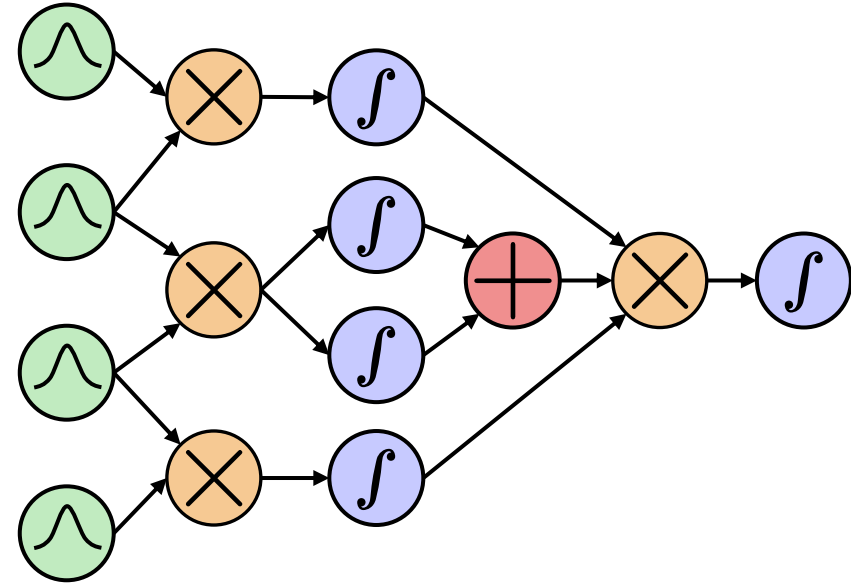


Scaling Continuous Latent Variable Models as Probabilistic Integral Circuits



TL;DR: We learn continuous hierarchical mixtures as DAG-shaped PICs, and scale them using neural functional sharing techniques.



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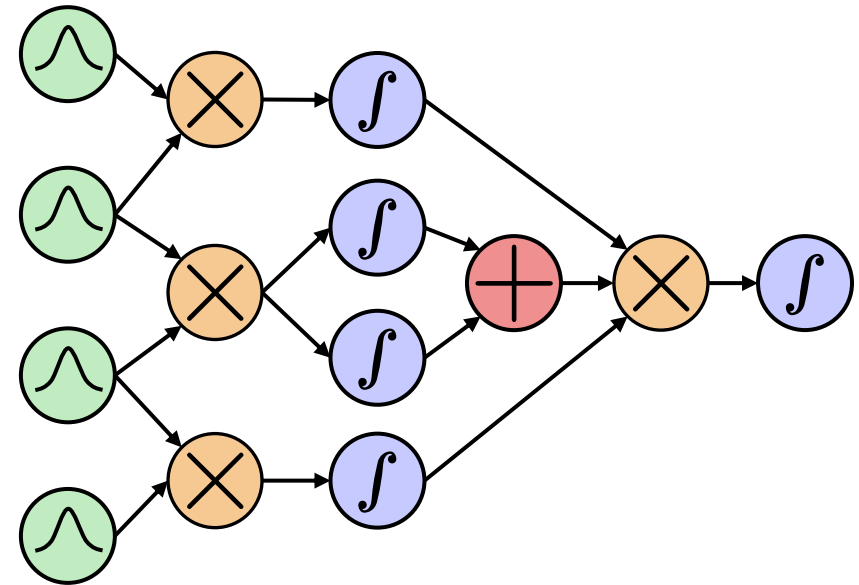
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University of
Technology, NL



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Edinburgh, UK

Background – Probabilistic Integral Circuits

- PICs are symbolic computational graphs over possibly non-normalized distributions, and represent hierarchical continuous mixture models using input $\hat{\wedge}$, product \otimes , sum \oplus and integral \int units.
- Non-input units take one or more functions as input and output a single function
- Functions are ‘attached’ to input and integral units only



