

# Sum of Squares Circuits



Paper



Code



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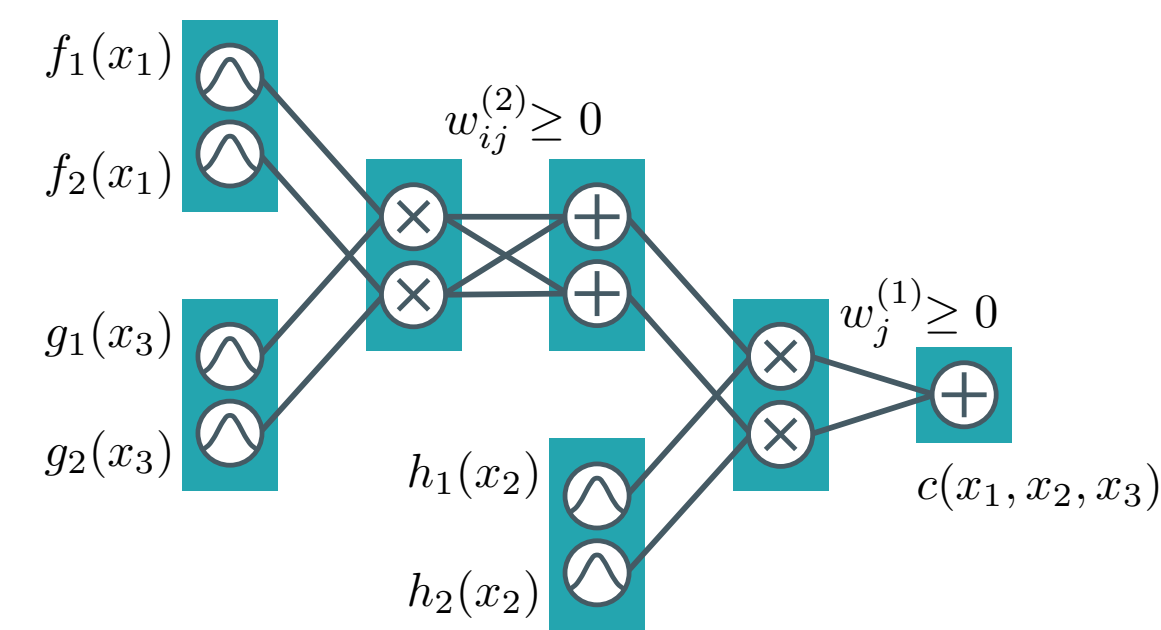
**TL;DR:** “We show an expressiveness hierarchy including many tractable probabilistic model classes, when represented as deep structured computational graphs called circuits”

Circuits are computational graphs unifying probabilistic models that support efficient and exact inference

Tasks  $\begin{cases} \text{lossless (de)compression}^{[1]} & p(x_i | x_1, \dots, x_{i-1}) \\ \text{neurosymbolic reasoning}^{[2]} & \mathbb{E}_{\mathbf{x} \sim p(\mathbf{x})}[\kappa(\mathbf{x})] \end{cases}$

