# **Hyperparameter Optimization and Fine-Tuning**

Improving Model Performance Beyond Training

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### Introduction

- Machine learning models depend on parameters (learned from data) and hyperparameters (set before training).
- Proper hyperparameter tuning can drastically improve accuracy, generalization, and efficiency.

### Parameters vs. Hyperparameters

- Parameters: Internal model values learned during training (e.g., weights in neural networks).
- Hyperparameters: User-defined settings (e.g., learning rate, number of layers, regularization strength).
- Key difference: Hyperparameters are not learned automatically.

## Why Hyperparameter Optimization Matters

- Controls bias-variance tradeoff.
- Prevents overfitting/underfitting.
- Reduces training time and computational cost.
- Boosts performance on unseen data.

### Common Hyperparameters

- For Neural Networks: learning rate, batch size, number of layers, dropout rate.
- For Decision Trees: max depth, min samples split, criterion.
- For SVMs: kernel, C, gamma.

## Few Hyperparameter Optimization Methods

#### Manual Search

- Trial-and-error, domain knowledge.
- Simple but inefficient.

#### **Grid Search**

- Tests all combinations in a grid.
- Exhaustive but computationally expensive.

#### Random Search

- Samples random combinations.
- Often more efficient than grid.

## Fine-Tuning

- Process of adjusting pre-trained models to a new dataset/task.
- Common in deep learning with transfer learning.

### Fine-Tuning vs. Hyperparameter Tuning

- Hyperparameter Tuning: Optimizing training configuration (finding the best combination of hyperparameters that makes training efficient and improves accuracy).
- Fine-Tuning: Reusing and adapting pre-trained models.
- Often used together.

### **Applications**

- NLP (BERT, GPT fine-tuning).
- Computer Vision (ResNet, EfficientNet transfer learning).
- Time-Series Forecasting (hyperparameter-tuned models like XGBoost).

### Conclusion

- Hyperparameter optimization and fine-tuning are essential for high-performing models.
- The right combination saves resources and improves results.