Multi-Fidelity Bayesian Optimization for Simulation Based Autonomous Driving Systems Testing

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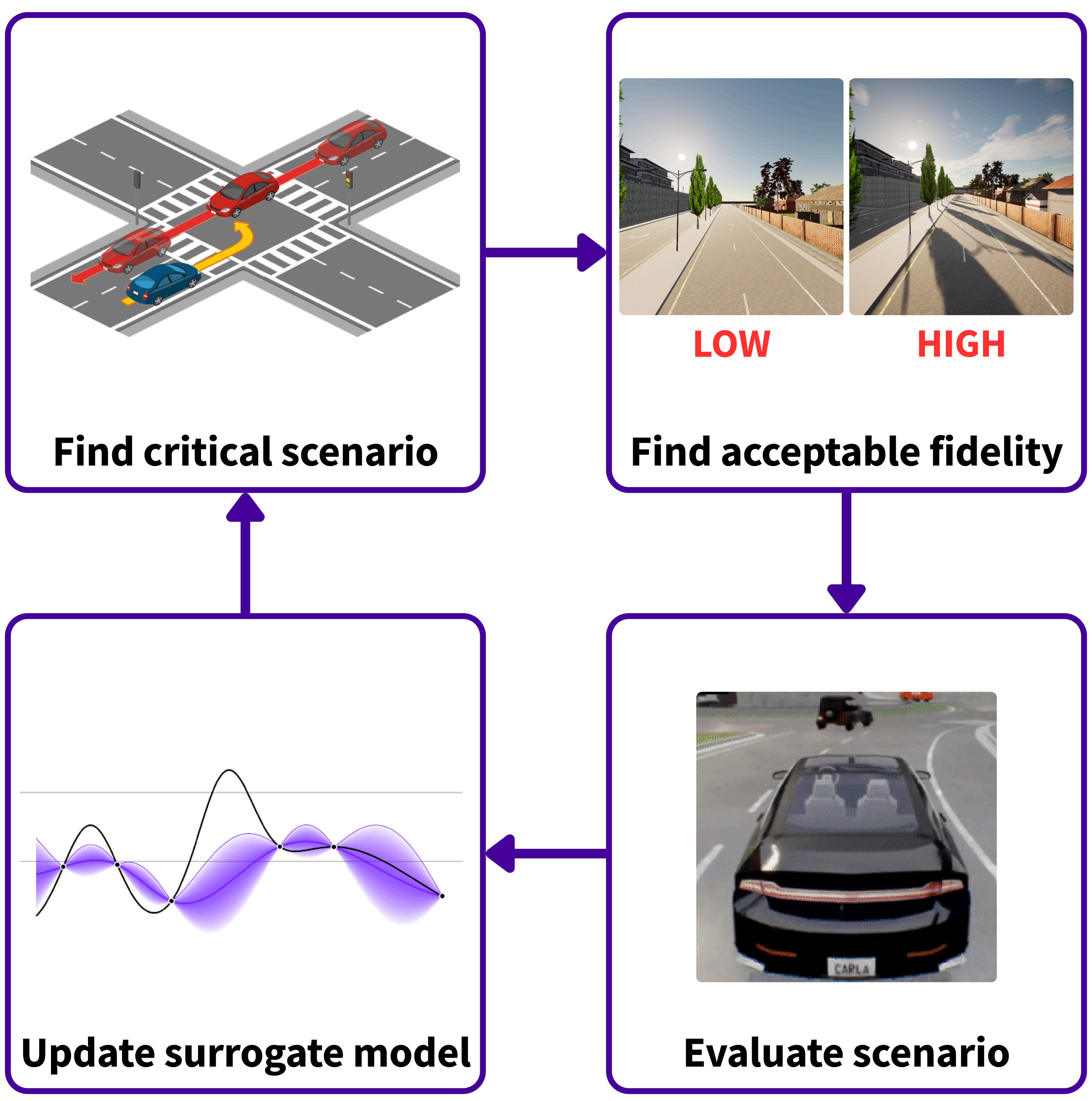
Motivation

- Extensive Testing Autonomous Driving Systems (ADS) is required to ensure safety and reliability
- Search-based ADS testing is dominant approach but simulators are **computationaly expensive**
- Simulators expose fidelity parameters which allow to balance computational cost and accuracy



