Semester Report

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PhD Program: Statistical physics

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Introduction:

For two different directions:

1. Zero risk describes an investment or security in which the return is known with certainty. Under No-short model, zero risk results have been produced with probability by optimization. To dig out the boundary of zero risk which has 50% ratio, Now we focus on the relation between $r = N/T$ and zero risk boundary r_c i.e., r at the solution of optimization which has 50% zero risk. For simplicity, we assume that the returns are independent Gaussian random variables with zero expectation value and variance is σ_i. The behavior at r ≤ 2 was discussed by *I. Kondor et al*, which also indicate that $r_c = 2$. However, the behavior at $r > 2$ is unknown, that is what we concern about. It is natural to assume that stocks of companies belonging to a given industrial sector are more strongly correlated than those belonging to different sectors. Accordingly, we expect that the covariance matrix displays a block diagonal structure. For simplicity, we assume that the elements outside the diagonal identity (that describe some general correlation with the whole market) are all equal to ρ, and $-1 < \rho \leq 1$. The relation among zero risk, proportion of zero weights n_0 and ρ at $r > 2$ is an interesting point for discussion.

2. The other work is about application of neutral network in Lattice QCD. In high energy theory, the hadron spectral function is a key as which encodes all the information about the hadron. Topically, the relation between spectral function and correlation function is given by the well known *Källen-Lehmann* spectral representation. However, calculating the correlation function from a given spectral function is straightforward, but the inverse is an ill-condition problem, because the correlation function is the integration with the spectral function multiplied by an integral kernel in frequency space. Fortunately, the data of correlation function can be computed directly from experiments of Lattice QCD, which helps us to reconstruct spectral function. Here we propose a new approaching to reconstruct spectral function based on neural network. The advantage of this method is that it can fit any functions with high precisions, but the key is that the output depends on the training dataset. In order to ensure that the network's results have real physical meaning, we divide the spectral function into three parts: transport, resonance and continuum. In addition, by comparing the results with maximum entropy method(MEM) method, the reconstruction accuracy is found to be at least comparable, and potentially superior in particular at larger noise levels.

Description of research work carried out in current semester:

1. By setting zero risk rate as function of r for various values of N, a comparison between $N = 100$, $N = 200$ and $N = 300$ with fixed ρ, which clear show that r_c is related with N and increases with ρ. To study the relation between r_c and N, we introduce a virtual sample size N_f as a ruler to measure real size N. And a virtual covariance matrix element ρ_0 is built as $\rho = \rho_0 N/N_f$. Where ρ is the real covariance matrix element as before. By a fixed N_f, ρ becomes a scale of N and $\rho = \rho_0$ when $N_f = N$. Here a limitation is clearly that $N_f \leq N$ to keep the constraint of real covariance matrix element $0 \leq \rho \leq 1$ from virtual one $0 \leq \rho_0 \leq 1$. As large bias are generated in numerical calculation when we choose small T for $r \sim N$ and $\rho \sim 1$, so we only consider the results for $\rho \leq 0.7$. To collect all r_c with $N_f = 100$ fixed, a linear function of ρ_0 can be fit to r_c. Then by testing the results of $N_f = 200$, $N_f = 300$ and $N_f = 400$, a more general law can be addressed: $r_c \approx 0.29 \times N_f \rho_0 + 2$. From above, it cleanly shows that zero risk boundary r_c depends on the virtual sample size N_f and virtual covariance matrix element ρ_0, which means it is stable without the effects of sample size N but only ρ. Theoretically, the peak value of n_0 and zero risk boundary coincide with same r. However, each of them corresponds to different value as a function of r in numerical calculation and r corresponding to peak value of n_0 are usually smaller r_c. To find the "real" n_0 at r_c, an effective method is to distinguish the "true" data which risk is not zero from zero risk values. Some good results come out for discussion from this "true" n_0, but the behavior between n_0 and ρ is still on working.

2. First principle lattice QCD has been a useful tool to study the in-medium properties of hadrons as well as the transport properties of the medium. However, despite the importance of the spectral functions to understand in-medium behaviors of the strong interaction matters, the spectral functions cannot be calculated directly using lattice QCD. Instead, what one can calculate is the Euclidean correlation function, $G(\tau, \mathbf{p})$, which is related to the spectral function, $\rho(\omega)$. Practically, the correlation function is only given at $O(10)$ discrete imaginary-time distances, τ, with some errors while, at least $O(1000)$ data points in frequency, ω, are needed for sufficiently good resolution of the spectral function. This is a typical ill-posed problem. The inverse problem as defined has an exact solution in the case of exactly known, discrete correlator data. However, as soon as noisy inputs are considered, this approach turns out to be impractical. Therefore, the most common strategy to treat this problem is via Bayesian inference. The Gaussian Mixture Model (GMM) is a powerful method commonly used in statistics. The GMM attempts to fit the mathematical quantity by generating a certain number of prior probabilities which satisfy the Gaussian distribution. The objection of GMM is to find out the mean and standard deviation of all these Gaussian distributions. From the loss function of $G(\tau, \mathbf{p})$ which contains three condition probabilities $P(\rho|z)$, $Q(z|\rho, G)$ and $P(z|G')$, so we can assume all of them as Gaussian distribution To solve this problem, we introduce neural network alternative to these conditional probabilities. In theory, if we succeed in finding networks alternative to $P(\rho|z)$, $Q(z|\rho,G)$ and $P(z|G')$, then the result of GMM models is achieved. However, the prior probability $P(z)$ is unknown. As we

assumed before, z depends on ρ, so it can be directly generated from ρ as an intermediate variable. Our purpose is to reconstruct ρ from training data of ρ by the intermediate z, which is similar to the process of Variation Autoencoder(VAE). By testing and building different constructions of network, finally we found good results for both pseudoscalar and vector channel and compare them to the model of maximum entropy method(MEM) and default model(DM). It shows the peak location in different models are all in the range of systematic error and statistical error district from DL method. As we know, MEM result is close to bare mass, however that of DL network is comparable to physical mass. Thus, both results of MEM and DL are acceptable. By cooperation with Shiyang Chen from Central China Normal University, most of that work have been done and the paper is on writing.

Studies in current semester:

ELTE courses:

FIZ/3/084 Data Mining and Machine Learning

Conferences in current semester:

Statistical Physical seminar at ELTE Institute of Physics:

“Tipping phenomena and resilience: two sides of the same coin?”, Ulrike Feudel, October 2.

“The effect of intermittent upwelling events on plankton blooms”, Ksenia Guseva, October 16.

“Exoplanetary mass constraints based on topology of interacting networks”, Tamás Kovács, November 13.

Awards:

Stipendium Hungaricum Scholarship

Research Allowance of CCNU For PhD, 2019.09 - 2019.12

Research Allowance of Institute of Particle Physics of CCNU For PhD, For Autumn Semester