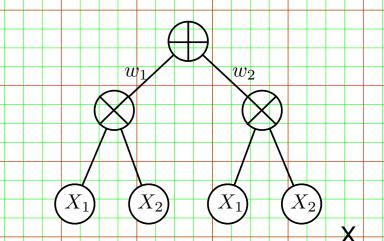
LACAM

**Machine Learning** 

Product nodes define factorizations over independent vars, sum nodes mixtures. Leaves are tractable univariate distributions. Products over nodes with different scopes (decomposability) and sums over nodes with same scopes (completeness) guarantee modeling a pdf (validity).

Considering only valid SPNs of alternated layers of sum and products.





### 32 How and Why to perform Structure Learning

Fixed structures are hard to engineer and train (fully connected Tayers). Structure learning is more flexible and enables automatic 3 detent features discovery.

Constraint-based search formulation. Discover hidden variables for 3 sum node mixtures and independences for product node 4 components:

greedy top-down: KMeans on features [1]; alternating clustering 420on instances and independence tests on features, LearnSPN [2] greedy bottom up: merging feature regions by a Bayesian-Dirichlet

460ID-SPN: turning LearnSPN in log-likelihood guided expansion of sub-networks approximated by Arithmetic Circuits [7]

independence test, and reducing edges by maximizing MI [6]

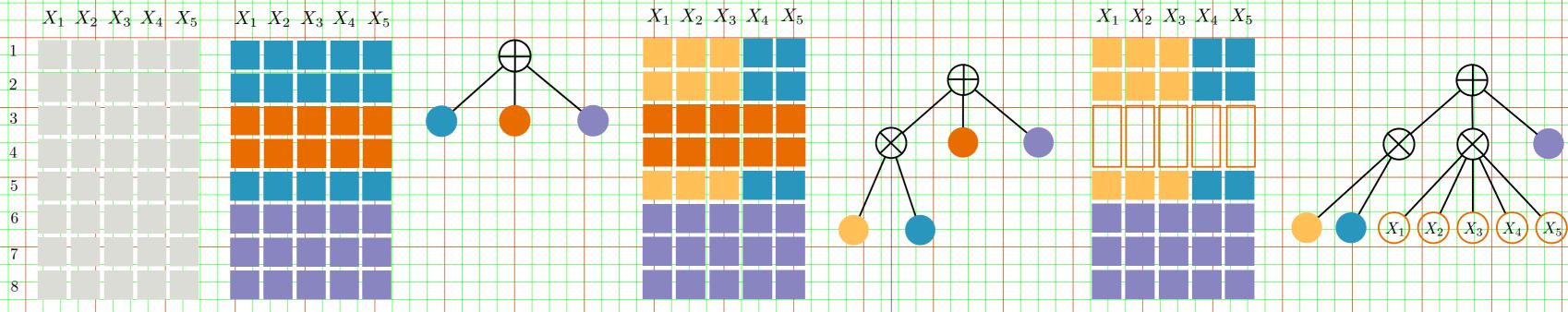
LearnSPN [2] builds a tree-like SPN by recursively split the data matrix:  $\oplus$  splitting columns in pairs by a greedy **G** Test based procedure with threshold  $\rho$ :

 $G(X_i, X_j) = 2 \sum_{x_i \sim X_i} \sum_{x_j \sim X_j} c(x_i, x_j) \cdot \log \frac{c(x_i, x_j) \cdot |T|}{c(x_i)c(x_j)}$ 

 $X_1$   $X_2$   $X_3$   $X_4$   $X_5$   $X_1$   $X_2$   $X_3$   $X_4$   $X_5$ 

clustering instances with **online Hard-EM** with cluster penalty  $\lambda$ :  $Pr(\mathbf{X}) = \sum_{C_i \in \mathbf{C}} \prod_{X_i \in \mathbf{X}} Pr(X_j | C_i) Pr(C_i)$ 

if there are less than m instances, put a **naive factorization** over leaves each univariate distribution get **ML estimation** smoothed by lpha



### 5 Simplifying by Limiting Node Splits

520 rem ipsum dolor sit amet, consectetuer adipiscing elit. Etiam lobortis facilisis sem. Nullam nec mi et neque pharetra sollicitudin. 540 Praesent imperdiet mi nec ante. Donec ullamcorper, felis non 5 sodales commodo, lectus velit ultrices augue, a dignissim nibh lectus placerat pede. Vivamus nunc nunc, molestie ut, ultricies vel, Semper in, velit. Ut porttitor. Praesent in sapien. Lorem ipsum dolor sit amet, consectetuer adipiscing elit. Duis fringilla tristique neque. Sed interdum libero ut metus. Pellentesque placerat. Nam 620trum augue a leo. Morbi sed elit sit amet ante lobortis sollicitudin. Praesent blandit blandit mauris. Praesent lectus tellus, aliquet aliquam, luctus a, egestas a, turpis. Mauris lacinia lorem sit

6 amet ipsum. Nunc quis urna dictum turpis accumsan semper.