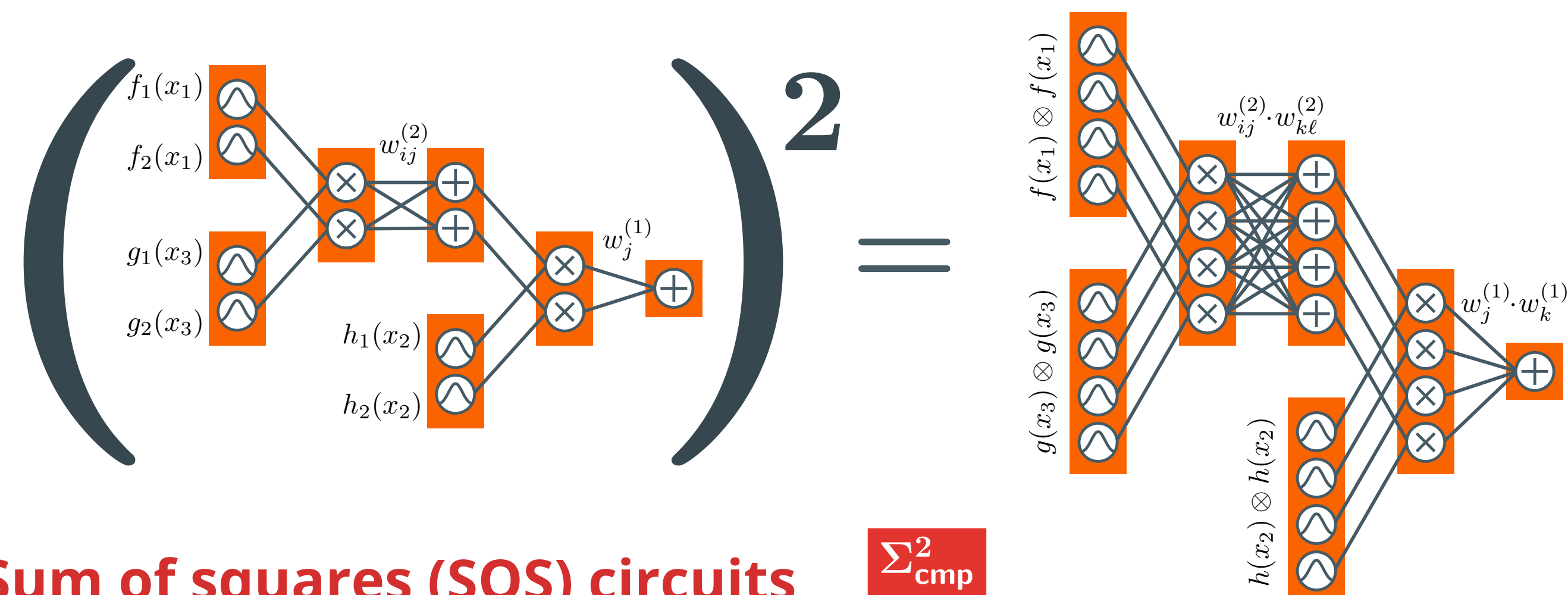
## Monotonic circuits $\pm_{sd}$

$p(\mathbf{x}) \propto c(\mathbf{x})$ , with  $c(\mathbf{x}) \geq 0$ , positive parameters only



## Squared circuits $\pm_{\mathbb{R}^2}$

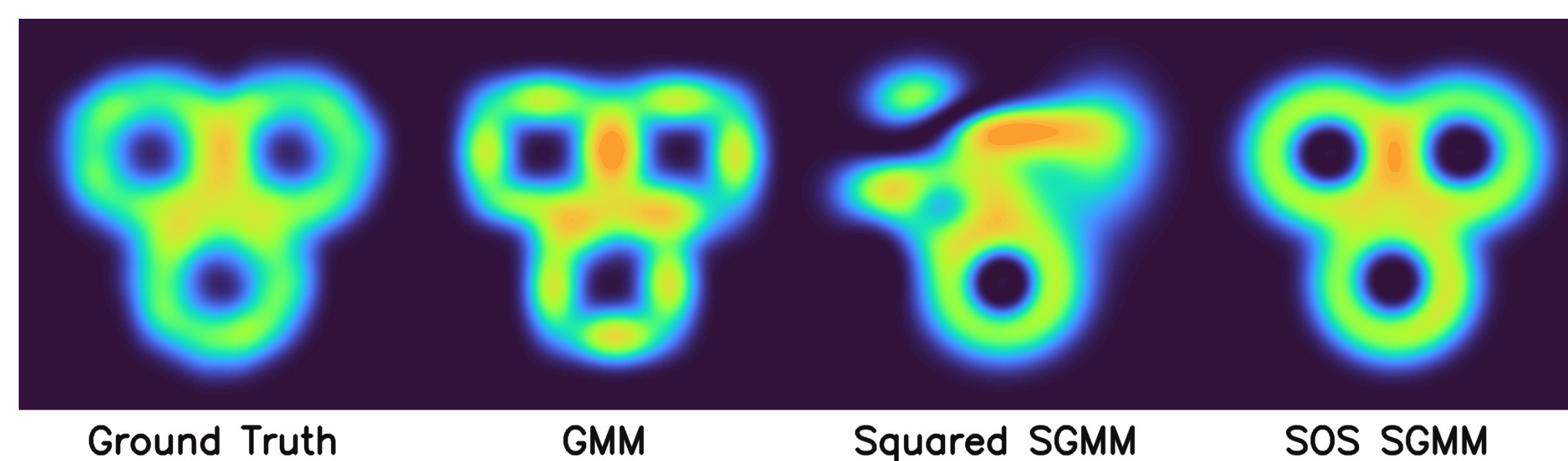
$p(\mathbf{x}) \propto c^2(\mathbf{x})$ , with  $c(\mathbf{x}) \in \mathbb{R}$ , parameters are reals



