Applying Q-Learning Agents to Distributed Graph Problems

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About Me

Jeff McCrea – mccreajeff@gmail.com

> Master of Science in Computer Science & Software Engineering – University of Washington Bothell.

> Research Interests: Distributed computing, agent-based modeling, and reinforcement learning.

> Professional Experience: IT consultant specializing in enterprise IT environments.

> Academic & Industry Focus: Scalable computing solutions, multi-agent systems, and AI-driven optimization.

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Distributed Systems Laboratory(DSL)

- Led by Prof. Munehiro Fukuda at UW Bothell, focusing on parallel & distributed computing.
- Current research includes agent-based computing, graph database, and large-scale simulations.
- Future directions focus on improving scalability, optimizing parallel performance, and integrating AI/ML techniques.
- https://depts.washington.edu/dslab/

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Introduction - Why Do We Need Q-learning for Graph Problems

- Large, complex graphs require scalable solutions
- Static frameworks struggle with dynamic graphs
- Q-learning agents can learn & adapt to changes dynamically

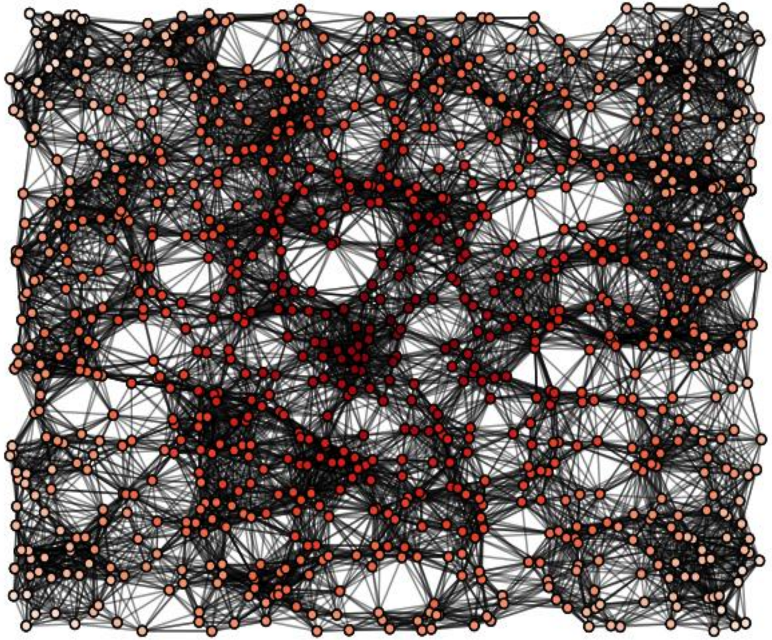


Image Source: Algorithms for Large-Scale Graph Processing

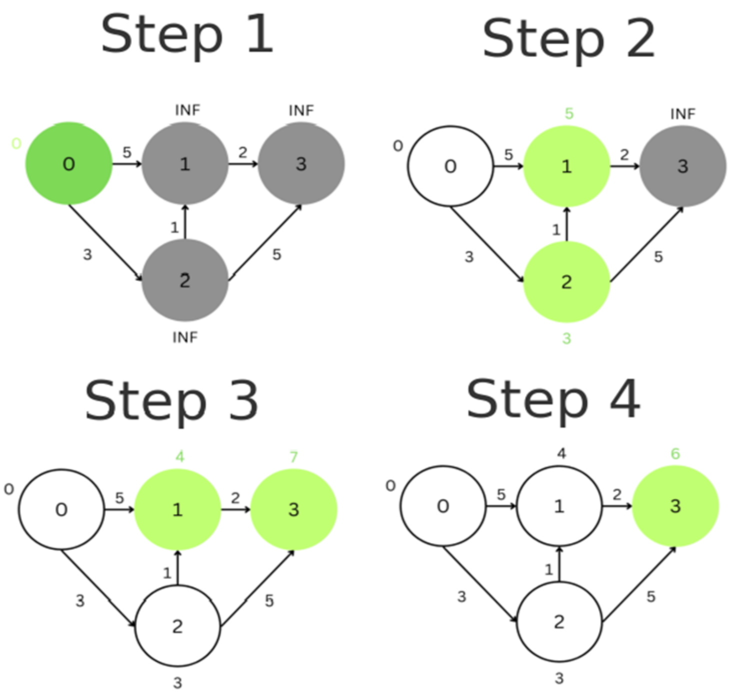
Introduction - Our Research Goals

Four main project goals:

1. Design agent-based Q-learning applications in MASS
    - Shortest Path
    - Closeness & Betweenness Centrality
2. Improve scalability & adaptability in dynamic graphs
3. Leverage MASS’ multi-agent capabilities to improve performance
4. Evaluate MASS agent-based machine learning capabilities

Background – Traditional Graph Computing vs. Q-learning

- Google's Pregel & Spark GraphX
  - Static, precomputed models
- Q-learning
  - Dynamic, adaptive, and reinforcement-driven
- Research Gap
  - Focuses on small, static graphs
  - Require preprocessing and computation to be effective



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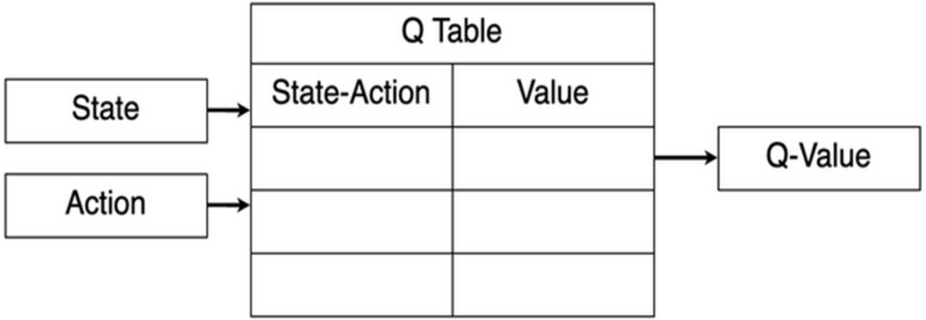
Related Work – How Q-learning Works



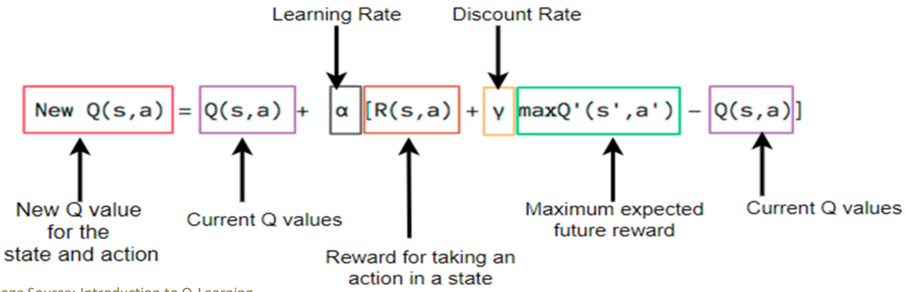
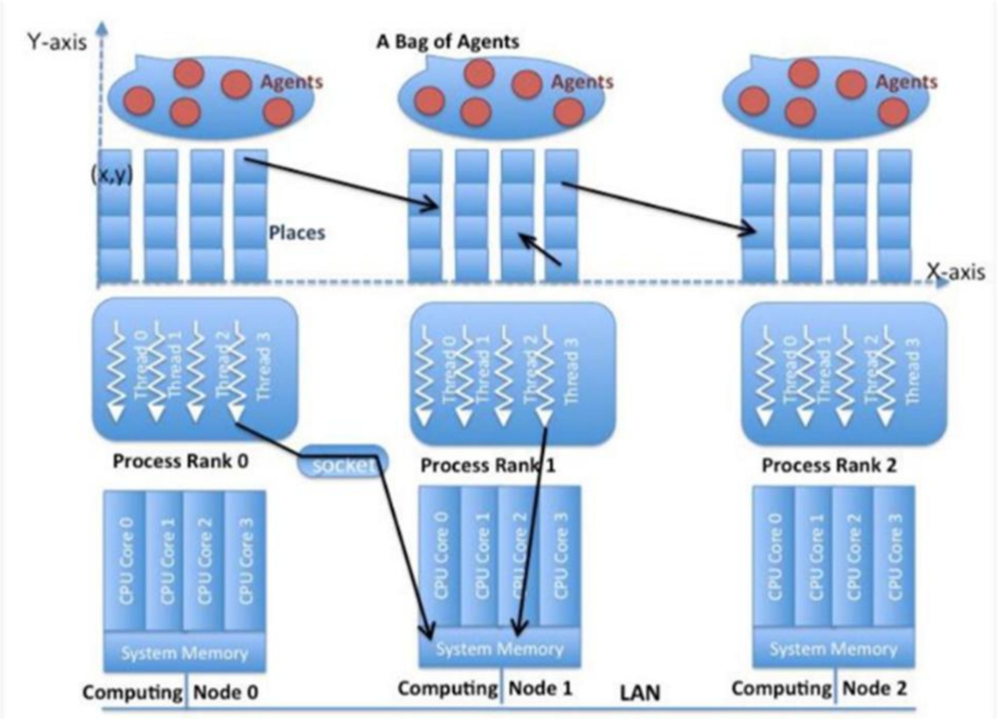


