Chuhuan Huang 黄楚焕

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Education

Ph.D. in Mathematics @ Johns Hopkins University, 08/2023 - Present
M.A. in Applied Mathematics @ University of Southern California, 08/2021 - 05/2023
B.S. in Math – Computer Science @ University of California San Diego, 08/2016 - 03/2020

Languages / Skills / Research Interests

- Python/LaTeX/PyTorch (Daily programming/typesetting/framework with high proficiency), C++/java/R (Proficient degree-level training), Probability and Stochastic processes, Reinforcement Learning Theory & Algorithms, Mandarin/Chinese (native language), English (daily working language).
- Neural DEs, feature extracting via Signature Methods, and the applications in long time series against LLMs.

Awards

Fully funded by Graduate Fellowship @ Department of Mathematics, Johns Hopkins University, 2023 - 2024
Fully funded by Graduate Teaching Assistantship @ Department of Mathematics, University of Southern California, 2022 -2023
Provost Honors of Thurgood Marshall College @ University of California, San Diego, 2017 - 2019

Internships

Quantitative Researcher @ Penghua Fund Management, Department of Quantitative Research, 05/2023-08/2023

- Design and implement the framework for a Transformer-based reinforcement learning funds recommender system, together with several benchmarks.
- Model and train the industrial category standard transferring mapping using an Adam-trained Variational AutoEncoder.
- Design and encapsulate a ready-to-use the preprocessing workflow, Bokeh-based exploratory data analysis, and SHAP-based feature importance analysis for XGBoost-based model.

Data Analyst @ Founder Securities, Institute of Financial Technology, 01/2021- 04/2021

- Analyze the correlations and connections between and within the stock communities, using TensorFlow-implemented convolutional neural networks.

Recent Projects

Deep Reinforcement Learning funds recommender system, independent research reported to Dr. Binquan Kou @ Penghua Fund Management, 07/2023

- Our core model of the recommender system is built with two standard Transformers, together with a pre-trained BERT-based preprocessing layer and a pre-trained XGBoost-based reward model, and trained in the Asynchronous Advantage Actor Critic algorithm (A3C), where one Transformer acts as the actor and the other acts as the critic.
- Our benchmark model 1 is built with a BERT-based preprocessing layer and a Wide&Deep submodel, while the benchmark model 2 is built with a OneHotEncoding preprocessing layer and a XGBoost submodel; Both are trained by an Adam Optimizer.
- All codes were written in Jupyter Notebook in Python, including necessary packages imported from HuggingFace and PyTorch.

Approaching MAX-CUT thru reinforcement learning, independent research supervised by Professor Steven Heilman, 2022

- We approach the MAX-CUT problem by using Actor-Critic algorithm-trained LSTM-based pointer networks and compared with known Semidefinite programming benchmarks, using LSTM framework in Keras.
- Our approach is averagely 33% faster SDP benchmark in predicting and reaches 86% accuracy of the benchmark.
- Our approach is unfortunately unstable: when graphs with more than 150 vertices are fed, we sometimes run into NaN error in the training phase and sometimes poor performance in predicting phase.

Simulation of MDP and Decision-generating thru Value Iteration , independent project, 2021

- Modeling the transition distribution and cumulative reward in a game-related stochastic process using the Markov decision process, and implementing the policy generating mechanism through Value Iteration, a dynamic-programming-based algorithm, in Python.
- Our model successfully leads to around 500% rate of return with 2k dollar profits.

Thesis

A Survey on the Computational Hardness of Linear-structured Markov Decision Processes, 05/2023, advised by Professor Steven M. Heilman @ University of Southern California

- we are investigating i) the equivalent condition for the computational-statistical gap in Reinforcement learning ii) the relationship between the computational hardness of the linear-structured Markov decision processes and the rank of the transition matrix in the corresponding Markov chain.