IRIS-HEP Summer 2024 Fellow Program Project Proposal

Topological Rare Hadron Decay Tagging with DNN: Deep neural net topological tagger for rare hadron decay identification

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Project duration: 12 Weeks

Proposed start date: 3 June 2023

Introduction and Project Description

The $K^0_S \to \mu^+\mu^-$ [1] rare decay is a flavour-changing neutral current process which has not been observed yet. Observing or setting improved limits [2] on this decay can provide stringent tests of the Standard Model and potentially offer insights into new physics beyond the Standard Model. One of the main challenges of the analysis is an overwhelming amount of combinatorial background noise which should be strongly suppressed in order to increase sensitivity. Previously, by using XGBoost [3] BDT (Boosted Decision Trees) model and leveraging high-level features we managed to significantly enhance the analysis sensitivity improving it by an order of magnitude compared to traditional cut-based methods. However that is not enough.

We know that the dominant contribution to the combinatorial background is a cascade decay of B to D hadrons producing two close-by muons, which is a complex set of processes, but it's also a well defined problem. Taking this into account we will explore topological information about the dimuons and surrounding particles to separate signal and background. High dimensionality of the input features and non-trivial correlations make Deep Neural Networks [4] a more suitable option than BDT. That is why one of the main challenges of this project will be to identify and build an effective DNN architecture to train a new model that will not only match BDT in performance but gives a significant improvement to the analysis sensitivity. We plan to consider existing architectures used in particle physics such as DeepSet [5] and ParticleNet [6] as well as building a custom domain specific architecture.

Software Deliverables

During this project we will use Python, especially the Tensorflow, PyTorch and scikit-learn packages to build, optimize and train our models.

Preliminary Timeline

Week 1-2 Looking on existing approaches to solving similar problems. Learning DeepSet and ParticleNet architectures to understand how we can adapt them or gather hints on our own design.

Week 3-4 Studies on data. Finding or extracting useful parameters for our future model (Feature Engineering).

Week 5-9 Exploring and implementing advanced DNN models.

Week 10-11 Rigorously assessing the performance of our models ensuring that the new model provides a tangible improvement in analysis sensitivity.

Week 12 Preparing a report with description of a work done.

References

[1] Dery A., Ghosh M., Grossman Y. and Schacht S. (2021). $K \rightarrow \mu^+\mu^-$ as a clean probe of short-distance physics. arXiv:2104.06427. Retrieved from https://arxiv.org/abs/2104.06427

[2] Becker, S. (2024). Confidence limits: Definition. Statistics How To. Retrieved from https://www.statisticshowto.com/confidence-limits-definition/

[3] Chen T., Guestrin C. (2016). XGBoost: A scalable tree boosting system. In Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining (pp. 785-794).

[4] LeCun, Y., Bengio, Y. Hinton, G. Deep learning. Nature 521, 436–444 (2015). https://doi.org/10.1038/nature14539

[5] Zaheer M., Kottur S., Ravanbakhsh S., Poczos B., Salakhutdinov R. R. and Smola A. J. (2017). Deep sets. Advances in neural information processing systems, 30. Retrieved from https://arxiv.org/abs/1703.06114

[6] Qu H., Gouskos L., and CMS Collaboration. (2020). ParticleNet: Jet tagging via particle clouds. Physical Review D, 101(5), 056019.