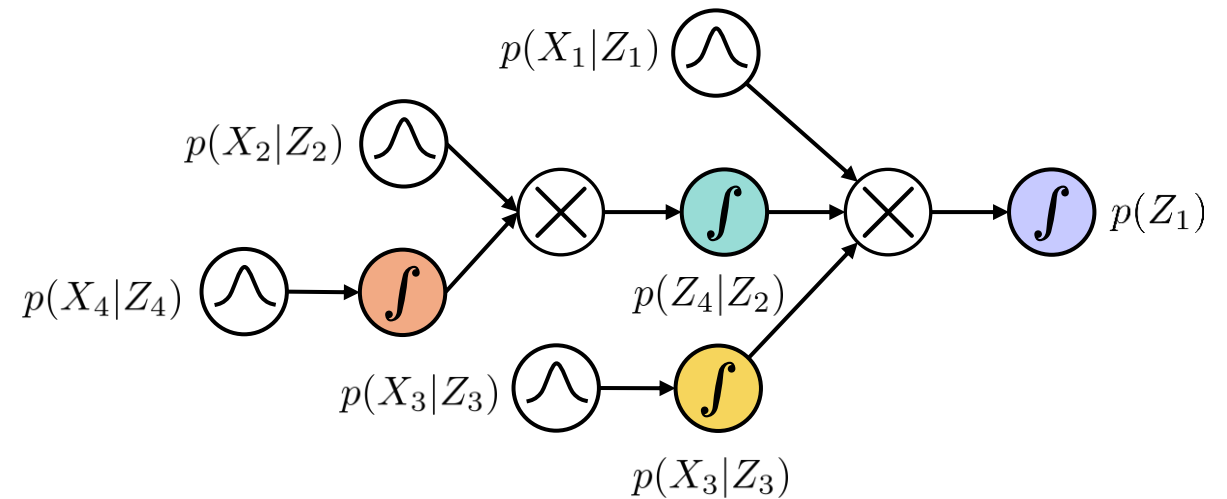
X input variable
 Z latent variable

$$f_1(X_1, Z_1) \longrightarrow \int \longrightarrow g_2(X_1, Z_2) = \int f_2(Z_2, z_1) f_1(X_1, z_1) dz_1$$

$f_2(Z_2, Z_1)$

Previous work & its limitation

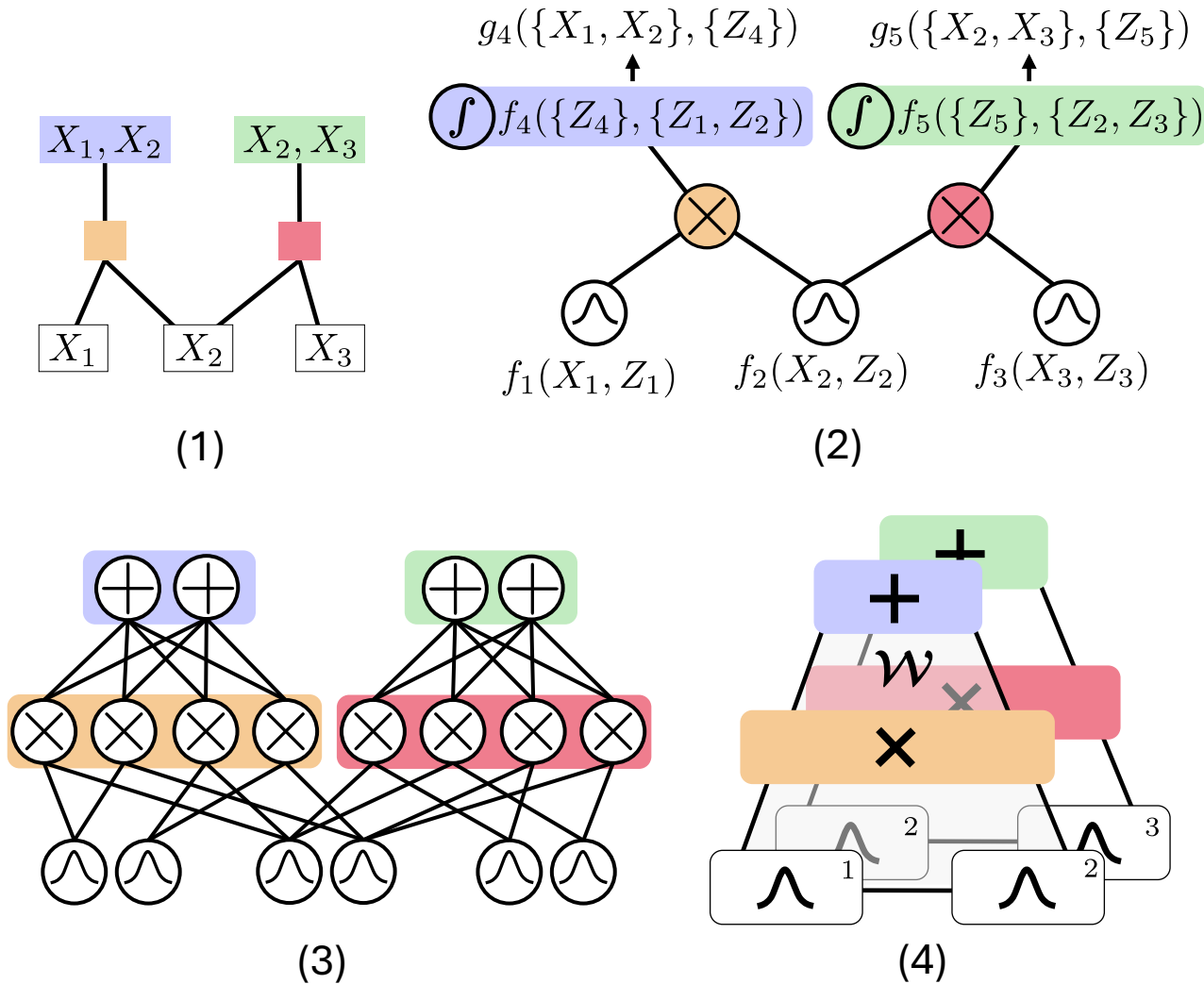
- In previous work [1], PICs where **(i)** limited to tree-shaped structure and **(ii)** only used univariate dependencies between latent variables as to make training feasible
- **RQ:** *How can we build more intricate structures and allow for multivariate latent relationships while providing scalable training?*