## Sum of squares (SOS) circuits $\Sigma_{\text{cmp}}^2$

$p(\mathbf{x}) \propto \sum_{i=1}^r c_i^2(\mathbf{x})$ , with  $c_i(\mathbf{x}) \in \mathbb{R}$

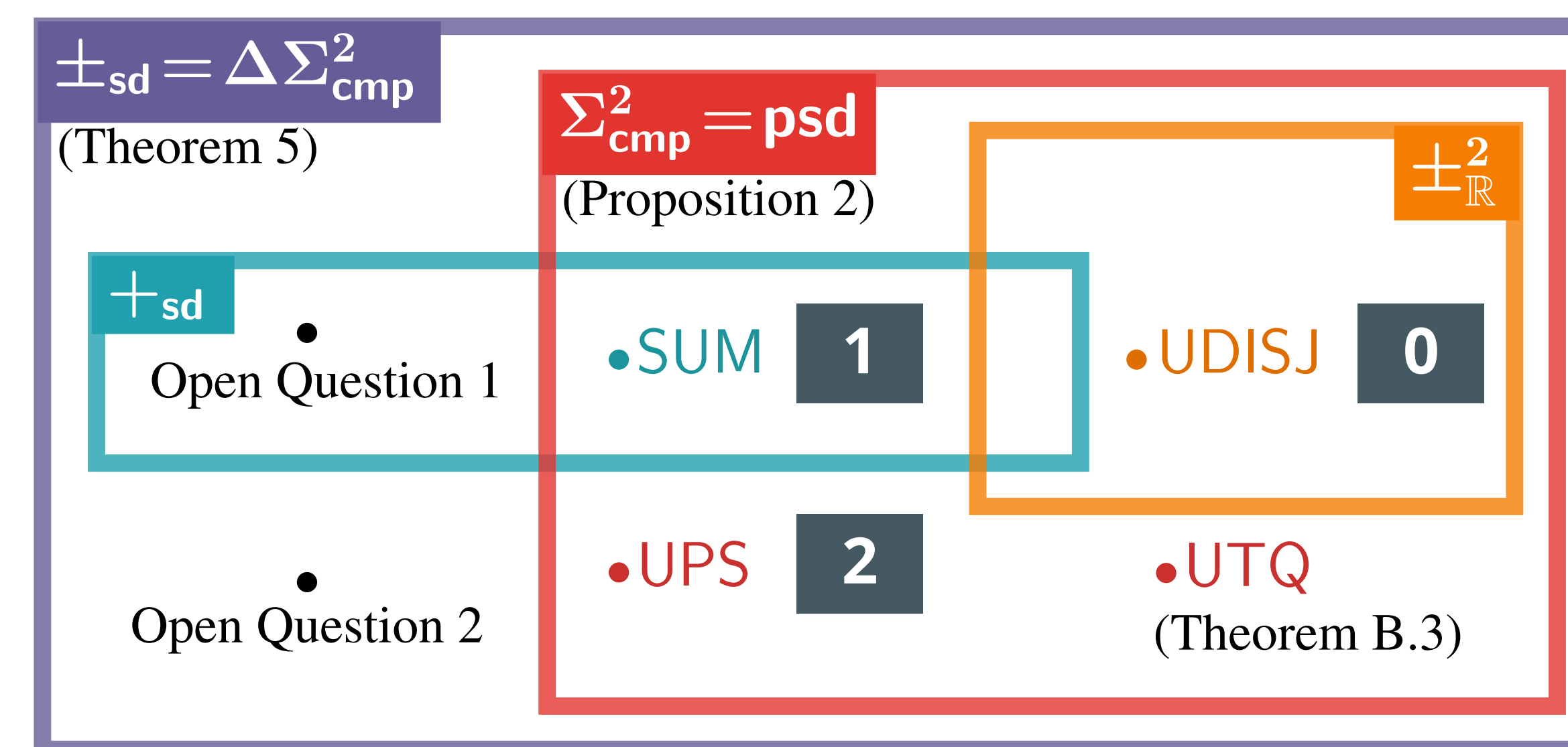
Why SOS?



