

Quantum Theory and Application of **Contextual Optimal Transport**

aka **QontOT**

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International Conference on Machine Learning 2024

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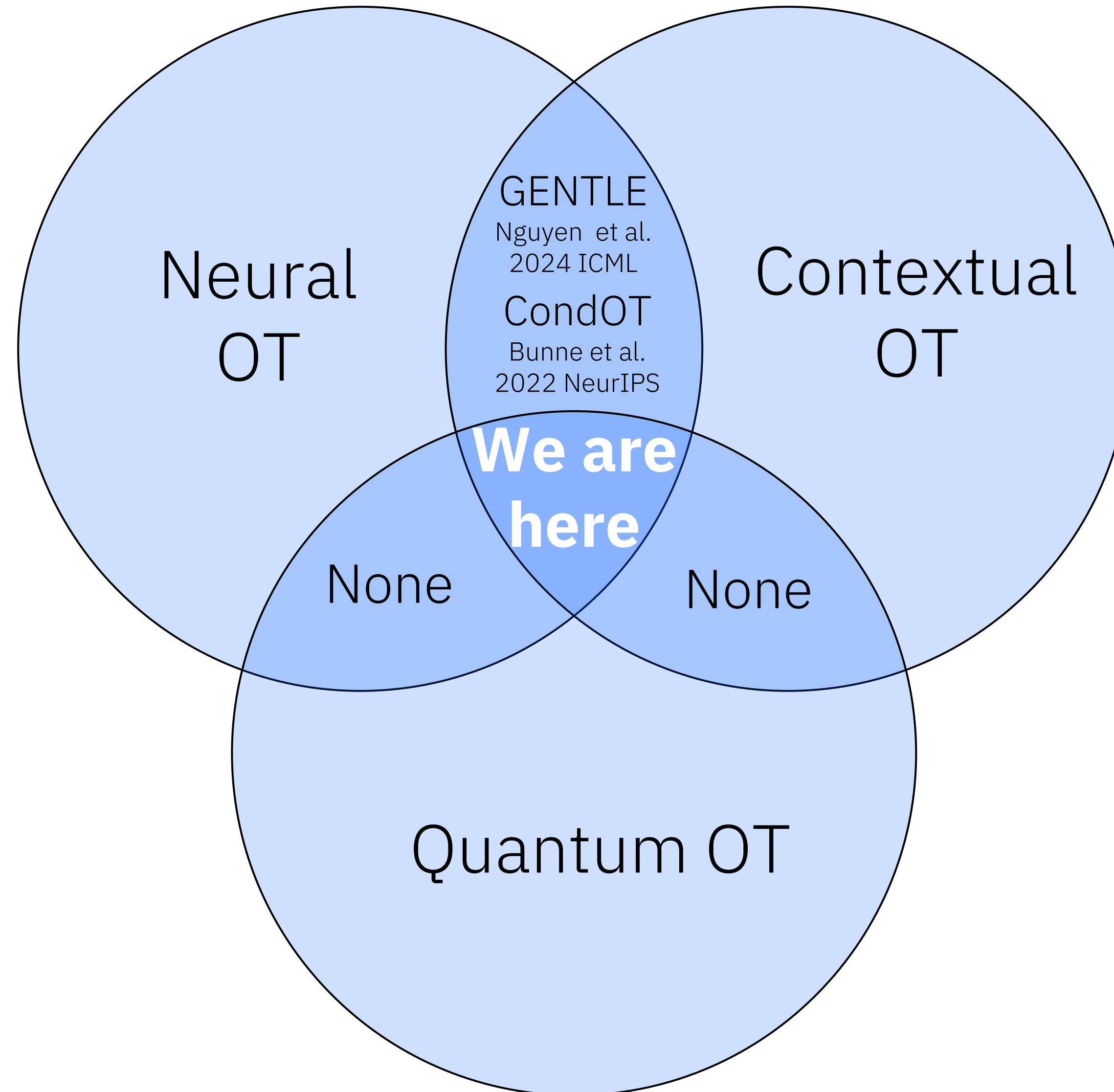
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Quantum **C**ontextual **O**ptimal **T**ransport = QontOT