Image Source: Introduction to Q-Learning

- Model-free and off-policy
- Trial & error learning
- Q-Learning Process:
  1. Initialize Q-Table
  2. Set hyperparameters
  3. Choose an action
  4. Perform action & observe the outcome
  5. Update Q-value with:
  6. Repeat until training episodes are completed or convergence

Implementation - Multi-Agent Spatial Simulation Framework

> **Multi-Agent Spatial Simulation Library(MASS)**
> **Designed to facilitate spatial simulations and big data analysis in a parallel environment**
> **Two primary components:**
  – **Places – distributed individual dataset members**
  – **Agents – computation entities that traverse data**
> **Threads are assigned to Place objects and can communicate with other Places and agents that reside on them**



Implementation - Multi-Agent Spatial Simulation Framework

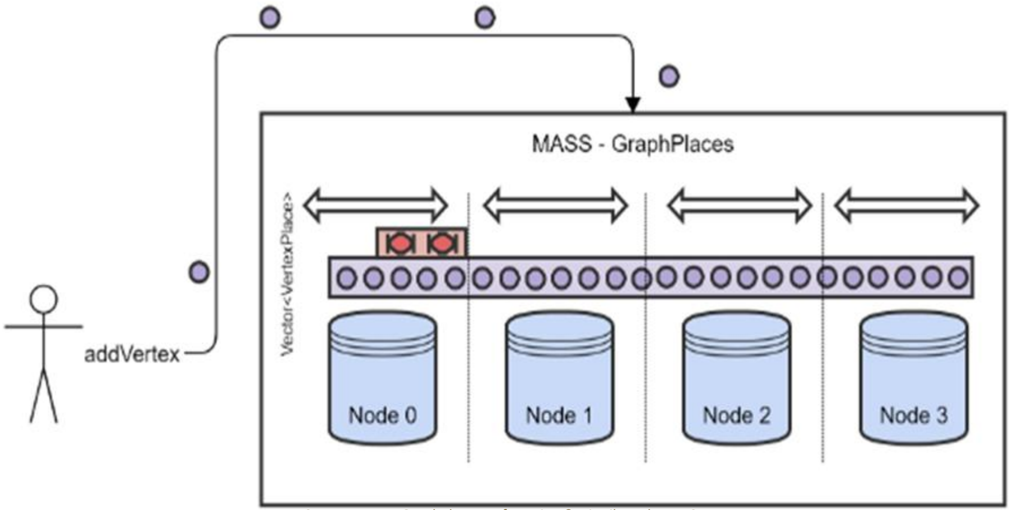


Image Source: Luger, GraphPlaces Refactoring & Distributed Data Structures

- MASS has been extended to support explicit graph structures

GraphPlaces
- Place -> VertexPlace

Agents
- Agent -> GraphAgent

Dynamic graph creation:
- AddVertex & AddEdge
- LoadDSL()

Balanced vertex distribution

Implementation - Q-Learning in MASS

- Comprised of four main classes:
  - ShortestPath – driver
  - Node – environment
  - QLAgent – intelligent agent
  - PathAgent – path enumeration agent
- Agent-Based Learning: Q-learning agents explore a distributed graph, updating a shared Q-table to learn optimal paths.
- MASS-enabled Q-learning Improvements
  - Multi-agent Training
  - Distributed Q-table & Reward Window
  - Dynamic Hyperparameter Tuning

Evaluation - Experimental Setup

> Synthetic Graph Dataset:
  - 500-16,000 Nodes
  - Random graph generation
> Road Network Dataset:
  - 1,861-19,096 Nodes
  - OpenStreetMap data
> Synthetic Centrality Dataset:
  - 8-256 Nodes
  - Random Graph Generation
> Computing Cluster:
  - 8 VMs, Intel Xeon Gold 6130, 16GB RAM
> Performance measured in training time & adaptability

