Effect of anisotropy on critical temperature estimation using machine learning

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We check how aspect ratio and interaction anisotropy can affect the accuracy of the critical temperature estimate using a neural network. We study two cases of the Ising model. We have trained a model for the classification of paramagnetic and ferromagnetic phases, which makes it possible to predict the phase to which the test sample belongs [1]. Supervised learning was carried out for the Ising model on a square lattice with the same couplings M. There are two sets of testing tasks. We first test the classical Onsager case with different horizontal M and vertical M couplings on a square lattice [2]. Second, we test Ising model on a square lattice with couplings M equipped with couplings N in one of the diagonal directions. The critical temperature is known for both cases [2, 3].

The first result is that the bond aspect ratio N/M does not affect the accuracy of the temperature estimate for the Onsager case. The second result is that the anisotropy caused by the diagonal ratio N/M leads to a systematic deviation of the calculated critical temperature from a well-known critical temperature. It is well known that anisotropy changes the value of the Binder cumulant [4] and thus determines the limitations of universality [5]. Instead, we demonstrate the limitations of knowledge transfer in machine learning due to anisotropy. This result is very practical - if randomly tested samples contain anisotropy, the trained neural network will predict the wrong critical temperature of the sample. However, we have a good message - the extracted correlation length critical exponent ν is still reliable and does not seem to be biased by the anisotropy parameter.

Research supported by the grant 22-11-00259 of the Russian Science Foundation.

The simulations were done using the computational resources of HPC facilities at HSE University.

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