Given contextual data

$$((\mu_i, \nu_i), c_i) \in X \times K_d^2$$

learn a global map T_θ

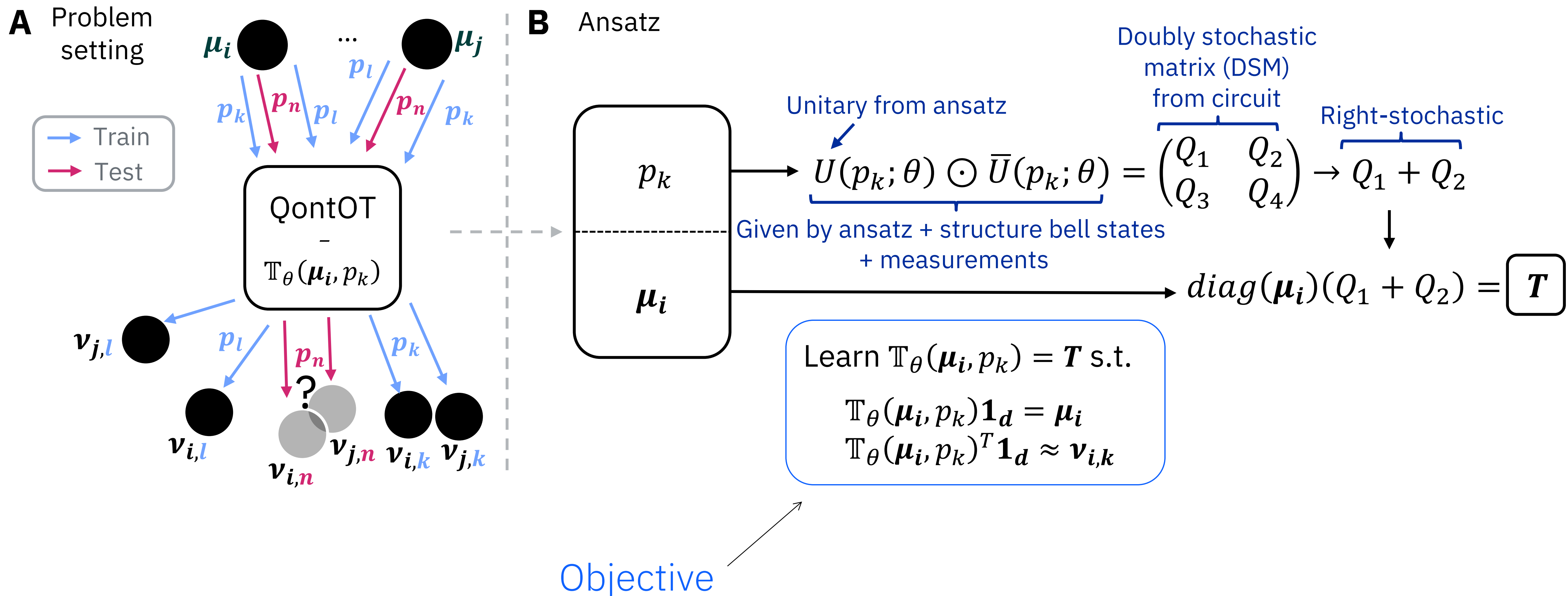
$$\text{s.t. } T_\theta(c_i) \# \mu_i = \nu_i$$

Linking Optimal Transport and Quantum

If U is a unitary matrix
then $U \odot U$
is doubly stochastic

It is unknown whether a similarly natural classical approach exists that can produce DSMs parametrically

Problem setting and QontOT ansatz



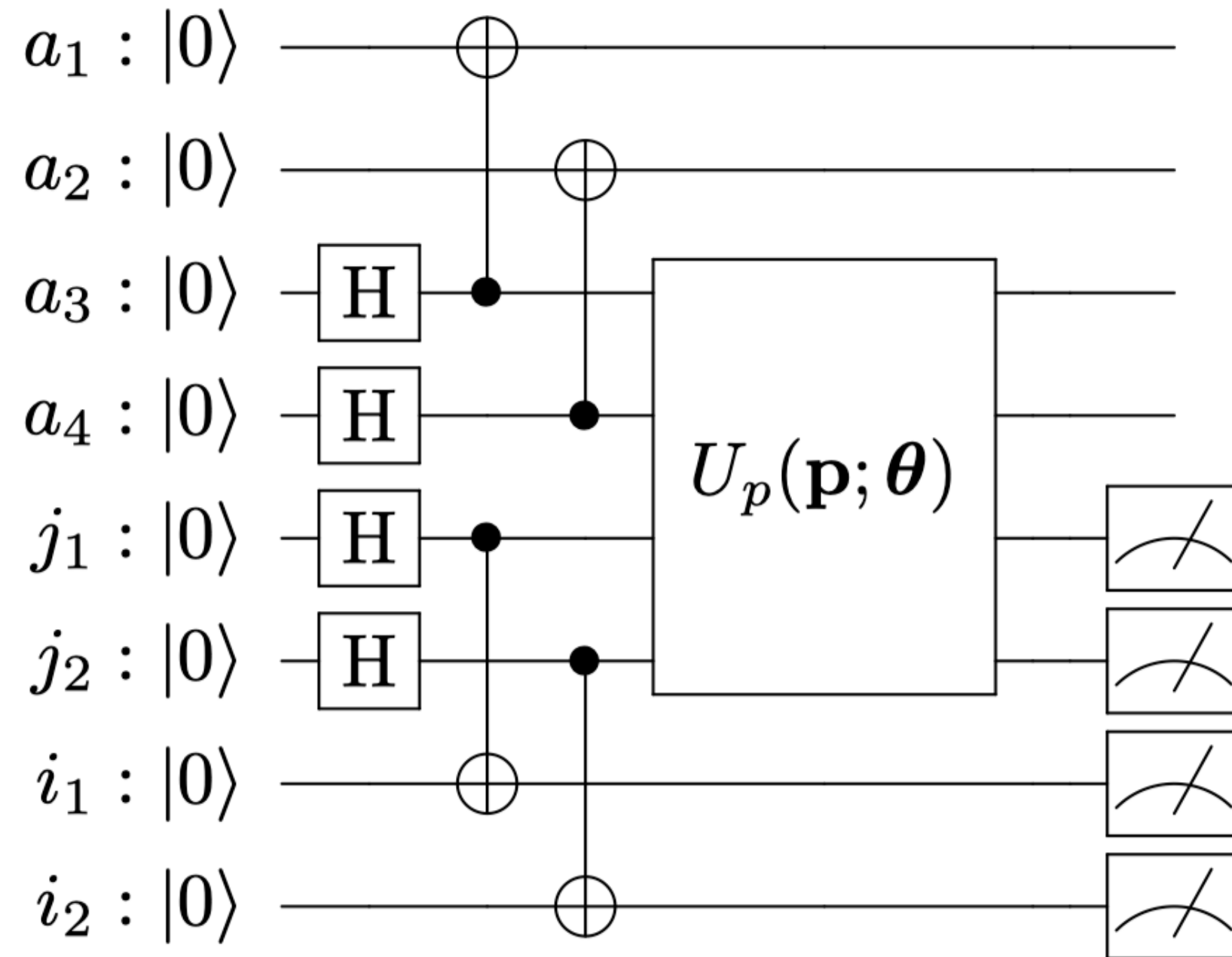
Comparison of conditional neural OT methods

