

Entanglement Classification and Machine Learning

Outline

1. Introduction

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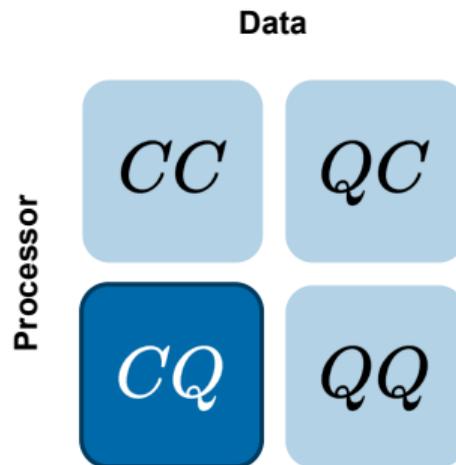


Introduction

Quantum Particle Workgroup

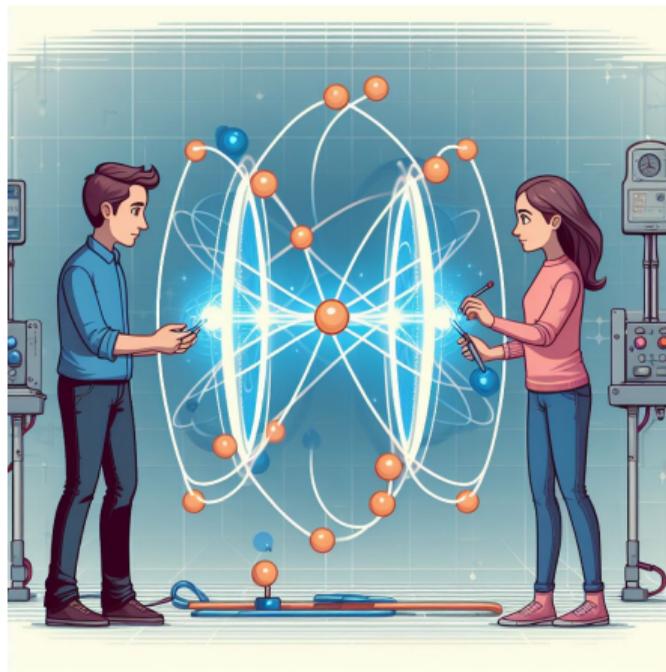
Beatrix C. Hiesmayr, Christopher Popp, Tobias C. Sutter

- Quantum Information Theory
- Bound Entanglement and Bell States
- Quantum Machine Learning



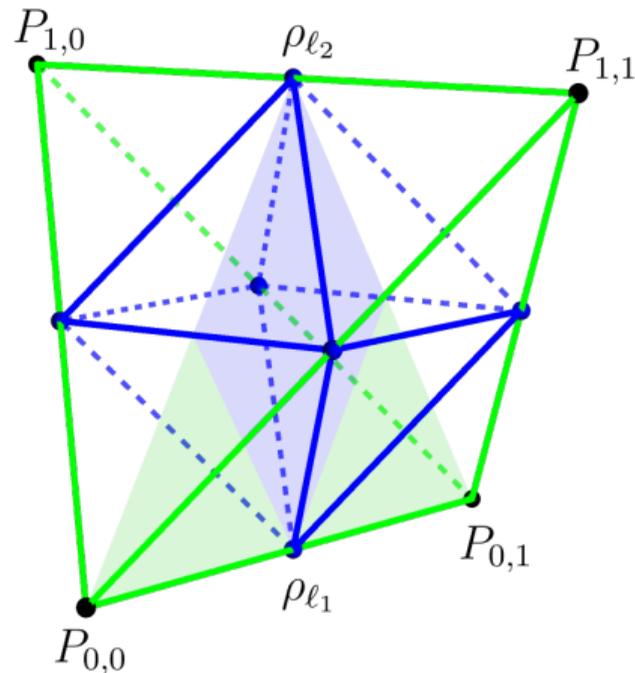
Entanglement and Bell states

- Entangled quantum state:
 - State cannot be described locally.
 - Stronger than classically possible correlations.
- Verifying a state as entangled is a hard problem ("Separability Problem").
- Bell states $|\Omega_{i,j}\rangle$, $P_{i,j} = |\Omega_{i,j}\rangle\langle\Omega_{i,j}|$
 - Maximally entangled states for general dimension d .
 - e.g., $d = 3$: $|\Omega_{0,0}\rangle \propto |0,0\rangle + |1,1\rangle + |2,2\rangle$