## References

- [1] A. Liu, S. Mandt, and G. V. den Broeck. “Lossless Compression with Probabilistic Circuits”. In: *ICLR*. 2022.
- [2] K. Ahmed et al. “Semantic probabilistic layers for neuro-symbolic learning”. In: *NeurIPS*. 2022.
- [3] L. Loconte et al. “Subtractive Mixture Models via Squaring: Representation and Learning”. In: *ICLR*. 2024.
- [4] A. Rudi and C. Ciliberto. “PSD Representations for Effective Probability Models”. In: *NeurIPS*. 2021.
- [5] R. Tsuchida, C. S. Ong, and D. Sejdinovic. “Squared Neural Families: A New Class of Tractable Density Models”. In: *NeurIPS*. 2023.
- [6] I. Glasser et al. “Expressive power of tensor-network factorizations for probabilistic modeling”. In: *NeurIPS*. 2019.

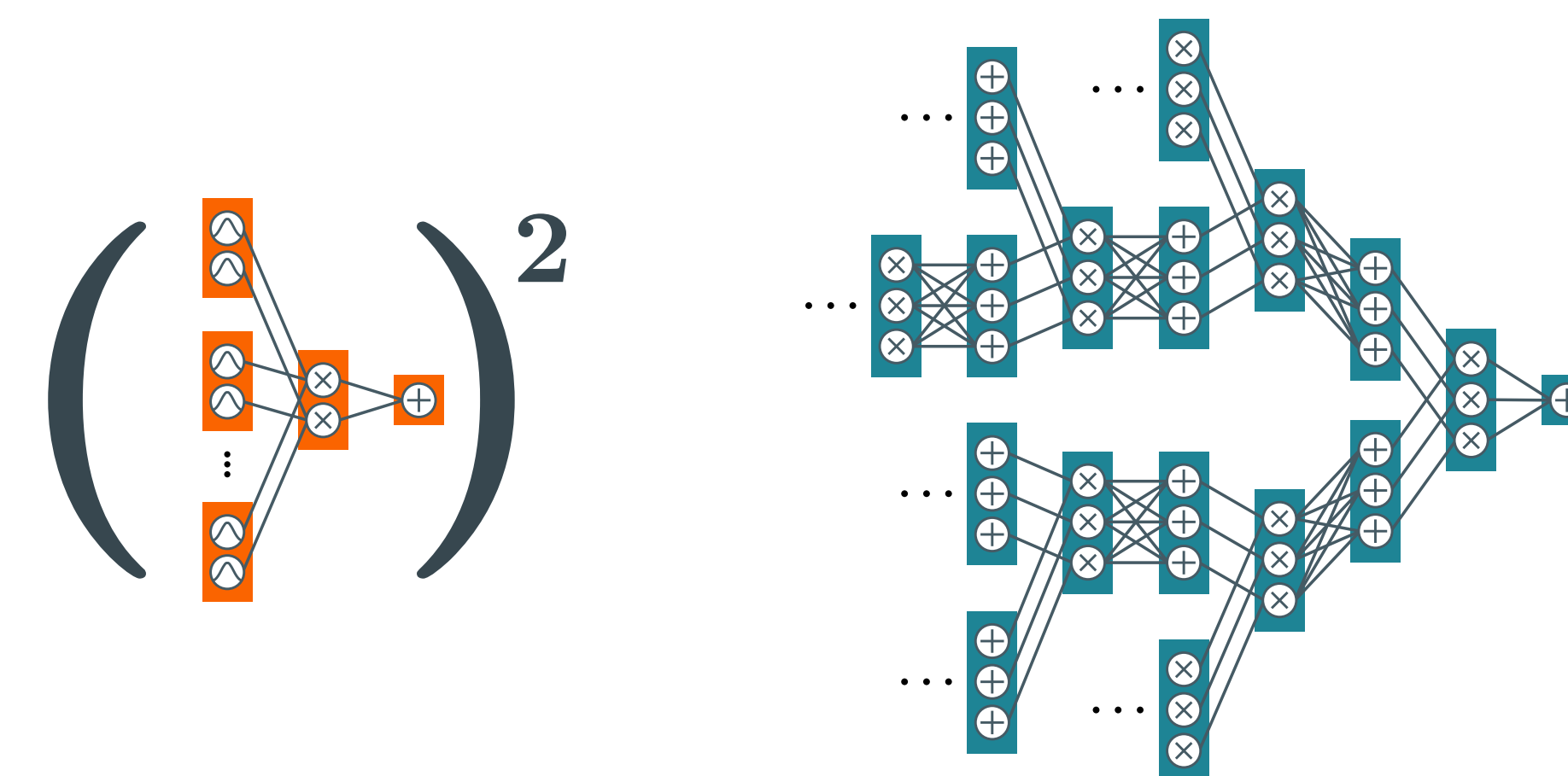
We build an expressiveness hierarchy around sum of squares circuits, with open questions!