Conditional neural OT	CondOT	GENTLE	QontOT
Cost-agnostic	✗	✓	✓
Explicit OT plan	✗	✗	✓
Gradient descent	✓	✓	✗
Quantum	✗	✗	✓

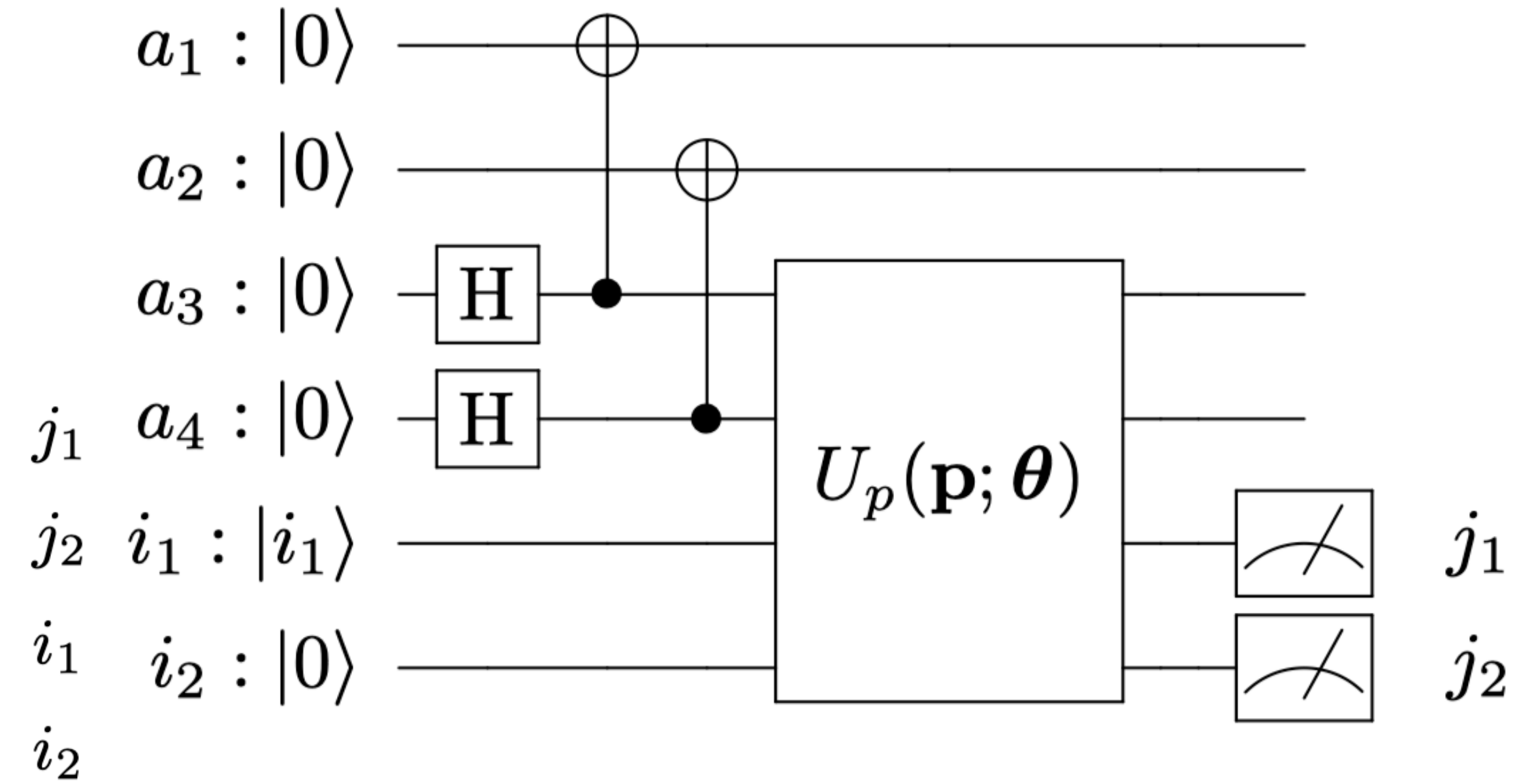
Circuit to produce DSMs

🚀 The circuit only emits DSMs

🚀 Every DSM can be produced



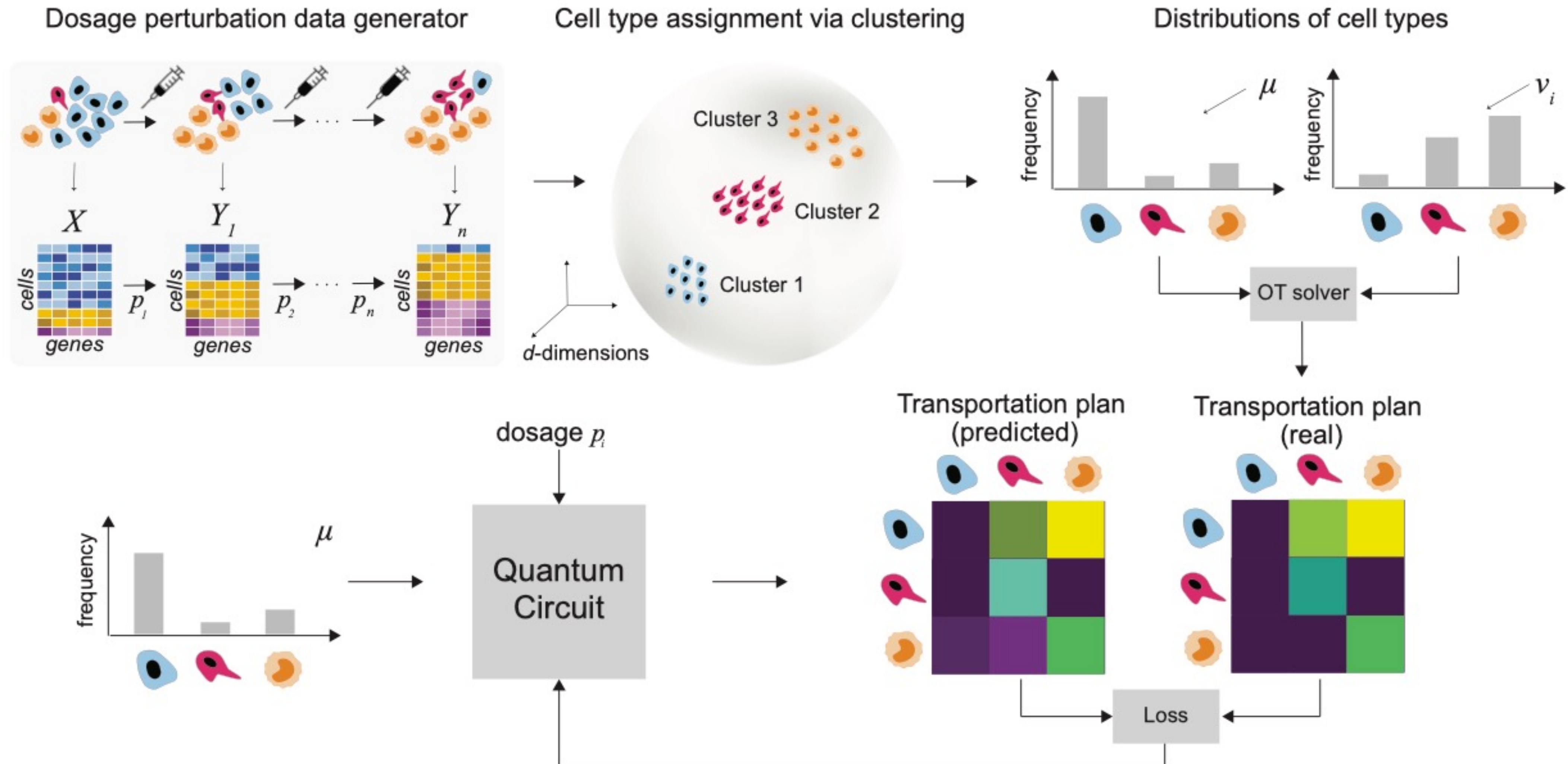
Circuit to embed transport maps



- Circuit scales **logarithmically**. Precisely we need at least $4(\log_2 n + 1)$ qubits to predict $n \times n$ matrices
- We need to collect at least $O(n \log n)$ circuit shots
- For satisfactory sampling error $\varepsilon = 0.01$ we even need $\geq O(n^2 / \varepsilon^2)$ shots