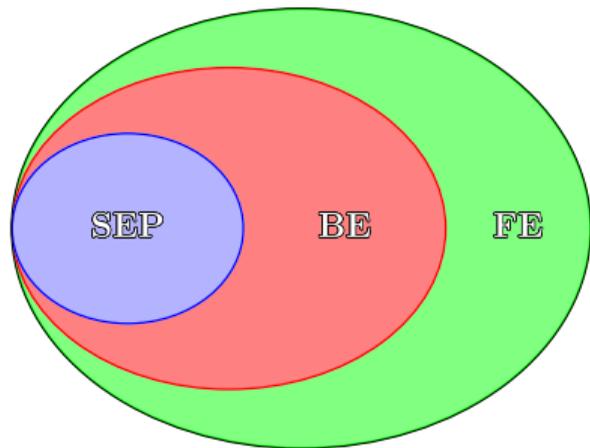
Bell-diagonal states

- Noise affects states:
 - $|\Omega\rangle \rightarrow \rho = \sum_{k,l} c_{k,l} P_{k,l}$ “Bell-diagonal state”
 - $c_{k,l} \geq 0, \sum_{k,l} c_{k,l} = 1$, “mixing probabilities”
- Noise affects entanglement:
 - Weak mixing \rightarrow “free entangled” (“distillable”) state
 - Strong mixing \rightarrow “separable” (not entangled) state
 - $d > 2$: “Bound entangled” (“undistillable”) states exist.



The separability problem

- Given a quantum state ρ , is it
 - separable (SEP)
 - or entangled ($ENT = BE \cup FE$)?
- BE states make the separability problem NP-hard.
- Apply ML-methods for Bell-diagonal states.
- **Focus:**
 - How useful are simple neural networks for the separability problem of Bell-diagonal states?
 - Can we learn something from successful classifiers?



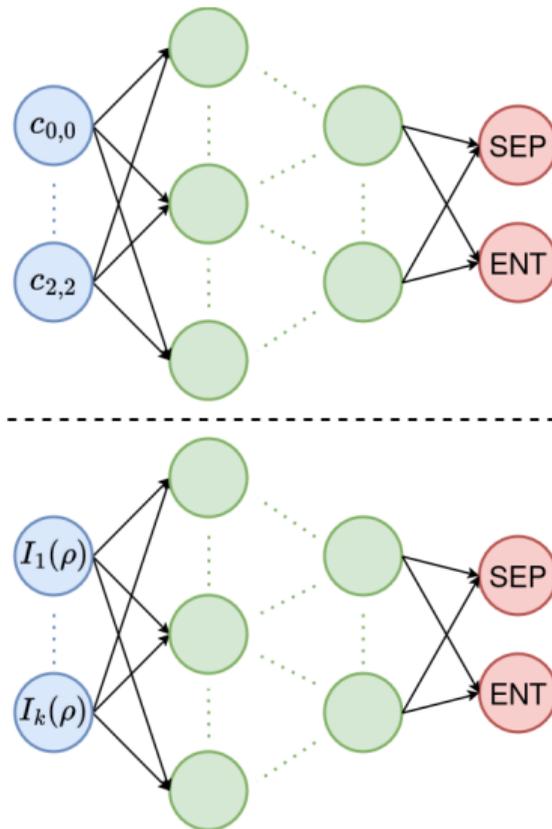
Data and Implementation

Data

- Uniformly distributed Bell-diagonal qutrit states $\rho = \sum_{k,l=0}^2 c_{k,l} P_{k,l}$.
- Classified as "SEP" or "ENT" (BE) via analytical and numerical methods.
- Strongly leveraging algebraic and geometric properties of Bell states.
- Related publications:
 - Popp, C., Hiesmayr, B.C. Almost complete solution for the NP-hard separability problem of Bell diagonal qutrits. Sci Rep 12, 12472 (2022).
 - Popp, C., Hiesmayr, B.C. Comparing bound entanglement of bell diagonal pairs of qutrits and ququarts. Sci Rep 13, 2037 (2023)
 - Popp, BellDiagonalQudits: A package for entanglement analyses of mixed maximally entangled qudits. J.Open Source Softw. 8 (2023)

