Learned Critical Probabilistic Roadmaps for Robotic Motion Planning

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Introduction

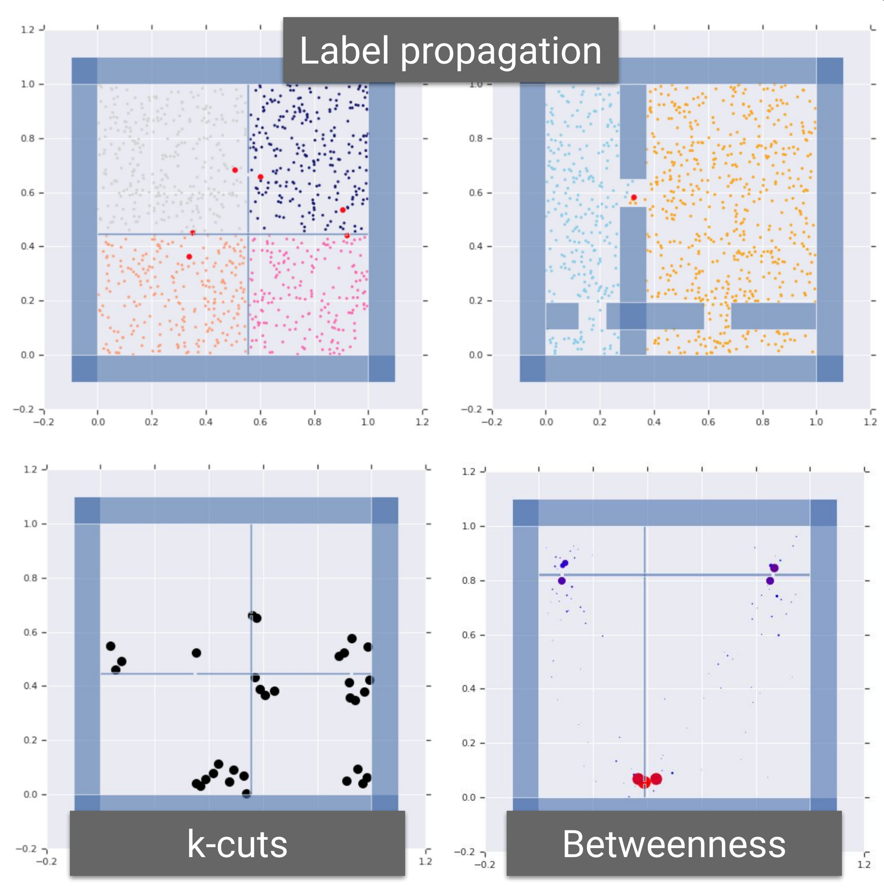
- Sampling-based motion planning uses *uniform* probing samples to build an arbitrarily accurate, implicit representation of the state space
- Often only a few critical states are necessary to parameterize solution trajectories
- **Key Idea:** Learn to recognize the critical states and use them to construct a hierarchical PRM, leveraging these critical states more heavily

Contributions

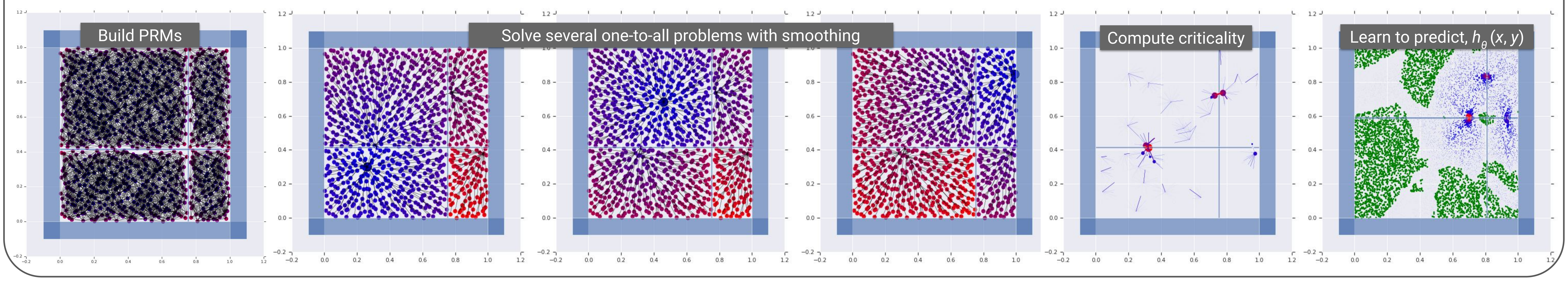
- Compute criticality via *betweenness centrality*, a graph-theoretical importance to shortest paths
- **Offline:** Learn to predict criticality from local features with a Convolutional Neural Network
- **Online:** construct a *Critical Probabilistic Roadmap*
  - Connect non-critical points locally
  - Connect critical points globally
- **Shows 100x improvement in success, 10x in cost**