Lorem ipsum dolor sit amet, consectetuer adipiscing elit. Etiam lobortis facilisis sem. Nullam nec mi et neque pharetra sollicitudin. Praesent imperdiet mi nec ante. Donec ullamcorper, felis non sodales commodo, lectus velit ultrices augue, a dignissim nibh lectus placerat pede. Vivamus nunc nunc, molestie ut, ultricies vel, semper in, velit. Ut porttitor. Praesent in sapien. Lorem ipsum dolor sit amet, consectetuer adipiscing elit. Duis fringilla tristique neque. Sed interdum libero ut metus. Pellentesque placerat. Nam rutrum augue a leo. Morbi sed elit sit amet ante lobortis sollicitudin. Praesent blandit blandit mauris. Praesent lectus tellus, aliquet aliquam, luctus a, egestas a, turpis. Mauris lacinia lorem sit amet ipsum. Nunc quis urna dictum turpis accumsan semper.

#### Experiments

Classical setting for generative graphical models structure learning [2]: comparing the *average log-likelihood* on predicting instances from a test set 19 binary datasets from classification, recommendation, frequent pattern mining...[4] [3]

Training 75% Validation 10% Test 15% splits (no cv)

Model selection via grid search in the same parameter space:

 $\otimes \lambda \in \{0.2, 0.4, 0.6, 0.8\},\$  $\otimes \rho \in \{5, 10, 15, 20\},\$ 

 $\otimes m \in \{1, 50, 100, 500\},\$ 

 $\otimes \alpha \in \{0.1, 0.2, 0.5, 1.0, 2.0\}$ comparing our variants against LearnSPN, ID-SPN and MT [5]

## Regularizing by introducing tree distributions as leaves

Lorem ipsum dolor sit amet, consectetuer adipiscing elit. Etiam 720bortis facilisis sem. Nullam nec mi et neque pharetra sollicitudin. Praesent imperdiet mi nec ante. Donec ullamcorper, felis non dales commodo, lectus velit ultrices augue, a dignissim nibh 7 dectus placerat pede. Vivamus nunc nunc, molestie ut, ultricies vel, semper in, velit. Ut porttitor. Praesent in sapien. Lorem ipsum / blor sit amet, consectetuer adipiscing elit. Duis fringilla tristique neque. Sed interdum libero ut metus. Pellentesque placerat. Nam rutrum augue a leo. Morbi sed elit sit amet ante lobortis 830 llicitudin. Praesent blandit blandit mauris. Praesent lectus tellus, aliquet aliquam, luctus a, egestas a, turpis. Mauris lacinia lorem sit amet ipsum. Nunc quis urna dictum turpis accumsan semper.

Lorem ipsum dolor sit amet, consectetuer adipiscing elit. Etiam lobortis facilisis sem. Nullam nec mi et neque pharetra sollicitudin. Praesent imperdiet mi nec ante. Donec ullamcorper, felis non sodales commodo, lectus velit ultrices augue, a dignissim nibh lectus placerat pede. Vivamus nunc nunc, molestie ut, ultricies vel, semper in, velit. Ut porttitor. Praesent in sapien. Lorem ipsum dolor sit amet, consectetuer adipiscing elit. Duis fringilla tristique neque. Sed interdum libero ut metus. Pellentesque placerat. Nam rutrum augue a leo. Morbi sed elit sit amet ante lobortis sollicitudin. Praesent blandit blandit mauris. Praesent lectus tellus, aliquet aliquam, luctus a, egestas a, turpis. Mauris lacinia lorem sit amet ipsum. Nunc quis urna dictum turpis accumsan semper.

Lorem ipsum dolor sit amet, consectetuer adipiscing elit. Etiam lobortis facilisis sem. Nullam nec mi et neque pharetra sollicitudin. Praesent imperdiet mi nec ante. Donec ullamcorper, felis non sodales commodo, lectus velit ultrices augue, a dignissim nibh lectus placerat pede. Vivamus nunc nunc, molestie ut, ultricies vel, semper in, velit. Ut porttitor. Praesent in sapien. Lorem ipsum dolor sit amet, consectetuer adipiscing elit. Duis fringilla tristique neque. Sed interdum libero ut metus. Pellentesque placerat. Nam rutrum augue a leo. Morbi sed elit sit amet ante lobortis sollicitudin. Praesent blandit blandit mauris. Praesent lectus tellus, aliquet aliquam, luctus a, egestas a, turpis. Mauris lacinia lorem sit amet ipsum. Nunc quis urna dictum turpis accumsan semper.