$$p(\mathbf{X}) = \int p(z_1) p(X_1|z_1) \int p(z_2|z_1) p(X_2|z_2) \int p(z_4|z_2) p(X_4|z_4) \int p(z_3|z_1) p(X_3|z_3) dz_4 dz_2 dz_3 dz_1$$

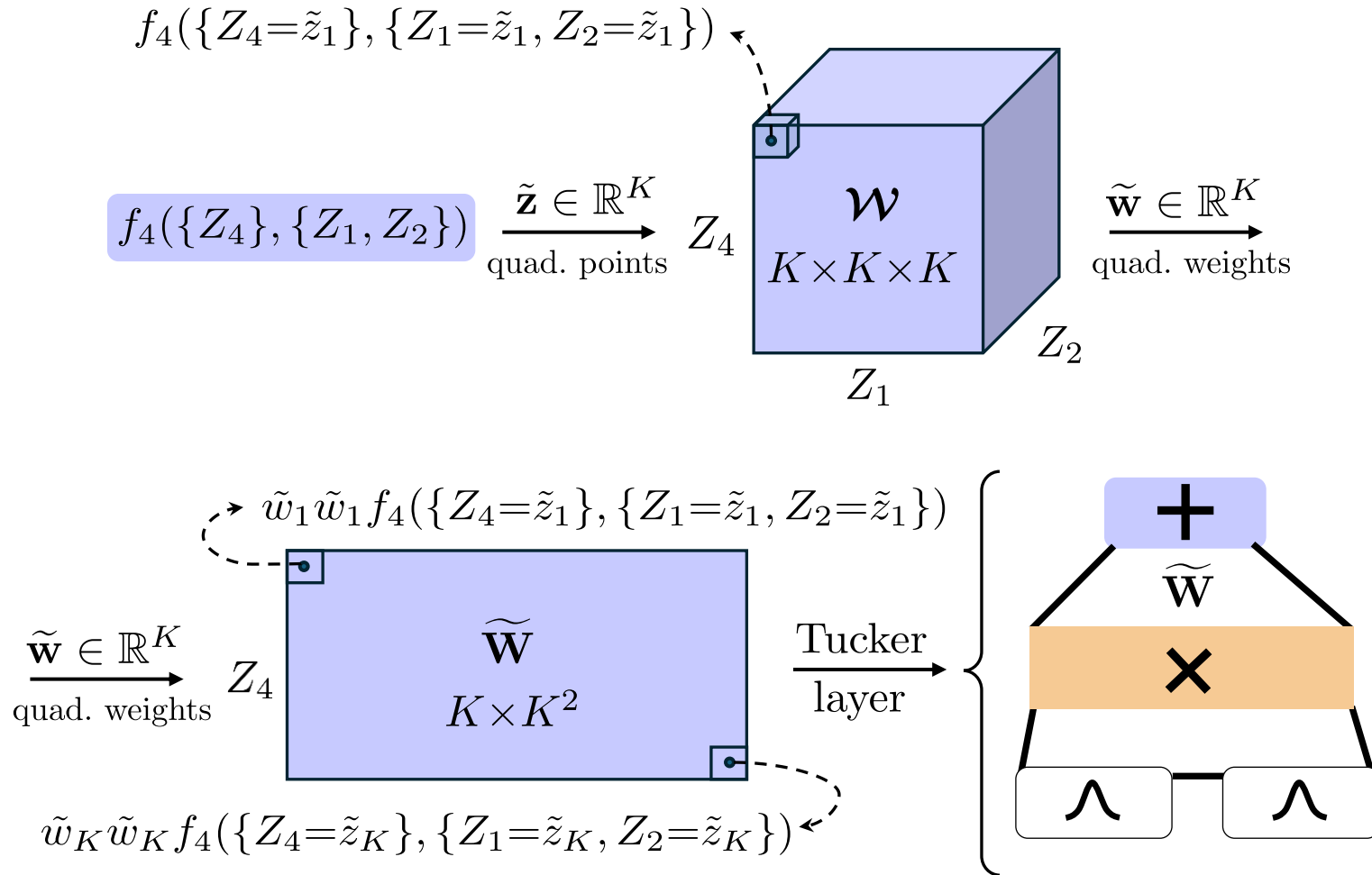
[1] Gala et al. "Probabilistic integral circuits." AISTATS 2024.

A scalable pipeline to build & learn PICs



We present a pipeline that from arbitrary variable decompositions (1) builds DAG-shaped PICs (2), that we train by materializing them as tensorized circuits (aka *tensor networks*) called Quadrature-PCs (QPCs) (3), which we also fold to allow fast inference (4).