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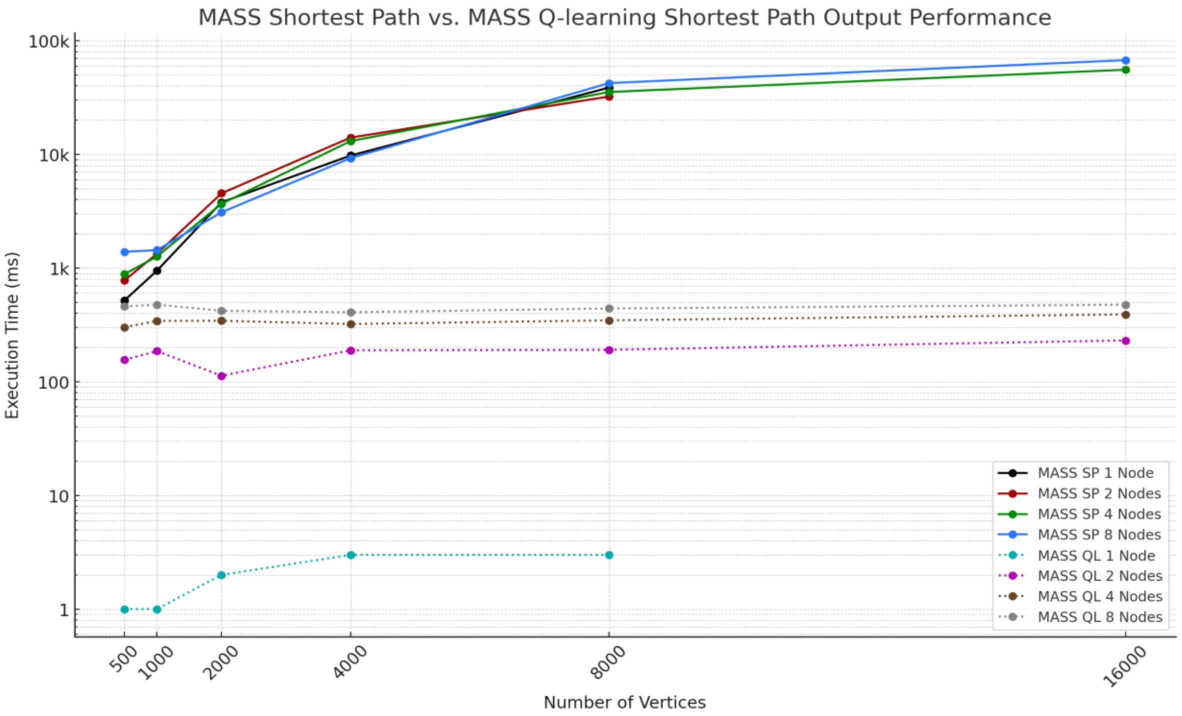
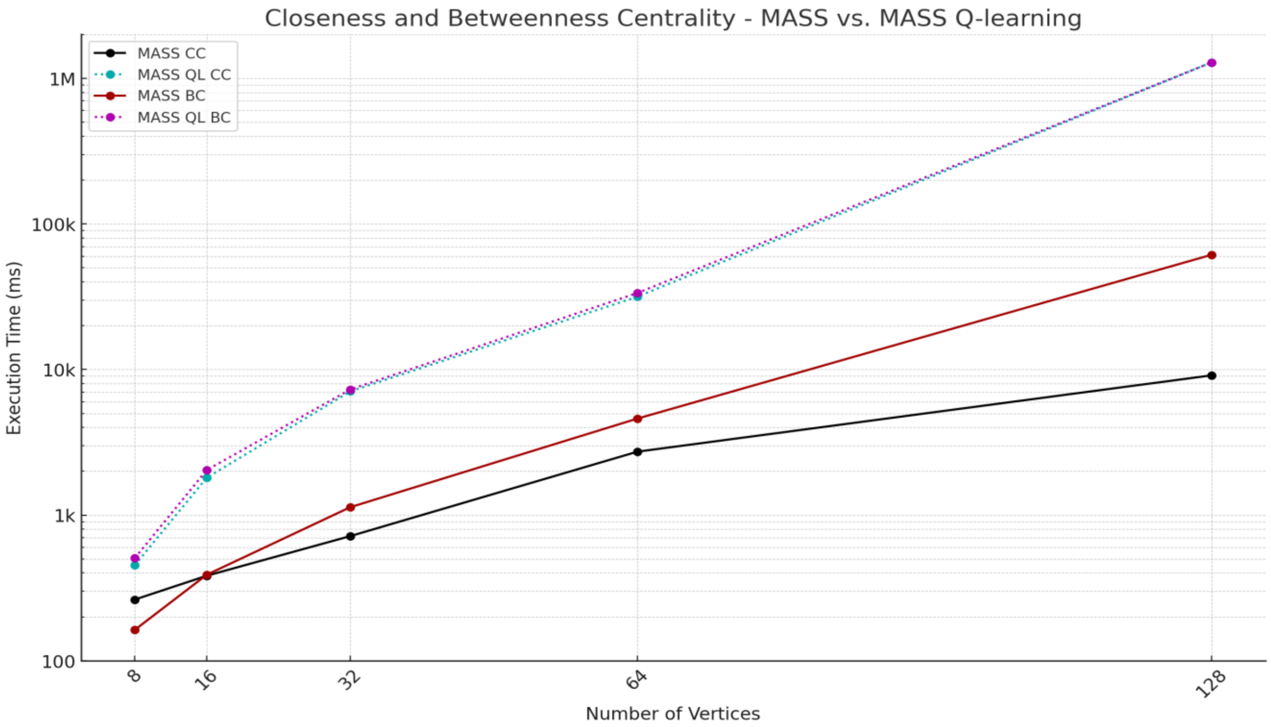
Evaluation – Q-learning Shortest Path



