HOW NON-CLASSICAL IS A QUANTUM STATE?

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MOTIVATION

Non-classicality, defined in the sense of quantum optics, is a resource: If a non-classical state is mixed with vacuum in a beamsplitter, the resulting state will be entangled. Hence, quantifying the non-classicality of a quantum state is crucial to gauge its potential for quantum advantage in an experiment, for instance in a Boson Sampler. However, academic non-classicality measures fail as a practical tool for experimentalists.

Here, we implement a data-based, devise-specific approach which quantifies the non-classicality of a state by the ability of a neural network to distinguish the state from a classical one. In this approach, snapshots from photon-number measurements are input to a permutation invariant Vision-Transformer [1].

In the past, it was shown that a simple model can be trained to identify a single mode state's non-classicality based on its photon-number statistics [2].

CLASSICAL STATES

Classical states are defined as those with a non-negative P-representation

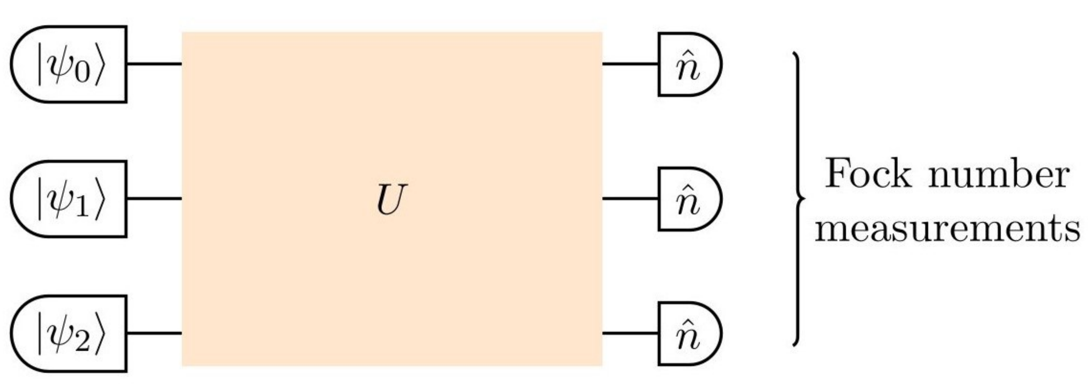
$$\hat{\rho} = \int \mathrm{d}^2\alpha \; P(\alpha, \alpha^*) |\alpha\rangle\langle\alpha|$$

Example: Coherent state

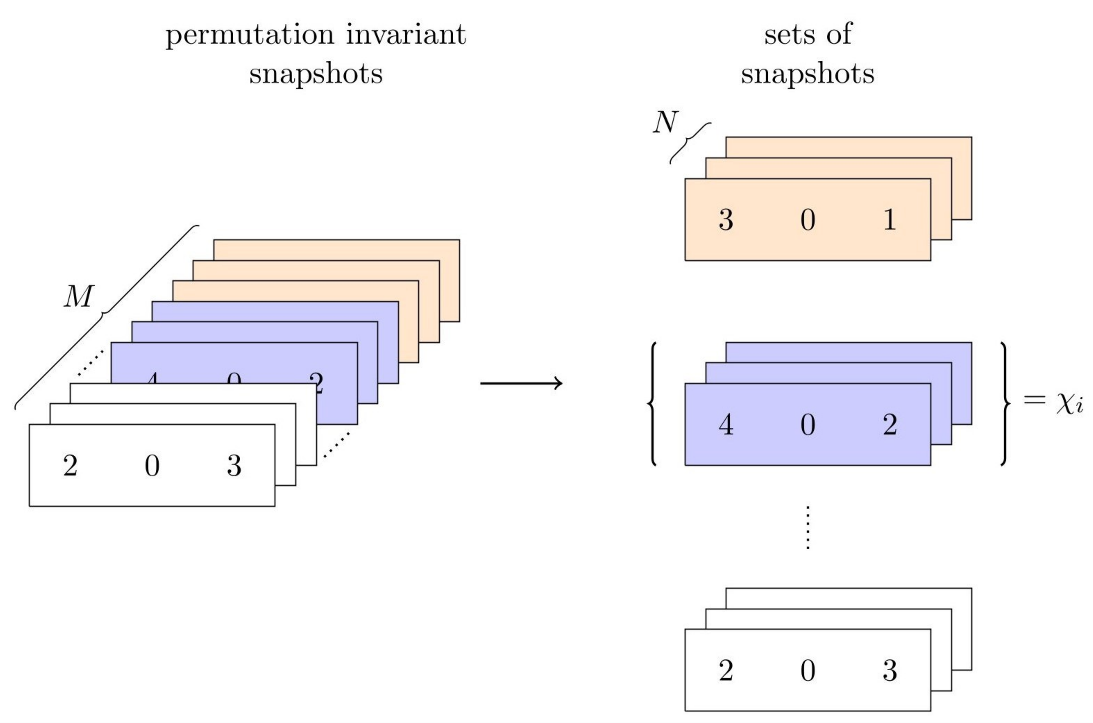
$$|\beta\rangle\langle\beta| \quad \rightarrow \quad P(\alpha, \alpha^*) = \delta(\alpha - \beta)$$