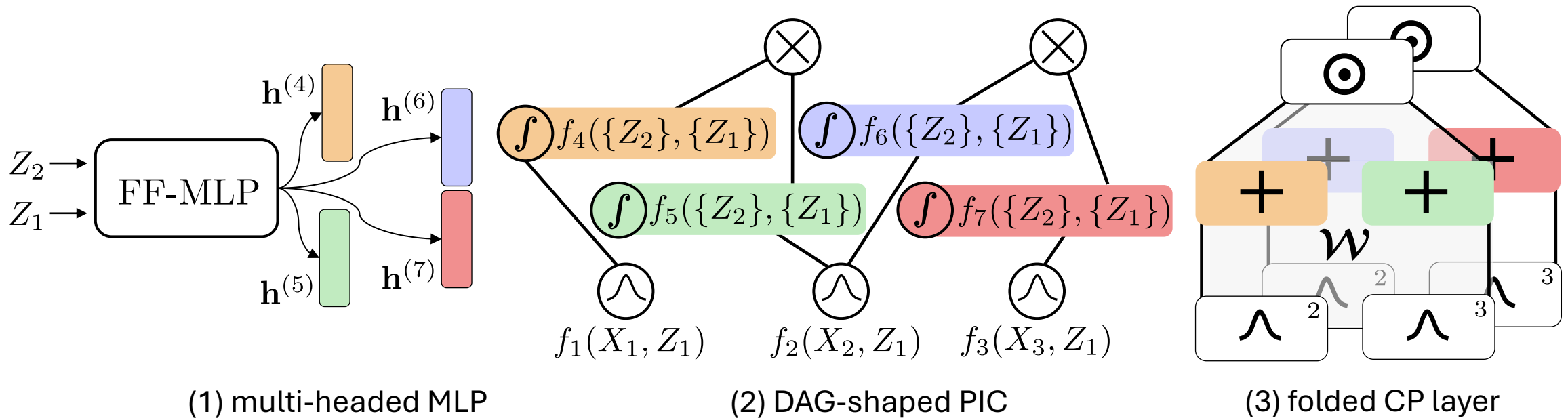
PIC2QPC: The Tucker layer case



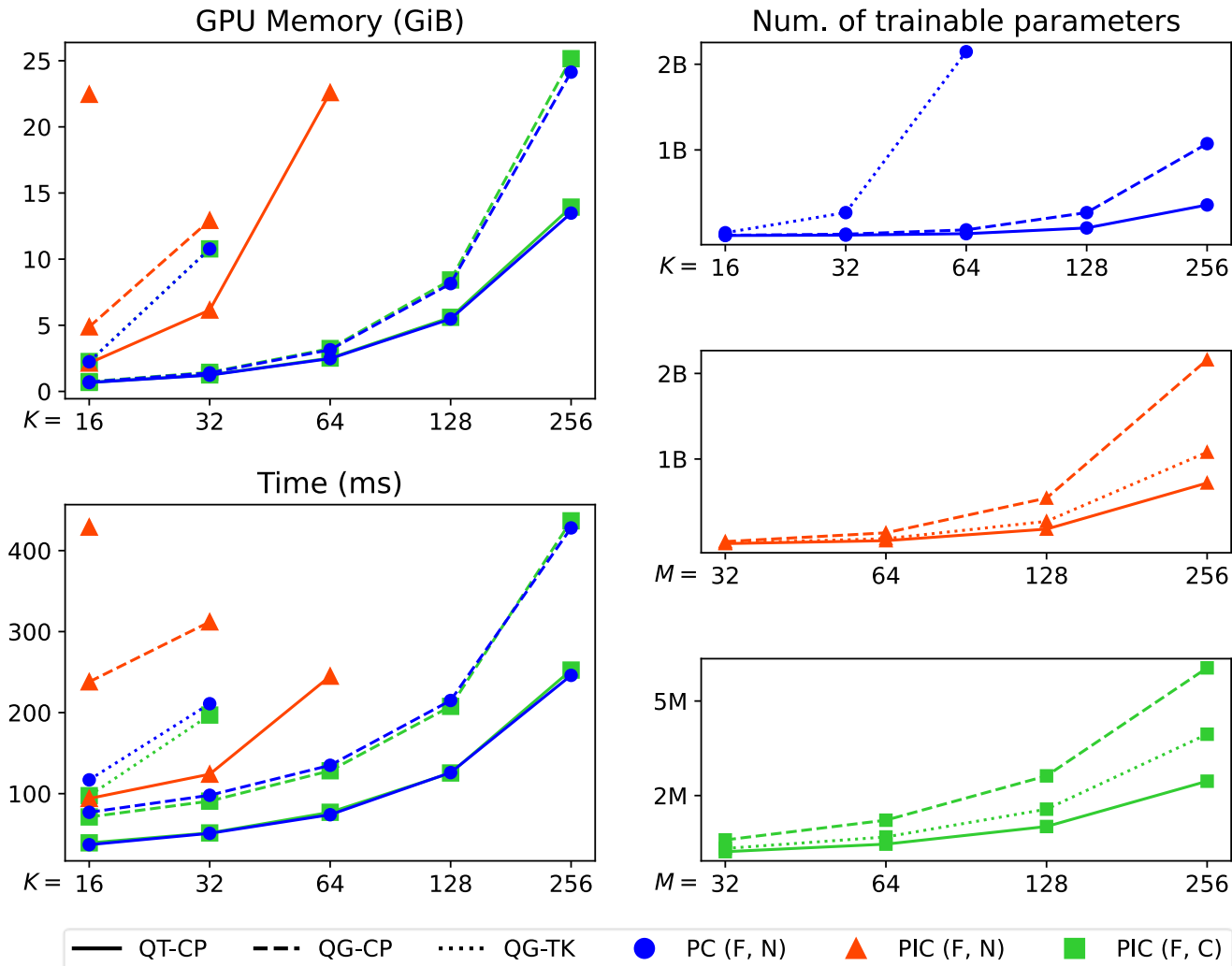
- Zooming-in the QPC materialization, we show how the function f_4 can be discretized via numerical quadrature and used to parameterize a Tucker layer.
- The two gaussian blocks are just vectors of size K , which get multiplied via an outer product that is then matrix-multiplied by $\tilde{\mathbf{W}}$

Neural functional sharing for faster & cheaper QPC materialization

- Materializing QPCs is expensive when function evaluation is costly, so we present **neural functional sharing**: We parameterize all integral units with the same functional form and at the same depth using a multi-headed MLP.