## 0 Squared circuits are more expressive than monotonic circuits

### Theorem 0 (Loconte et al. [3])

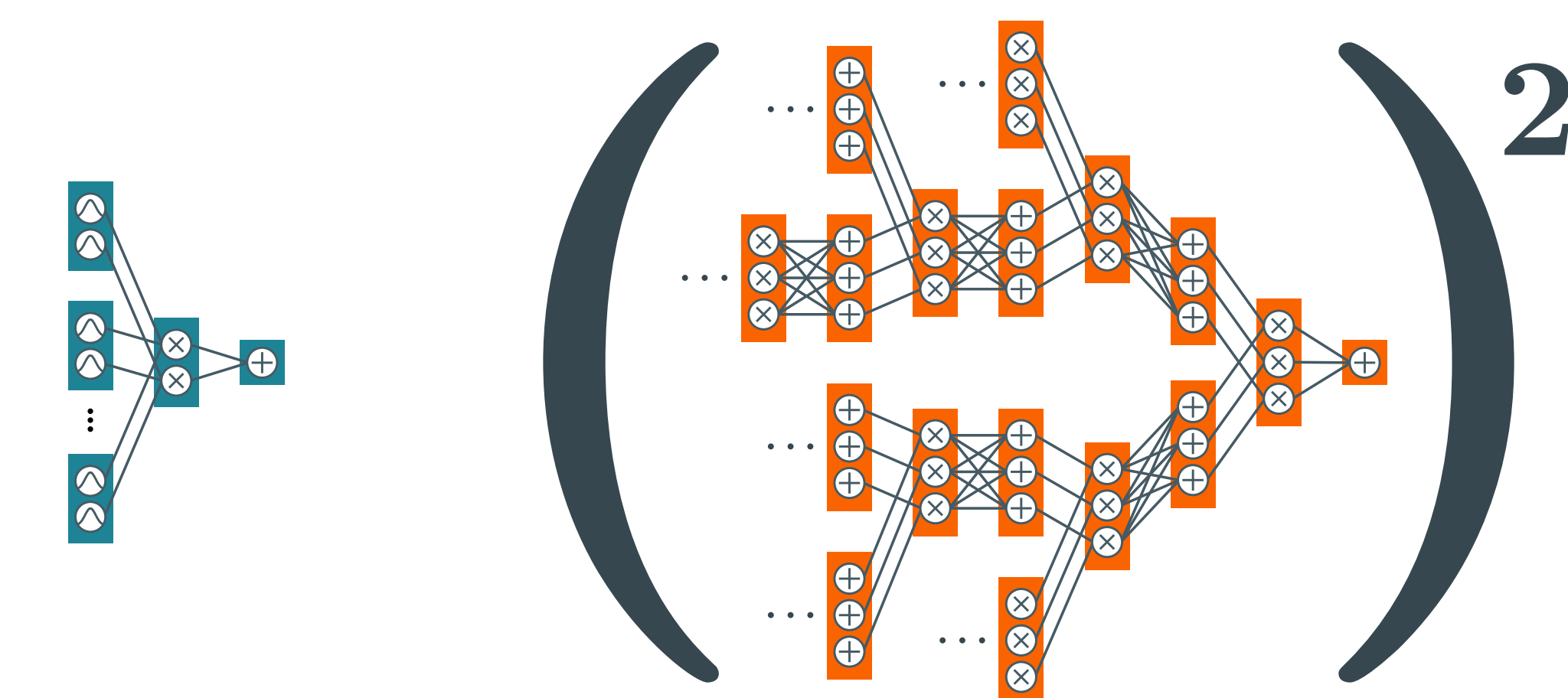
There exists distributions  $\mathcal{F}$  over  $\mathbf{X}$  that can be compactly represented as squared circuits  $\pm_{\mathbb{R}^2}$ , but the smallest monotonic circuit  $\pm_{sd}$  computing any  $F \in \mathcal{F}$  has size  $2^{\Omega(\sqrt{|\mathbf{X}|})}$ .