THE DATA

The training data consists of photon-number measurements taken after a quantum optical circuit. Input states are classical (coherent and thermal) as well as non-classical (Fock, cat, squeezed, and photon-added thermal) states. For each input, M snapshots are taken.
Here, we choose U to be the identity. This might sound trivial at first, but in fact, passive linear transformations, like beam-splitter and phase shifters, correspond to free operations that do not alter the non-classicality of a quantum state.



Key to the parameter-efficient architecture is a preprocessing of the data: The M snapshots are split into sets of N snapshots. The model will then be trained to learn correlations within these sets χ_i.



ARCHITECTURE

The architecture is inspired by the state-of-the-art permutation invariant Vision-Transformer developed by Kim et al. [1].
The preprocessed input snapshots $\{\chi_i\}_i$ are parallelly processed by Self-Attention Blocks (SAB) and then decoded in a Pooling Attention Block respecting the permutation invariance.
After L SAB layers, correlations up to order 2^L are accessed.
In this context, the number N of snapshots in each set serves as a measure of how much statistics is necessary for a correct classification of the input state.

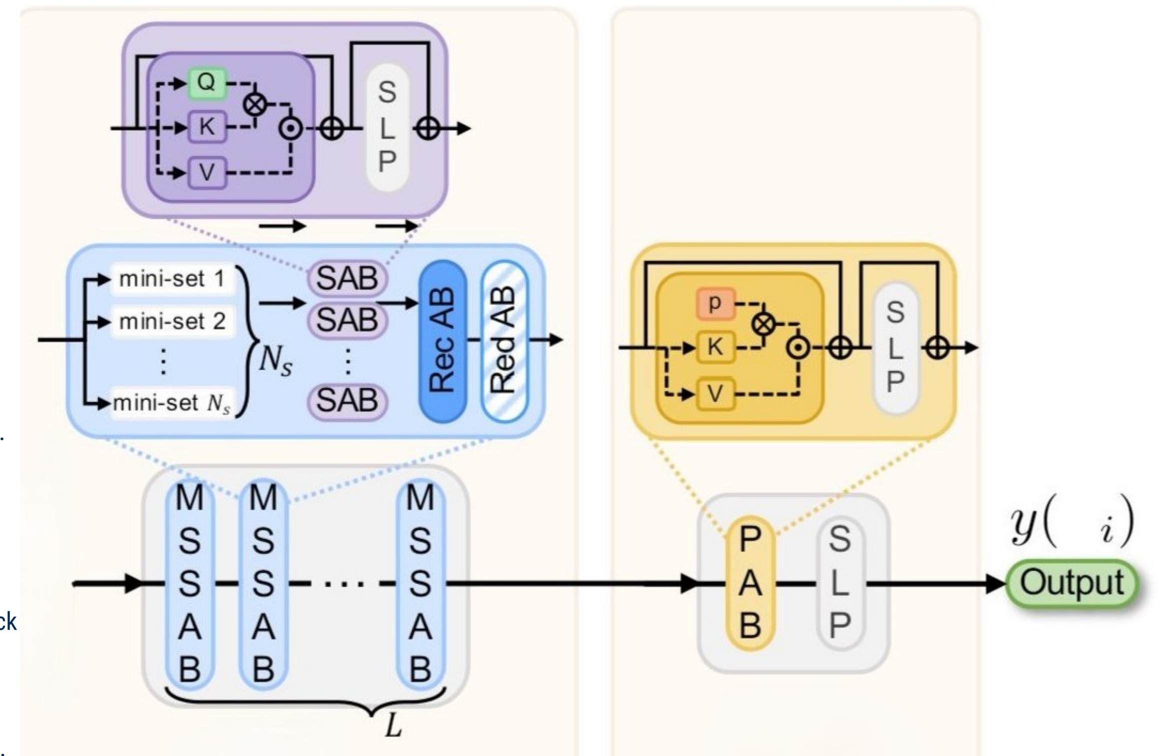


Fig 1.
Encoder-Decoder architecture of the Transformer classifier. Here, we set N_S=1, hence the Recursive and the Reduction Attention Block are omitted, and the Mini-Set Self Attention Block (MSSAB) reduces to a single SAB.
Taken from [1] and modified with AI-tools.

RESULTS

As loss function, we use the binary cross entropy with a weighted L1-Norm, forcing the model to focus on the correct prediction of classical input states. Here y is the model's prediction and $\tilde{y} \in \{0,1\}$ is the correct label:

$$\mathcal{L}(y, \tilde{y}) = \frac{N}{M} \sum_{n}^{M/N} -[\tilde{y}\log(y_n) + (1-\tilde{y})\log(1-y_n)] \; + \; \lambda(1-\tilde{y})|\tilde{y} - y_n|$$

Fig. 1: Higher N yields more confident predictions. But: For low N, the accuracy is still high (>80%) indicating that the samples are correlated.

Fig. 2: λ is not a reliable tool to drive the model's bias towards classical states. Note that vacuum is the only Fock state that is non-classical, hence difficult to learn for the model. However, this problem might be lifted when training on snapshots resulting from a non-trivial unitary.