Methods

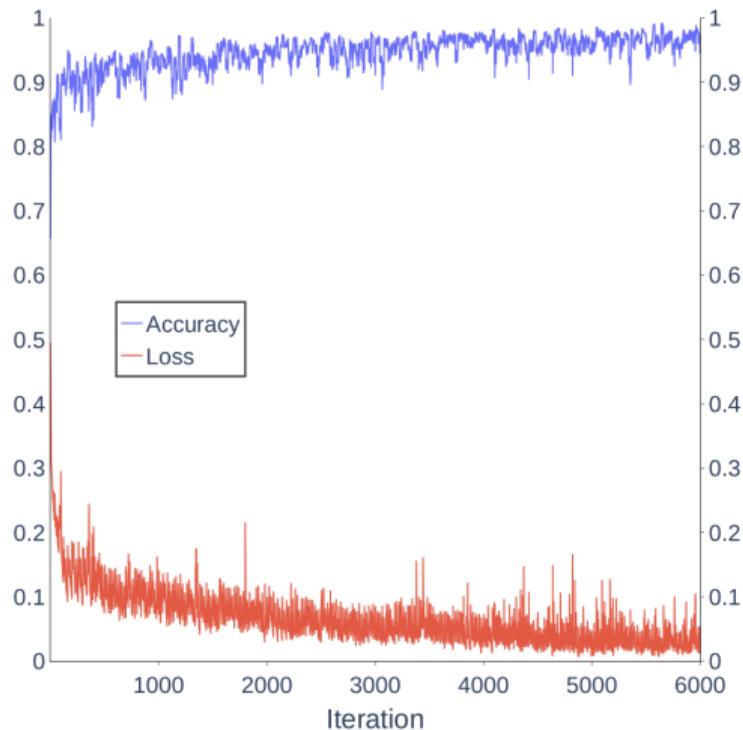
- NN classifiers:
 - Feedforward neural networks (FNN)
 - Convolutional neural networks (CNN)
- Compare two feature sets:
 - Mixing probabilities $c_{k,l}$ ("Noise features")
 - Quantum Information features I (e.g., entropies, purity)



Results

Entanglement classification

- Mixing probabilities $c_{k,l}$ as features:
 - Simple FNN (≈ 6000 parameters) with 95% – 98% accuracy.
 - Simple CNN (≈ 600 parameters) with $\approx 90\%$ accuracy.
- Information quantities I_k as features:
 - Simple FNN (≈ 1000 parameters) with 85% – 90% accuracy.
 - More complex model (≈ 6000 parameters) does not perform better.



Entanglement structure and CNN

- Algebraic relations of Bell states \leftrightarrow entanglement structure.
- Fact: 3 element mixtures are relevant (“line structure”).
- Example:
 - $\rho_s = \frac{1}{3}(P_{0,0} + P_{1,0} + P_{2,0}) \in SEP$.
 - $\rho_e = \frac{1}{3}(P_{0,0} + P_{1,0} + P_{0,1}) \in FE \subset ENT$.
- Can CNNs with kernels/filters f capture this structure?

$$\rho \propto$$

$c_{0,0}$	$c_{0,1}$	$c_{0,2}$
$c_{1,0}$	$c_{1,1}$	$c_{1,2}$
$c_{2,0}$	$c_{2,1}$	$c_{2,2}$

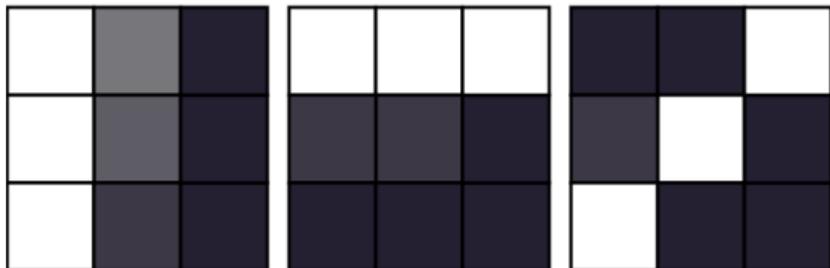
$$\rho_s \propto$$

$$\rho_e \propto$$

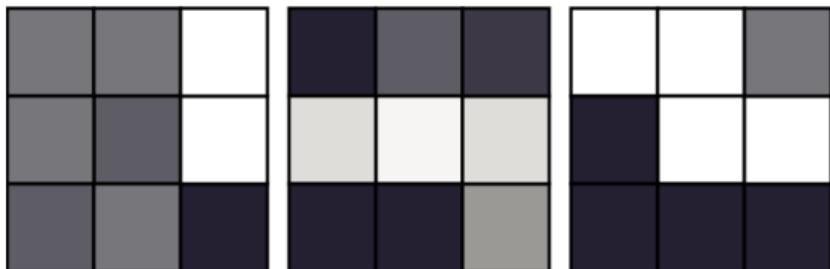
Entanglement structure and CNN

- Apply CNN with 3×3 kernels.
- Normalization of filters \leftrightarrow equivalent representation to states.
- Weights determine relevance of filters for classification of SEP or ENT.
- Visible structures in filters
→ "Explainable" relation to entanglement.

SEP-weighted filters



ENT-weighted filters



Takeaways

Takeaways

- Simple FNN can classify Bell-diagonal states (NP-hard separability problem) with high accuracy.
→ Dominant entanglement structures are not too complex.
- Noise features (mixing probabilities) are more effective than common information quantities features.
→ For these information quantities, the required information for classification is not easily accessible.
- Simple CNN models can capture relevant entanglement structures of Bell-diagonal states.
→ “Explainable” model provides insight about physics.