### Strengthening by Model Averaging

Lorem ipsum dolor sit amet, consectetuer adipiscing elit. Etiam lobortis facilisis sem. Nullam nec mi et neque pharetra sollicitudin. 92 Maesent imperdiet mi nec ante. Donec ullamcorper, felis non sodales commodo, lectus velit ultrices augue, a dignissim nibh 94ectus placerat pede. Vivamus nunc nunc, molestie ut, ultricies vel, semper in, velit. Ut porttitor. Praesent in sapien. Lorem ipsum dolor sit amet, consectetuer adipiscing elit. Duis fringilla tristique 980 que. Sed interdum libero ut metus. Pellentesque placerat. Nam rutrum augue a leo. Morbi sed elit sit amet ante lobortis sollicitudin. Praesent blandit blandit mauris. Praesent lectus tellus, 10 pliquet aliquam, luctus a, egestas a, turpis. Mauris lacinia lorem sit amet ipsum. Nunc quis urna dictum turpis accumsan semper. 1040

Lorem ipsum dolor sit amet, consectetuer adipiscing elit. Etiam lobortis facilisis sem. Nullam nec mi et neque pharetra sollicitudin. Praesent imperdiet mi nec ante. Donec ullamcorper, felis non sodales commodo, lectus velit ultrices augue, a dignissim nibh lectus placerat pede. Vivamus nunc nunc, molestie ut, ultricies vel, semper in, velit. Ut porttitor. Praesent in sapien. Lorem ipsum dolor sit amet, consectetuer adipiscing elit. Duis fringilla tristique neque. Sed interdum libero ut metus. Pellentesque placerat. Nam rutrum augue a leo. Morbi sed elit sit amet ante lobortis sollicitudin. Praesent blandit blandit mauris. Praesent lectus tellus, aliquet aliquam, luctus a, egestas a, turpis. Mauris lacinia lorem sit amet ipsum. Nunc quis urna dictum turpis accumsan semper.

Lorem ipsum dolor sit amet, consectetuer adipiscing elit. Etiam lobortis facilisis sem. Nullam nec mi et neque pharetra sollicitudin. Praesent imperdiet mi nec ante. Donec ullamcorper, felis non sodales commodo, lectus velit ultrices augue, a dignissim nibh lectus placerat pede. Vivamus nunc nunc, molestie ut, ultricies vel, semper in, velit. Ut porttitor. Praesent in sapien. Lorem ipsum dolor sit amet, consectetuer adipiscing elit. Duis fringilla tristique neque. Sed interdum libero ut metus. Pellentesque placerat. Nam rutrum augue a leo. Morbi sed elit sit amet ante lobortis sollicitudin. Praesent blandit blandit mauris. Praesent lectus tellus, aliquet aliquam, luctus a, egestas a, turpis. Mauris lacinia lorem sit amet ipsum. Nunc quis urna dictum turpis accumsan semper.

#### References

Aaron Dennis and Dan Ventura. \Learning the Architecture of Sum-Product Networks Using Clustering on Varibles". In: Advances in Neural Information Processing Systems 25. Curran Associates, Inc., 2012, pp. 2033-2041.

Robert Gens and Pedro Domingos. ``Learning the Structure of Sum-Product Networks''. In: Proceedings of the 30th International Conference on Machine Learning. JMLR Workshop and Conference Proceedings, 2013, pp. 873–880.

1 1 Op Jan Van Haaren and Jesse Davis. ``Markov Network Structure Learning: A Randomized Feature Generation Approach". In: Proceedings of the 26th Conference on Artificial Intelligence. AAAI Press, 2012.

Daniel Lowd and Jesse Davis. ``Learning Markov Network Structure with Decision Trees". In: Proceedings of the 10th IEEE International Conference on Data Mining. IEEE Computer Society Press, 2010, pp. 334–343. Marina Meila and Michael I. Jordan. Learning with mixtures of trees". In: Journal of Machine Learning Research 1 (2000), pp. 1-48

Robert Peharz, Bernhard Geiger, and Franz Pernkopf. ` Greedy Part-Wise Learning of Sum-Product Networks". In: Machine Learning and Knowledge Discovery in Databases. Vol. 8189. LNC\$. Springer, 2013, pp. 612-627.

1 1 40 Amirmohammad Rooshenas and Daniel Lowd. Learning Sum-Product Networks with Direct and Indirect Variable Interactions. The Proceedings of the 31st International Conference on Machine Learning. JMLR Workshop and Conference Proceedings, 2014, pp. 710–718

1160 ECML-PKDD 2015 - 8th September 2015, Porto, Portugal