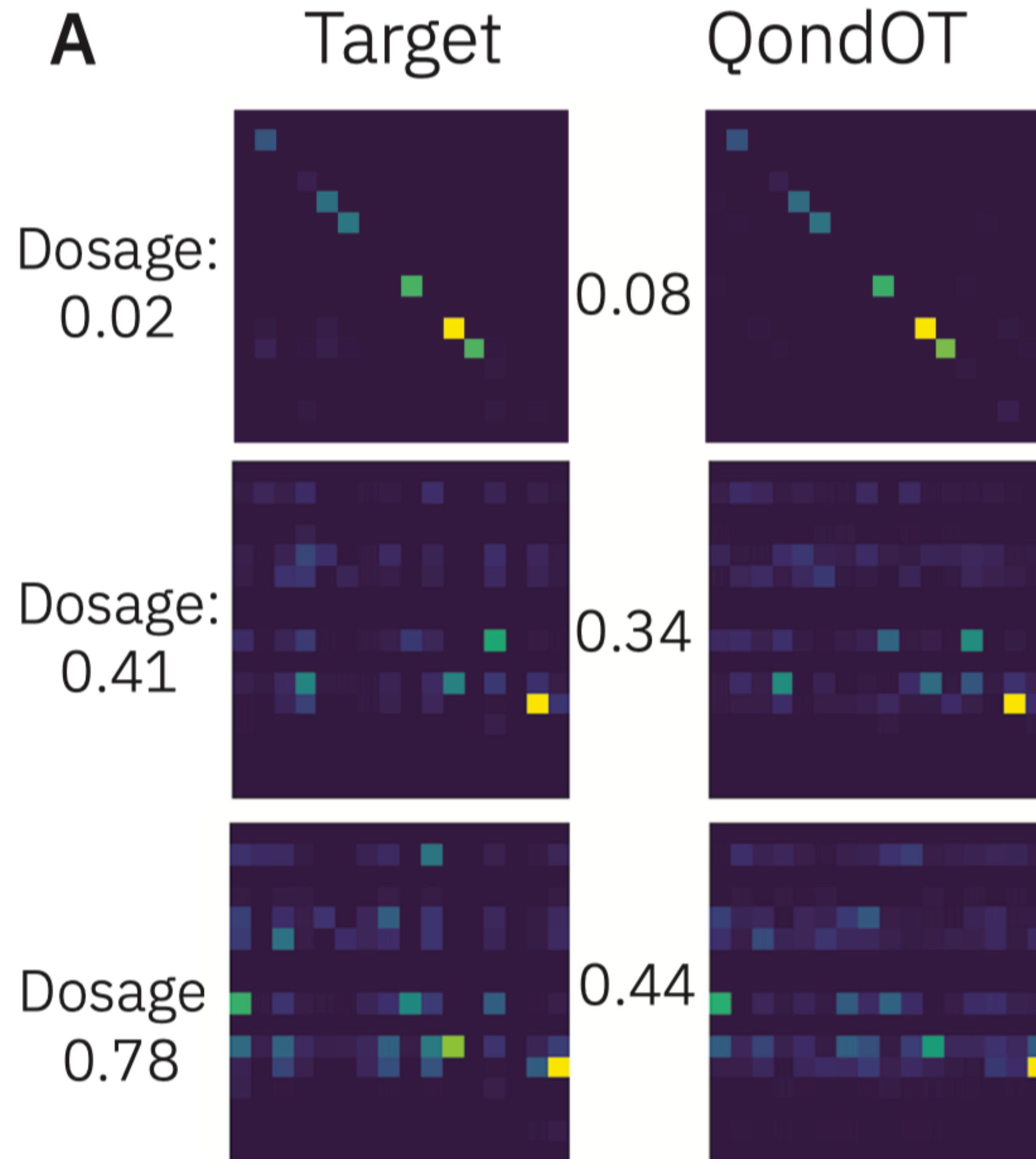
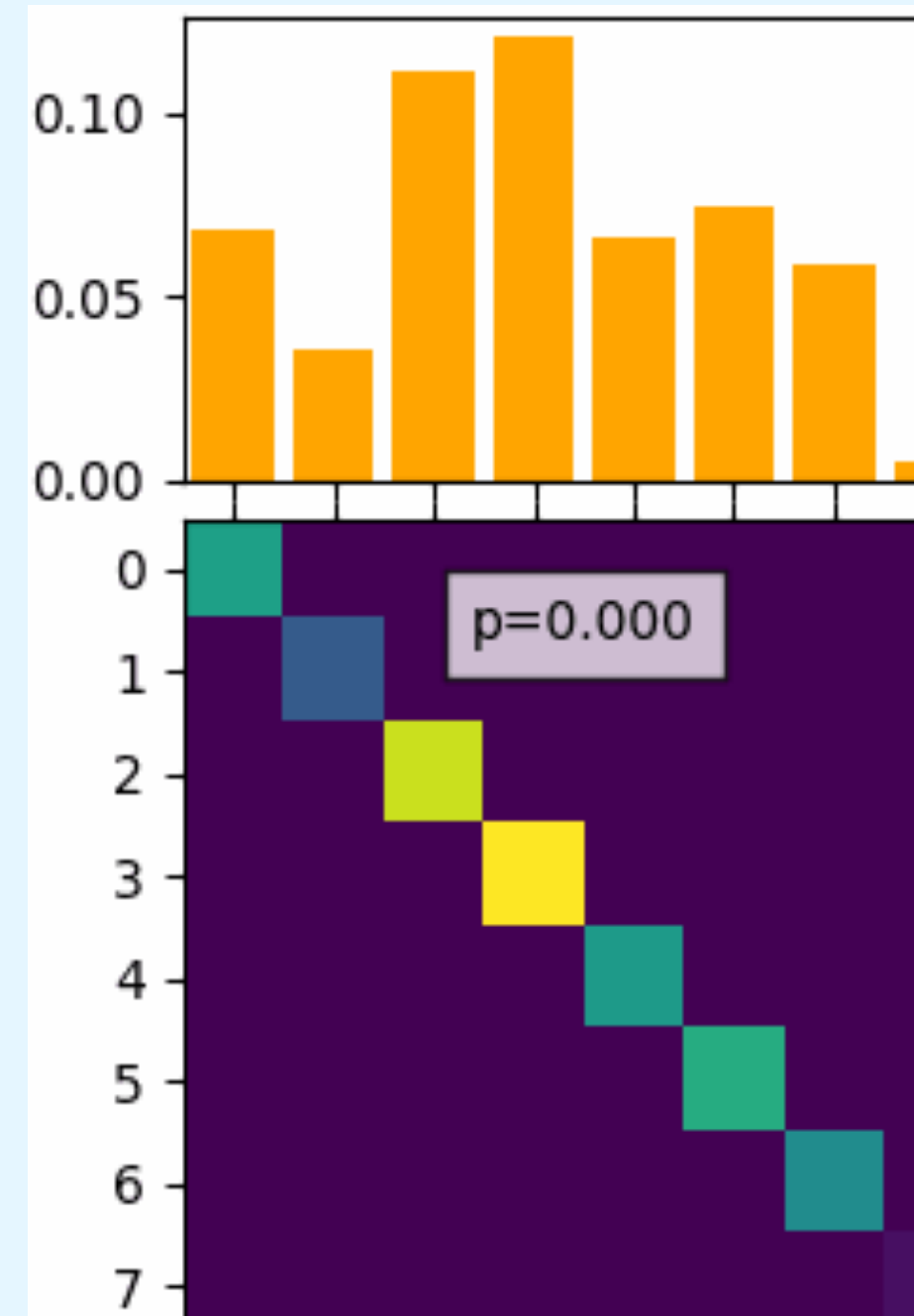
- Real data* would require $n \approx 10,000$, i.e., ≥ 56 qubits and with $\varepsilon = 0.01 > 1T$ shots
- We use data with $n = 16 \rightarrow \geq 20$ qubits and 2.5M shots

