# Statement of Purpose

I am interested in studying theoretical physics as it is the frontier of natural science, a natural application of modern mathematics, and tenable to be approached from a variety of angles. Within this field, I am particularly interested in further understanding various types of holography and the application of machine learning methods as an aide in finding directions of research in high energy physics. I would like to contribute to its further development by pursuing a PhD at the University of Washington for their research projects on fields in my interest.

During 2023, I participated in research on holographic calculation of correlation functions for curved spacetime under supervision by Prof. Chanyong Park. To understand the theory I participated in a directed study on field theory and cosmology, and used Mathematica for symbolic and numerical calculations to simulate late time evolution. While I was able to confirm the conjectured correspondence in many cases, I had difficulties obtaining analytical results for three point functions. While this was resolved by imposing a spacetime rotation symmetry, I would be interested in further research on the implications of this constraint.

I continued studying theory in spring 2024 by taking math courses and auditing a second course in QFT. I had the most fun discovering connections between courses I took, such as the formulation of Fock spaces via von Neumann algebras or Morse theory as a method of finding saddle points in TQFTs, and presenting a paper on the geometry of the BRST formalism and supersymmetry. Learning about formalism and its physical implications in depth is my passion, and I am eager to particpate in Prof. Paquette's research on holography and supersymmetry as it is not only at the intersection of many exciting developments in mathematics, but also contributes to such developments as well.

Alongside my research on holography, I worked on finding correspondences between diffusion and electromagnetic problems under Prof Chiok Hwang. I used PyTorch and its parallel programming/GPU acceleration functions for numerical calculations in tandem with taking a machine learning course. I used MCMC to sample the point where a particle first and last passes through a surface via diffusion to find which conjectured correspondence of two was valid, but the results suggested neither were true. After altering the methods like disabling parallelisation or changing sampling algorithm, we came to the conclusion that the Feynman-Kac relation could not explain these results. Prof. Loverde's research in neutrino cosmology interests me as they have implications for both the structure of the universe and fundamental particle physics, and my experience in utilising experimental data and both analytical and numerical calculations makes me well suited for such research.

During the latter half of 2024 I focused on machine learning and quantum computing, and conducted research under Prof. Keun-Yeong Kim. In the summer, initially reproducing papers on lattice QCD holography to learn how to use physically informed neural networks, I conducted a project to learn the interpolating function in a MOND model given initial and final dynamic data. As I implemented the physics model independently, it was prone to errors and not optimsed, and I would like to further improve this model to account for true astronomical data.

In the autumn, I worked together with a team to participate in the Korean Physics Society undergrad research competition, in performing quantum circuit optimisation by solving a modified version of the travelling salesman problem. The large number of nodes for even a few qubits made classical solutions untenable, and my role was to design and implement a reinforcement learning model to reduce the calculation time. Simultaneously, we investigated unsupervised neural network techniques to solving inverse spectral problems, recovering the potential of a system given its energy spectrum. The problem was very broad in scope and not well documented, and we ran into issues from high levels of degeneracy and singular behaviour of the potential. I identified a potential issue to be the low amount of accurate eigenvalues our model could reliably use, and focused my efforts on further understanding the numerical process; adapting current methods to be tenable for machine learning, comparing them based on a variety of parameters and finding heuristics for designing a robust model. Having