## 1 Monotonic and squared circuits are incomparable in terms of expressiveness

### Theorem 1

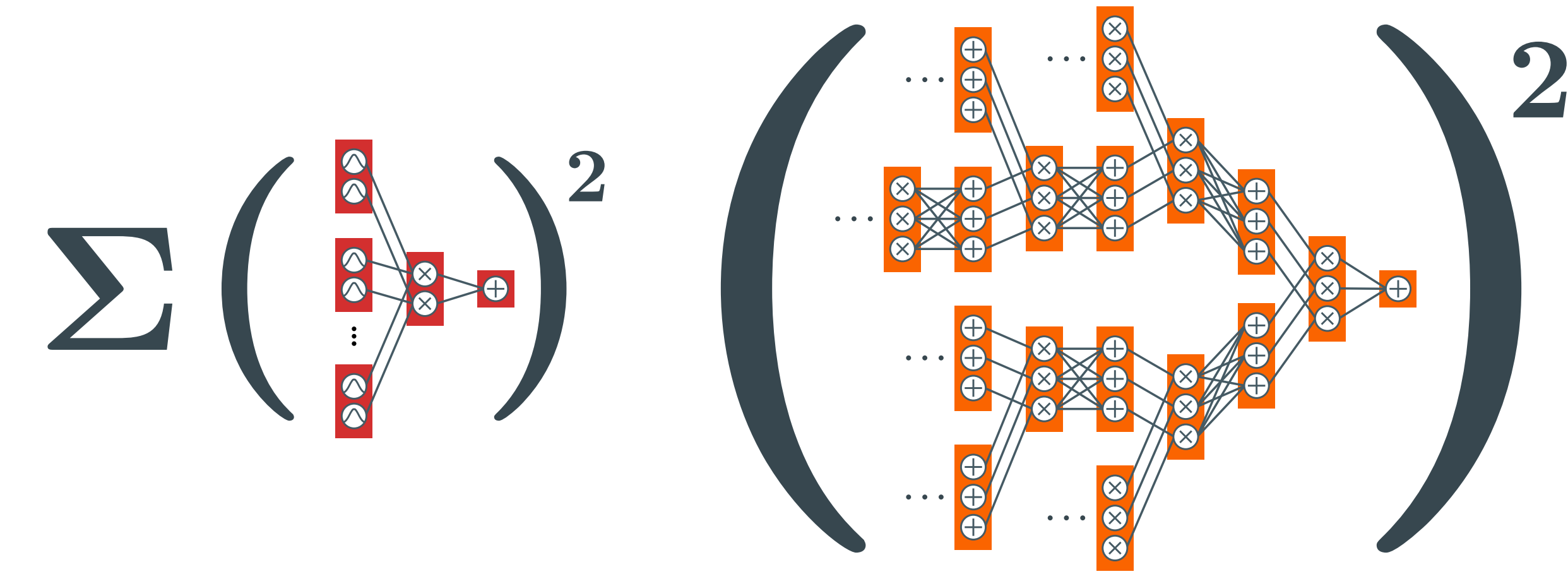
There exists distributions  $\mathcal{F}$  over  $\mathbf{X}$  that can be compactly represented as monotonic circuits  $\pm_{sd}$ , but the smallest squared circuit  $\pm_{\mathbb{R}^2}$  computing any  $F \in \mathcal{F}$  has size  $2^{\Omega(\sqrt{|\mathbf{X}|})}$ .



## 2 SOS circuits can be more expressive than both monotonic and squared circuits

### Theorem 2

There exists distributions  $\mathcal{F}$  over  $\mathbf{X}$  that can be compactly represented as SOS circuits  $\Sigma_{\text{cmp}}^2$ , but the smallest circuits in  $\pm_{sd}$  or in  $\pm_{\mathbb{R}^2}$  computing any  $F \in \mathcal{F}$  have size  $2^{\Omega(\sqrt{|\mathbf{X}|})}$ .



We understand why other models are expressive: we show models **PSD** **SNF** **BM** are SOS circuits

**PSD** Finite PSD models<sup>[4]</sup>  $p(\mathbf{x}) \propto \kappa(\mathbf{x})^\top \mathbf{A} \kappa(\mathbf{x})$

**SNF** Squared neural family<sup>[5]</sup>  $p(\mathbf{x}) \propto \mu(\mathbf{x}) \|\text{nn}_\sigma(\mathbf{t}(\mathbf{x}))\|_2^2$

**BM** Complex Born machines<sup>[6]</sup>  $p(\mathbf{x}) \propto \psi(\mathbf{x})\psi(\mathbf{x})^\dagger$

SOS circuits are expressive distribution estimators