Application: Drug dosage response prediction

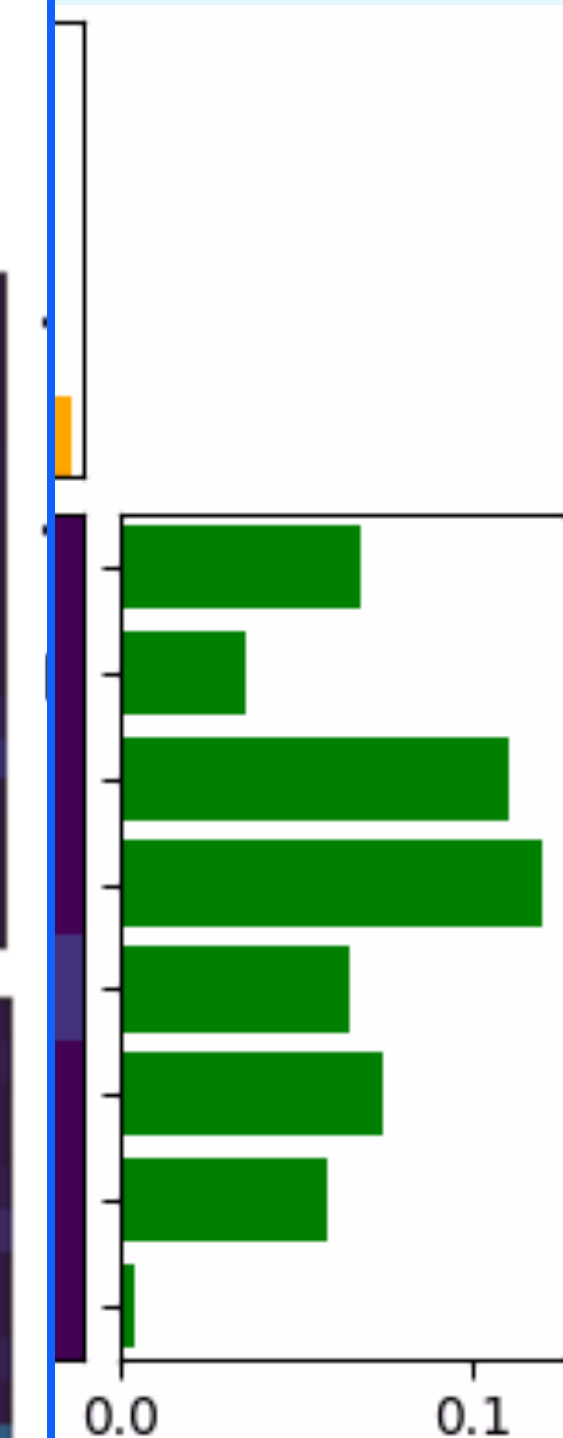


POC: Quantum can predict OT plans conditionally

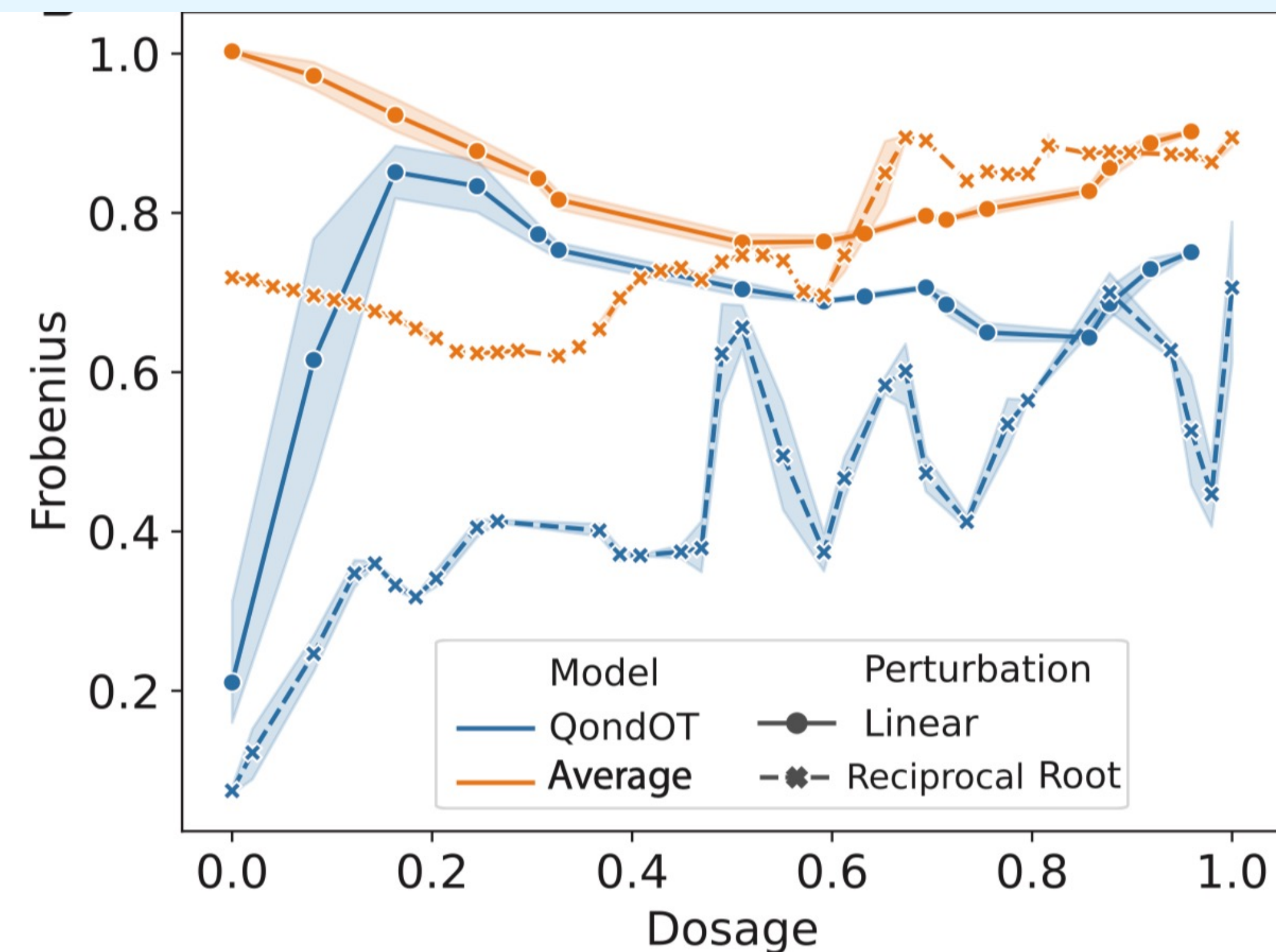
Same cells, different



dosage



Qualitative results on cell type distribution prediction



Method	OT plan metrics		Marginal metrics	
	SAE (↓)	Frob. (↓)	L_2 (↓)	R^2 (↑)
Identity	1.10	1.04	0.18	0.47
QontOT- \mathcal{L}_T	0.78	0.61	0.17	0.49
QontOT- \mathcal{L}_M	0.92	0.68	0.16	0.57
CellOT	0.46	0.41	0.17	0.52
CellOT-homo	0.68	0.60	0.29	0.37
CondOT	0.45	0.40	0.18	0.56