Critical States Identification

- Graph theoretic approaches allow state space critical states. Compared:
  - label propagation- unstable and poorly defined with less clear bottlenecks
  - K-cuts- requires fixed number of cuts, which heavily influences states
  - many graph centrality indicators
- Selected **betweenness centrality:**
  - computes the number of all-pairs shortest paths that pass through a node
  - can be computed approximately, very quickly
  - added an additional smoothing step to discount skippable free-space states
- Learn a network, $h_\theta(x, y)$, to predict sample x's criticality from problem features y



Offline: Identify and Learn Samples

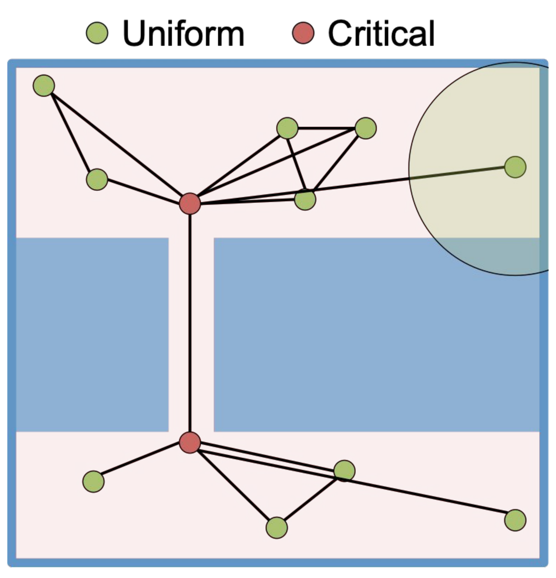


Online: Critical Probabilistic Roadmaps

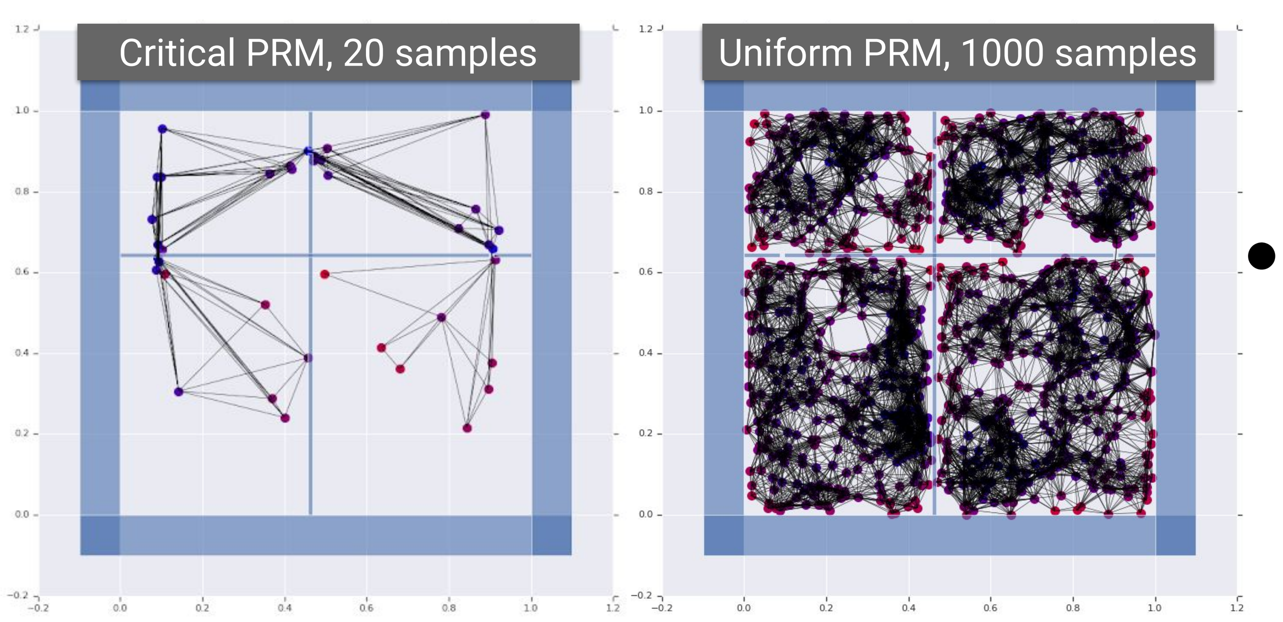
- Construct a Critical PRM by sampling:
  - ($\lambda \log n$) critical, globally connected states
  - ($n - \lambda \log n$) uniform, locally connected states
- Preserves the theoretical guarantees of SBMP, asymptotic optimality and $O(n \log n)$ complexity