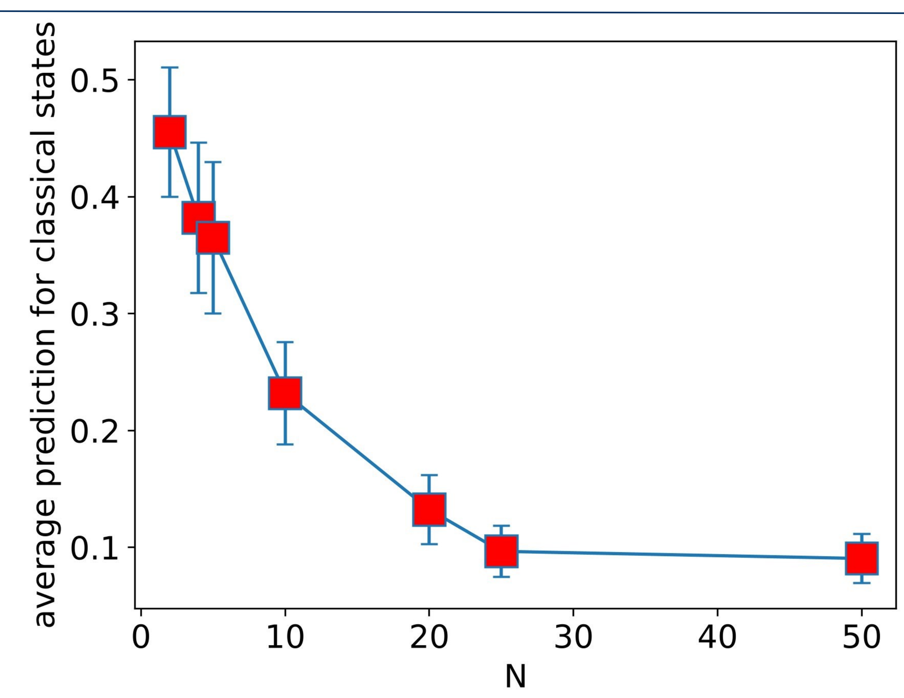


Fig. 2
Average prediction for a classical state against the number N of snapshots in a set. λ=1 for all points.

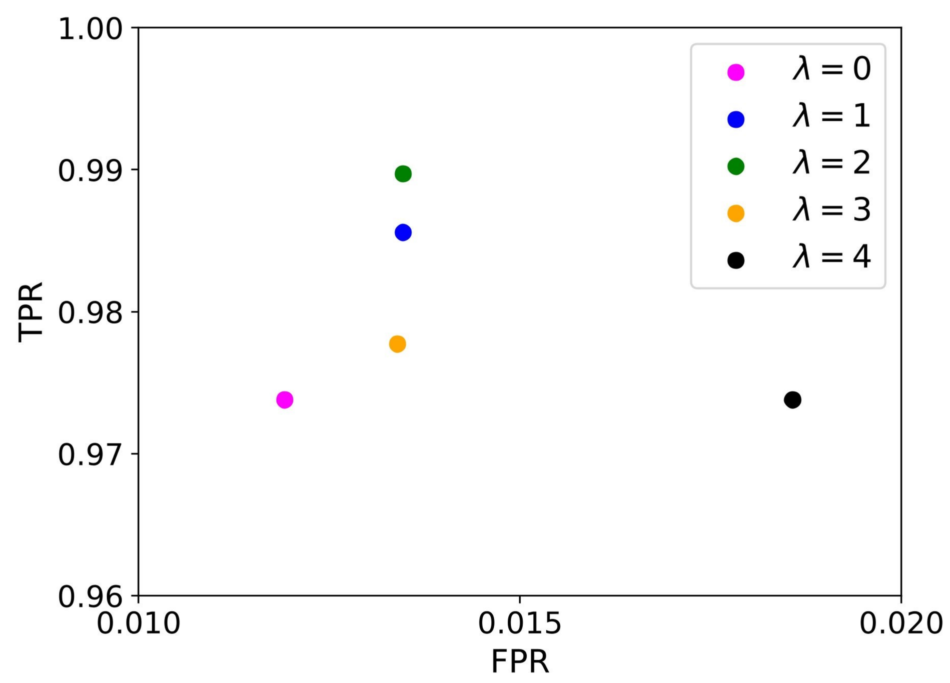


Fig. 3
True-Positive-Rate (TPR, correctly classified classical states) against False-Positive-Rate (FPR, wrongly classified non-classical states) for different choices of λ. N=50 for all points.

OUTLOOK

Make it realistic:
The model is able to correctly learn the labels of product states. The next step is to implement a non-trivial unitary that will generate quantum correlations within the output state. It would be interesting to see whether this facilitates or challenges the correct classification of non-classical states. Further, the model can be trained on lossy data.

Make it experimental:
An experimental device can be interpreted as a black-box that inherently includes some loss. Even if the input state is noise-free, its non-classicality will be altered by the device. Hence, the only non-classicality label we can confidently predict is the label of classical states. The procedure would then be to:
1. Train the model on experimentally measured classical data (to learn the noise of the device) and non-classical simulated data
2. Give the model snapshots of an unknown non-classical state
3. Model's deviation of average non-classical prediction learned in 1. then gives measure of how non-classical the input state is

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[1] Kim et al. arxiv:2405.11632 (2024)
[2] Gebhart et al. Phys. Rev. Research **2**, 023150 (2020)