- Learning distributions conditionally to dosage for different cost functions
- In out-of-distribution setting (not shown) still better than the two baselines (average & identity)
- Slightly inferior to SOTA classical neural OT when plans have arbitrary marginal distributions
- Next: Fix marginals to be uniform to better exploit inductive bias of QontOT

→ Contextual relaxed assignment problem

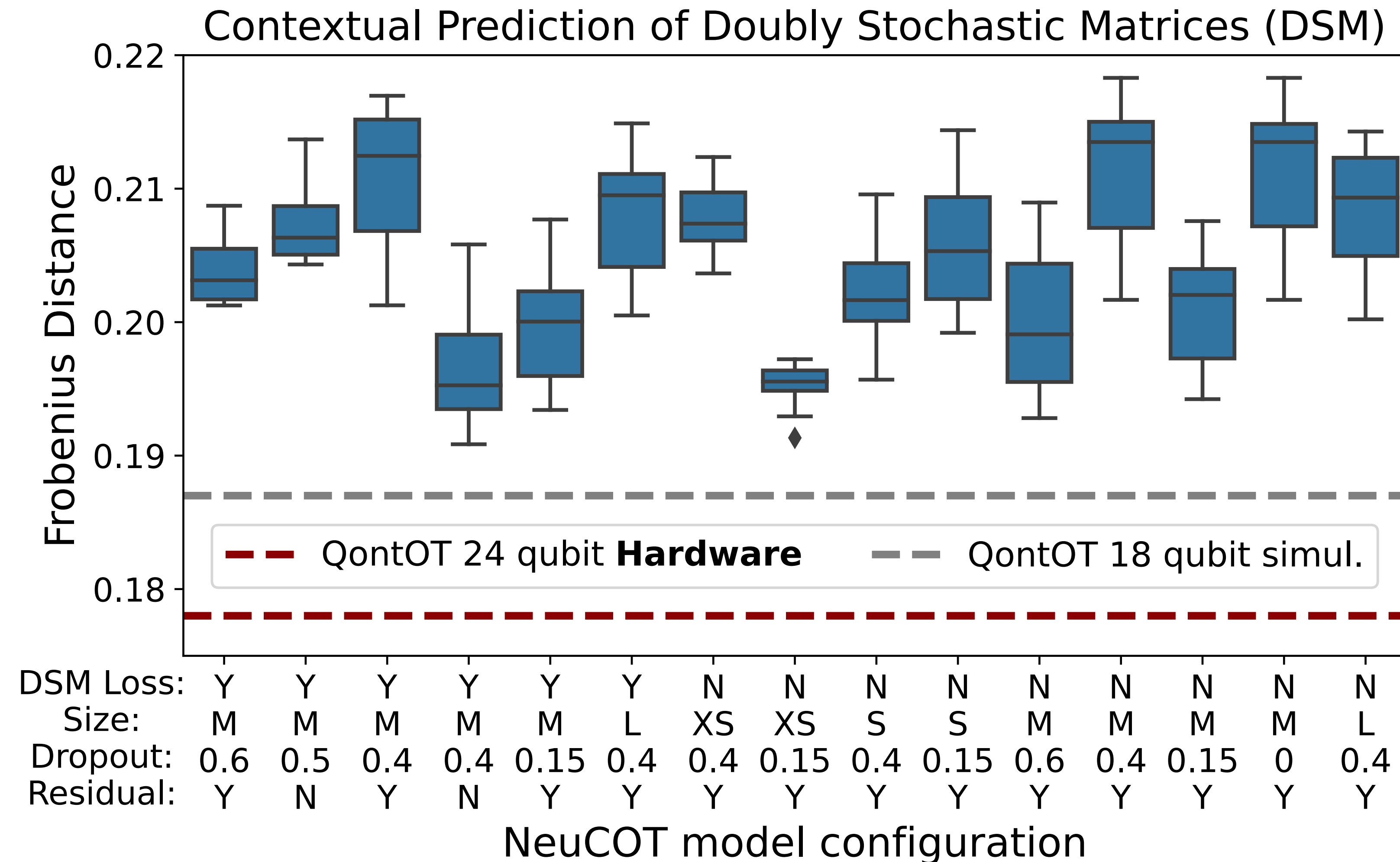
Hardware experiment on contextual relaxed assignment problem

Setup:

- 24 qubit experiment (IBM Sheerbroke)
- Depth 50, 70 ECR gates
- Dataset of 40 8x8 DSMs
- No error mitigation
- 235 optimization steps (gradient-free)

Result:

- Good convergence
- 24 qubit >> 18 qubit simulation
- Better performance than classical NNs (trained with Backprop)



Thank you for your attention

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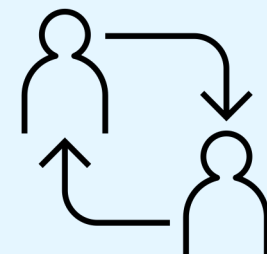
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 Quantum Theory and Application of Contextual Optimal Transport
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 Further details in the paper:

- Proofs on expressivity of circuit
- Generalization to multidimensional OT
- Comparison of optimizing marginals vs. transport plans
- Various circuit ablation studies (e.g., cost functions)
- ...

