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Report

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Summary

I created the GitHub repository **literature-alerts-bot** to monitor daily new articles from **arXiv** to a **Discord** server for the following topics:

1. **hep_ph**: searches for recent submissions in high-energy physics phenomenology
2. **qgp_ml**: searches for studies applying machine learning techniques to QGP and heavy-ion physics, including emulators, surrogate models, Gaussian processes, and ML-driven modeling of relativistic nucleus-nucleus collisions.
3. **qgp_bayesian**: searches for works on Bayesian inference and Bayesian analysis applied to QGP physics, including parameter estimation, uncertainty quantification, and model calibration in heavy-ion phenomenology.
4. **qgp_dkl**: searches for articles on Gaussian processes and deep kernel learning, including deep Gaussian processes, neural kernels, learned kernels, and hybrid GP-neural network models, with emphasis on modern kernel-learning

Historical Records

In addition, it is possible to retrieve the full search history by running the script directly via GitHub Actions.

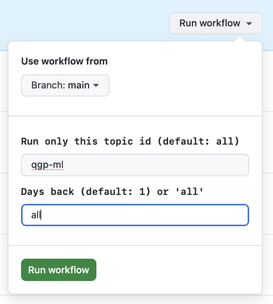

Figure: GitHub Actions interface illustrating how the workflow can be executed to retrieve the full search history for a specific topic.

Learned Concepts

Key insights from recent studies:

- Flow anisotropies (v_0, v_1, v_2) and collective behavior (correlations) provide evidence for the emergence of a hydrodynamic phase in heavy ion collisions [1].
- Although hydrodynamics is characterized by a short applicability timescale (low Reynolds number), collective behavior is still observed in small systems, including proton–nucleus collisions, in recent experiments [1, 2].

Next Steps: Toy Model

I identified and will study the following materials:

- **Error Theory** — lecture notes from *Experimental Physics IV* (e-aulas).
- **Gaussian Integrals and Gaussian Processes** — notes by Prof. Roland Köberle (IFSC).

Selected Paper

The promises and pitfalls of deep kernel learning

Sebastian W. Ober, Carl E. Rasmussen, Mark van der Wilk *Proceedings of the Thirty-Seventh Conference on Uncertainty in Artificial Intelligence*, PMLR 161:1206-1216, 2021.

Abstract

Deep kernel learning and related techniques promise to combine the representational power of neural networks with the reliable uncertainty estimates of Gaussian processes. One crucial aspect of these models is an expectation that, because they are treated as Gaussian process models optimized using the marginal likelihood, they are protected from overfitting. However, we identify pathological behavior, including overfitting, on a simple toy example. We explore this pathology, explaining its origins and considering how it applies to real datasets. Through careful experimentation on UCI datasets, CIFAR-10, and the UTKFace dataset, we find that the overfitting from overparameterized deep kernel learning, in which the model is "somewhat Bayesian", can in certain scenarios be worse than that from not being Bayesian at all. However, we find that a fully Bayesian treatment of deep kernel learning can rectify this overfitting and obtain the desired performance improvements over standard neural networks and Gaussian processes.

Figure: The promises and pitfalls of deep kernel learning" (Ober et al., 2021), providing a critical analysis of the strengths, limitations, and failure modes of deep kernel learning models.

References

[1] Jorge Noronha et al. "Progress and Challenges in Small Systems". In: *International Journal of Modern Physics E* 33.06 (June 2024). arXiv:2401.09208 [nucl-th], p. 2430005. ISSN: 0218-3013, 1793-6608. DOI: 10.1142/S0218301324300054. URL: http://arxiv.org/abs/2401.09208 (visited on 01/15/2026).

[2] Jean-Francois Paquet. "Characterizing the non-equilibrium quark-gluon plasma with photons and hadrons". en. PhD thesis.

Fim da apresentação!