A bidding graph-game is a two-player game in which in each turn a bidding determines which player moves the token. Both players simultaneously submit bids, the higher bidder moves the token, in Richman bidding, he pays the bid to the loser, and in poorman bidding, he pays the bid to the bank.

Our approach guarantees that the hybrid automaton model and the time-series data are close to each other.

We propose an abstraction-based approach to detect novel inputs to neural-network classifiers.

We show that exact monitoring is expensive, i.e., it requires at least one counter for every possible output value.

We introduce limit monitoring, which requires a monitor to converge in the long run. For connected Markov chains, we provide efficient monitoring algorithms that use only 4 counters, independent of the number of possible outputs.

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Quantization is a standard technique for making neural networks computationally more efficient. However, quantization introduces additional rounding operations that modify the semantics of the network. As a result, specifications that are satisfied by a neural network might become violated after quantization.

Suppose you watch the output generated by a black-box system. How much memory is required to watch frequency properties, like the mode (most frequent output) or median (“average” output), in real time?

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We show that robustness after quantization is nonmonotonic in the number of discrete bits. We also develop a verification method for quantized neural networks based on bit-exact SMT solving and efficient network encodings.