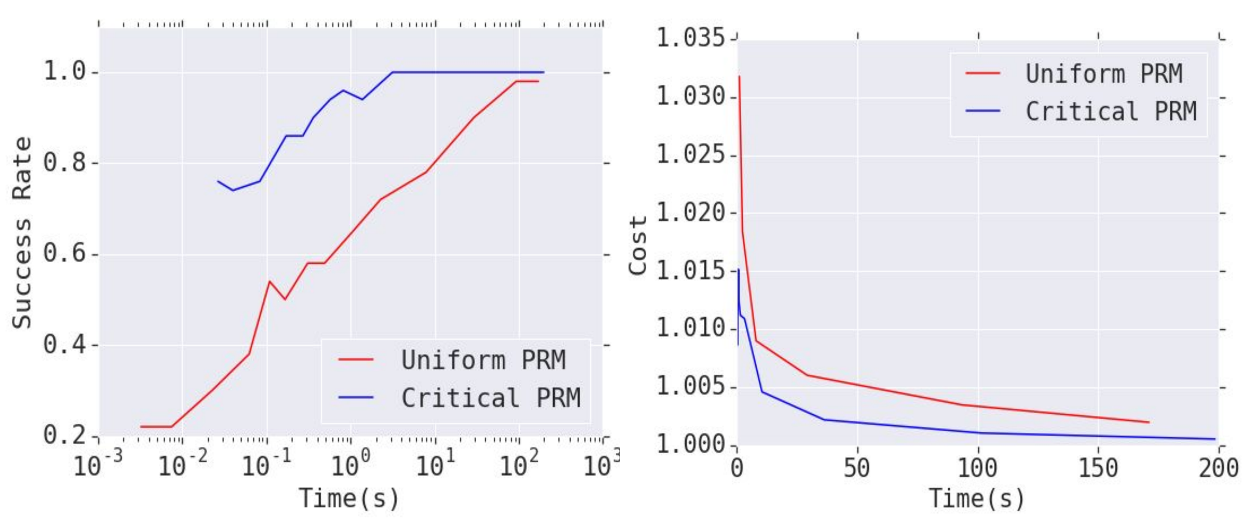
Algorithm 1 Online Critical PRM Construction

Input: Planning problem $(\mathcal{X}_{\text{free}}, x_{\text{init}}, \mathcal{X}_{\text{goal}})$, λ, n
Sample n configurations and compute criticality with $h_\theta(x_i, y)$.
Select $\lambda \log(n)$ critical samples proportional to criticality.
Connect critical samples to all samples.
Connect non-critical samples within an r_n radius.
Connect x_{init} and $\mathcal{X}_{\text{goal}}$ globally into the Critical PRM.
Search Critical PRM for shortest path from x_{init} to $\mathcal{X}_{\text{goal}}$.



Results





- On narrow passage problem:
  - Identifies narrow passages
  - 100x speedup in success rate
  - 10x speedup in solution cost
- On indoor dataset:
  - Trained on local image
  - Identifies doorways, hallways
  - Ignores open area
  - Success and cost to come