Probabilistic Wildfire Spread Modeling Using Markov Decision Processes: A Data-Driven Approach for Prediction and Mitigation

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Abstract

Wildfires pose a significant environmental and economic threat, necessitating accurate prediction models for effective prevention and mitigation. This study presents a data-driven approach to modeling wildfire spread using a **Markov Decision Process (MDP)** framework, leveraging historical wildfire datasets to derive probabilistic transition functions. Unlike traditional physics-based models, our approach integrates real-world fire behavior patterns by analyzing factors such as **terrain type, wind speed, moisture levels, and fire growth rates** to construct a dynamic environment where fire propagation follows probabilistic rules. MDP is chosen as the core modeling technique because it effectively captures the **stochastic nature of fire spread**, where state transitions depend on environmental conditions and probabilities derived from past wildfire records. This ensures the model adapts to real-world conditions rather than relying on theoretical assumptions. By mapping dataset-specific terrain classifications to real-world equivalents, the model improves interpretability while maintaining data integrity. Incorporating probabilistic functions for fire transition and growth allows for realistic **wildfire scenario simulations** under different environmental conditions. This technique is highly scalable and can be applied to **emergency response planning, resource allocation, and ecological risk assessments**. By providing a **computationally efficient and adaptive wildfire simulation**, this approach aids in predicting high-risk areas, guiding preemptive firefighting measures, and optimizing resource deployment. The integration of MDP and historical data offers a practical, data-driven solution for understanding and mitigating wildfire risks across diverse landscapes.