ANALYSIS OF HYPERPARAMETER TUNING TECHNIQUES:
PROPOSALS, BENEFITS AND FUTURE RESEARCH DIRECTIONS

[1] " BOHB : Robust and Efficient Hyperparameter Optimization at Scale " by Stefan Falkner, Aaron Klein and Frank Hutter in 2018.

[2] “Hyperparameter Tuning For Deep Reinforcement Learning Applications “ by Mariam Kiran and Melis Ozyildirim in 2022.

[3] “Bayesian optimization in Alphago “ by Yutian Chen, Aja Huang, Ziyu Wang, Ioannis Antonoglou, Julian Schrittwieser, David Silver & Nando de Freita in 2018.

[4] “Combination of Hyperband and Bayesian Optimization for Hyperparameter Optimization in Deep Learning “ by Jiazhuo Wang, Jason Xu, Xuejun Wang in 2018.

[5] “Sequential model-based optimization for general algorithm configuration” by Hutter, F., Hoos, H., Leyton-Brown, K in 2011.

[6] “Improving hyperparameter optimization by planning ahead” by Jomaa, H. S., Falkner, J., & Schmidt-Thieme, L. (2019) In Proceedings of the 2019 International Conference on Data Mining (ICDM) (pp. 1261-1266). IEEE.

[7] “Automated Reinforcement Learning: An Overview” by Reza Refaei Afshar, Yingqian Zhang, Joaquin Vanschoren, Uzay Kaymak (2022).

PAPER	PROPOSAL	STRENGTH	WEAKNESS	REVIEW
[1]	New state-of-the-art HPO method, which consistently outperforms both Bayesian optimization (BO) and Hyperband .	1. Strong anytime performance. 2. Fast convergence to optimal configurations. 3. Inculcating parallelism. 4. Best performance at deployment time. 5. Scalable to different hyperparameters. 6. Robust to noisy environments. 7. Flexible among different types of hyperparameters. 8. Bayesian Optimization can be used to use the information gained from previous evaluations of different hyperparameter configurations.	1. Search space are not well-explored 2. Evaluation on a small set of benchmark datasets. 3. Resources allocated to each configuration during each optimization are not evenly distributed. 4.	1. Local penalization approach to explore areas of search space. 2. Number of configurations allocated to each resource level can be dynamically adjusted during the optimization process.
[2]	A distributed variable-length genetic algorithm framework to systematically tune hyperparameters improving training time & robustness of architecture, via evolution.	1. Framework is distributed which provides improved performance and reduced time compared to BO. 2. Multiple HPs are allowed to evolve over some generations. 3. Handles hyperparameters with different types and lengths.	1. Evaluation done only on two benchmark RL tasks. 2. Less in-depth analysis of the framework.	

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[3]	Insights on BO techniques used in tuning HP in AlphaGo.	1. Tuned various hyperparameters associated with MCTS. 2. Meta-optimization to calculate search time per move. 3. Usage of self-play to estimate win-rate using BayesElo algorithm. 4.Proved better than high cost grid search. 5. Using a modified version of spearmint (software package for BO) with input warping. 6. Gaussian process model used with non-stationary gaussian observation noise model. 7. Importance of hyperparameters and correlations among hyperparameters.	1. BO can give increased preference to value network estimates than roll-out estimates. 2. Tuning on TPUs instead of GPUs.	1. Grid search is not suitable for high state space problems. 2. Meta-optimization of components of algorithm improves performance. 3. Input warping can be used when input space has some complex structure and hyperparameter constraints.
[4]	Combination of Hyperband with BO algorithm to achieve state of art performance on various hyperparameter optimization problems in the field of deep learning - Hyperband_TPE.	1. Small hyperparameter space - Reduce search space, efficient exploration.. 2. Comparison over various algorithms. 3. Efficiency in high dimension spaces. 4. Fewer function evaluation spaces. 5. Balance between exploitation and exploration.	1. Risk of overfitting as evaluated on a small set.	1. Combination of strength different state of art performance algorithms, provide novel algorithms with superior performance.

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[5]	An iterative, model-based optimization algorithm that uses a Bayesian optimization framework to efficiently search the space of hyperparameters. Sequential Model-Based Optimization (SMBO), is a probabilistic optimization framework that uses a surrogate model to predict the performance of different hyperparameter configurations.	1. First paper on a general algorithm configuration problem. 2. Probabilistic model to estimate the behaviour of objective function over the entire parameter space 3. Can be used to analyse the interactions between different hyperparameters 4. Introduces a way to handle categorical parameters 5. Two novel SMBO instantiations - Random Adaptive Online Racing procedure and Sequential Model-Based Configuration method.	1. Focuses only on deterministic target algorithms 2. Computationally expensive models 3. Assumption that all target algorithm runs have same computational cost 4. Early termination for poorly performing target algorithm runs not supported	1.General algorithm configurations: PARAMILS and GGA
[6]	Novel transfer learning approach, defined within the context of model-based reinforcement learning, where we represent the surrogate as an ensemble of probabilistic models that allows trajectory sampling.	1. Models HPO as an MDP 2. Transfer learning surrogate model represented by an ensemble of probabilistic neural networks 3. Novel Acquisition Function that implements a planning-ahead strategy paired with model predictive control 4. Takes into account the uncertainty in the evaluation of hyperparameter configurations. 5. The method uses a multi-fidelity optimization approach that combines low-fidelity and high-fidelity evaluations of hyperparameter configurations	1. Computationally slow and explorationally inefficient in continuous search spaces. 2. Performance hindered by a lack of sufficient training data to build an accurate surrogate model. 3. Assumption of stationarity. 4. Limited exploration. 5. Can be improved by integrating with other HPO methods 6. Comparison with state-of-the-art methods like BOHB, TPE, or Hyperband not done. 7. Incorporating early stopping.	
[7]	The paper discusses recent advancements in	Key takeaways from this review paper are:-	Potential Areas of Research:- 1. Developing more efficient and	Main challenges :- 1. Sparsity of reward function due to

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	AutoRL. AutoRL aims to automate the entire process of RL including (i) Problem Formulation (ii) Algorithm selection (iii) Hyperparameter Tuning Describes various AutoRL frameworks. Various challenges in AutoRL are stated.	1. Automating State Representation:- Adaptive Tile Coding, 2. Automating Actions 3. Automated Reward Function 4. Automated Algorithm Selection 4. Hyperparameter Optimization 5. Learning to Learn 6. Automating Neural Network Architecture	robust automated RL algorithms that can handle large-scale, real-world problems. 2. Investigating the use of transfer learning in automated RL, where knowledge gained from solving one problem is transferred to another related problem. 3.Developing methods to automatically generate new environments and tasks for reinforcement learning to aid discovery of new and interesting applications	large state space. 2. Model-Agonistic Meta-Learning 3. Gradient descent using RNN. LSTM RNN models interdependencies between outputs of different parts of the neural networks. RNN can also behave like an RL algorithm. 4. The Automatic framework for learning rate can be improvised and adopted in our project. The paper used variance and gradient of loss function. State representation is used to train policy using REPS algorithm, which also ensures policy updates to be close to each other by constraining the updates through a bound on KL divergence.