Approach

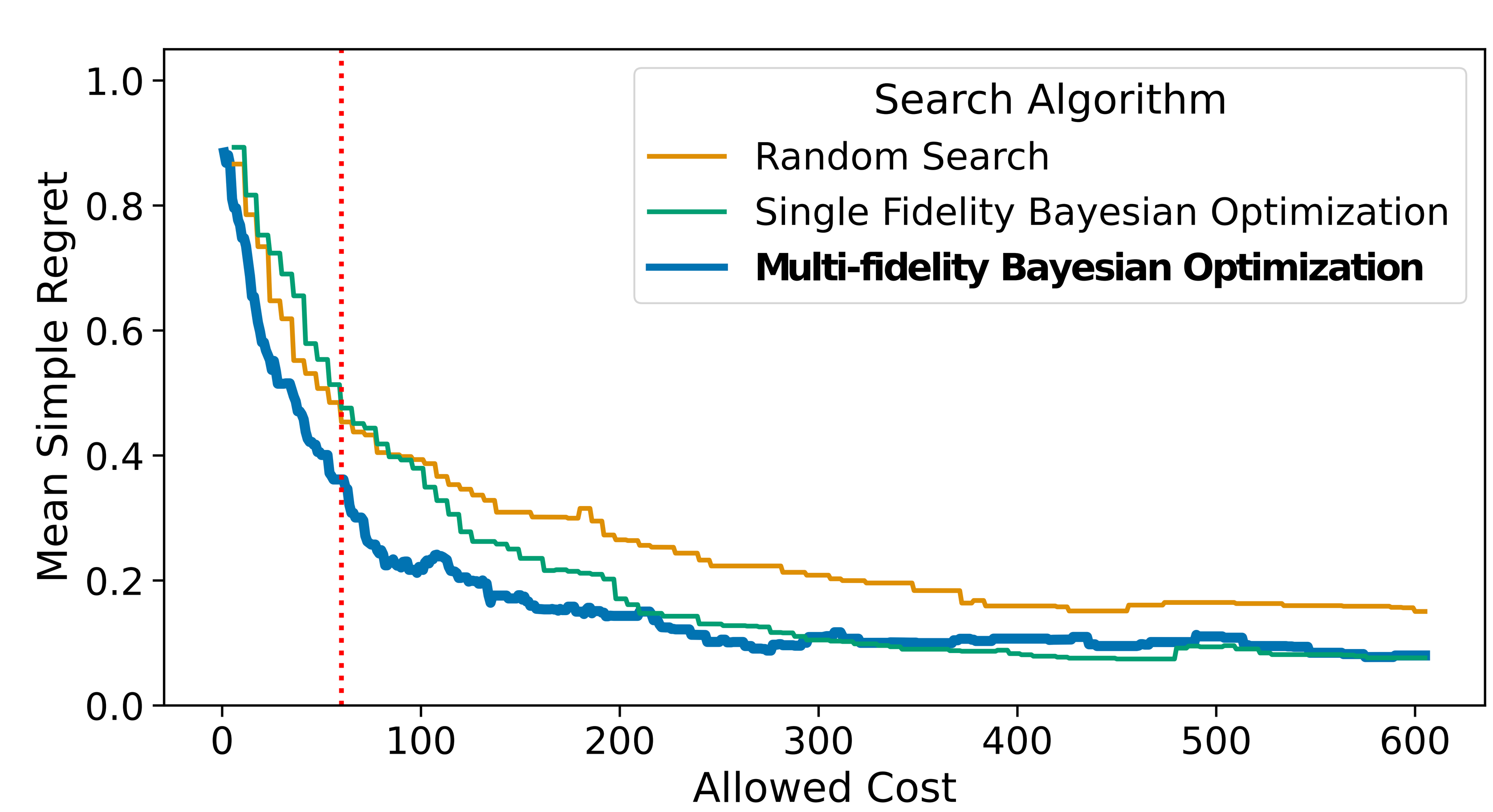
- Apply **Multi-fidelity Bayesian Optimization** (MFBO) to simulation-based ADS testing problem
- Build a Multi-fidelity surrogate model capturing relationship between test input, simulators fidelity and evaluation result
- Sample testing scenarios that have a potential of uncovering critical behaviours while minimizing evaluation cost
- **Intuition:** Always execute in the lowest fidelity possible without introducing error to test result

Evaluation

- How senstivie are driving scenario evaluation results to changes in fidelity parameters?
- Is MFBO-Drive effective and efficient compared to other scenario generation techniques?
- **Setup**: FPS as fidelity parameter in Metadrive simulator, testing on procedurally generated driving scenarios, assessing safety requirements (route completion, no collisions, no out-of-lane episodes) aggregated into a single *driving score*

Results

- **92.5%** of driving scenarios are not affected by changes in simulations fidelity settings showing a strong potential for multi-fidelity optimization
- MFBO-Drive significantly improves the **cost-effectiveness** of uncovering critical scenarios by **16.8%** compared to state-of-the-art Bayesian optimization, without sacrificing the effectiveness of the final solution



Search convergence for scenario generation, visualized as a mean simple regret over time for each search approach. The red dotted line indicates the end of the initialization phase.

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