Neural functional sharing makes PICs scale



PICs with functional sharing (■) - unlike those w/o (▲) - need same resources as PCs (●), and use up to 99% less params!

- QT-CP, QG-CP, QG-TK are tensorized circuit architectures, and K is the width of their layers.
- M is the size of the PIC MLPs.

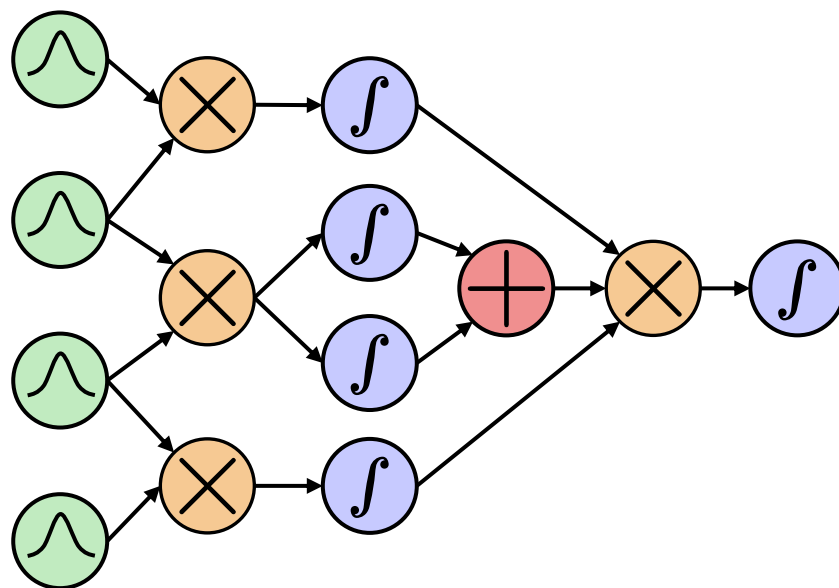
QPCs are performant tractable probabilistic models

	QPC	PC	Sp-PC	HCLT	RAT	IDF	BitS	BBans	McB
MNIST	1.11	1.17	1.14	1.21	1.67	1.90	1.27	1.39	1.98
F-MNIST	3.16	3.32	3.27	3.34	4.29	3.47	3.28	3.66	3.72
EMN-MN	1.55	1.64	1.52	1.70	2.56	2.07	1.88	2.04	2.19
EMN-LE	1.54	1.62	1.58	1.75	2.73	1.95	1.84	2.26	3.12
EMN-BA	1.59	1.66	1.60	1.78	2.78	2.15	1.96	2.23	2.88
EMN-BY	1.53	1.47	1.54	1.73	2.72	1.98	1.87	2.23	3.14
	QPC	PC	HCLT	LVD	LVD-PG				
CIFAR10	4.48	4.85	4.61	4.37	3.87				
IMGNET32	4.46	4.63	4.82	4.38	4.06				
IMGNET64	4.42	4.59	4.67	4.12	3.80				
CELEBA	4.11	4.16	-	-	-				

QPCs outperform standard PCs on distribution estimation benchmarks

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[1] Gala, Gennaro, et al. "Probabilistic integral circuits." *International Conference on Artificial Intelligence and Statistics*. PMLR, 2024.

[2] Loconte, Lorenzo, et al. "What is the Relationship between Tensor Factorizations and Circuits (and How Can We Exploit it)?" *arXiv preprint arXiv:2409.07953* (2024).

[3] Correia, Alvaro HC, et al. "Continuous mixtures of tractable probabilistic models." *Proceedings of the AAAI Conference on Artificial Intelligence*. Vol. 37. No. 6. 2023.