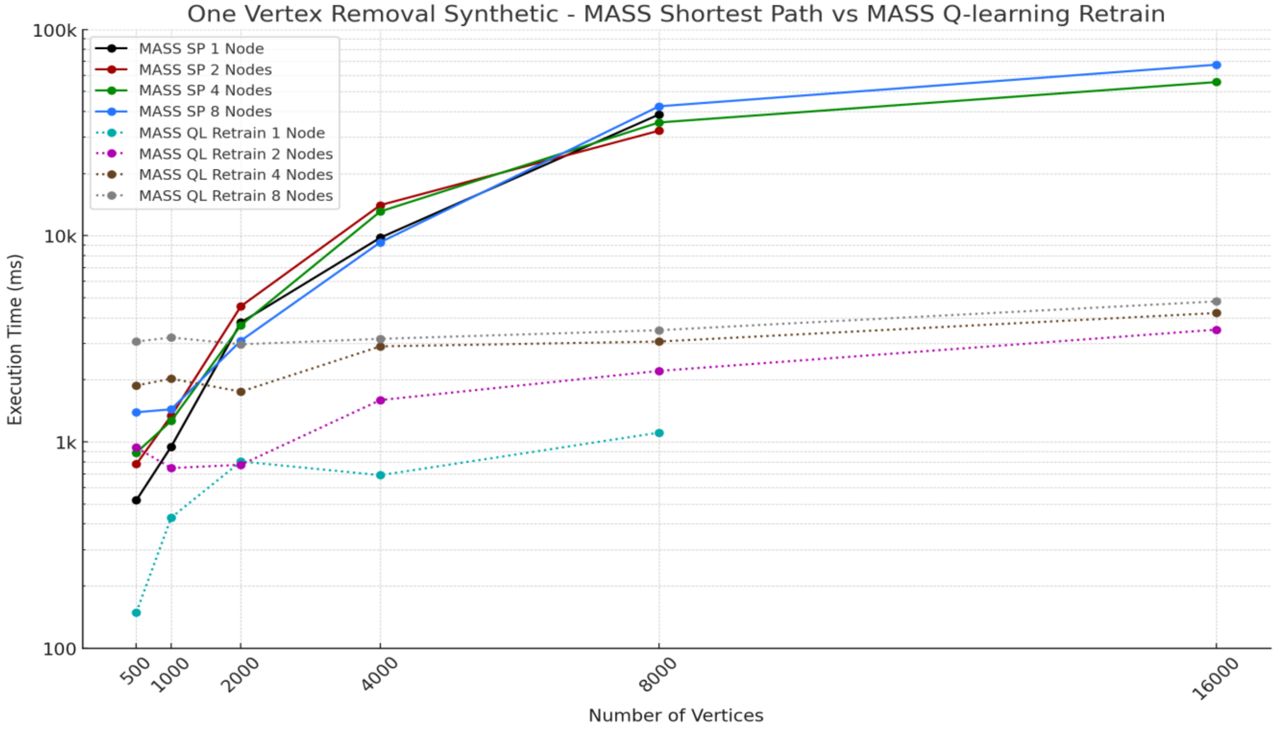
- Single node is optimal up to 8,000 nodes
- Above 8,000, multi-node execution is required
- Multi-agent training cuts training time by 190%

Evaluation – Closeness & Betweenness Centrality



- Performs well on small graphs
- Quadratically scaling as size grows – inefficient for large graphs
- High memory demands limit scalability

Evaluation – Dynamic Graph Adaptability



- Handles small changes efficiently
- Outperforms static methods in single-node removal
- Requires more significant retraining for larger topology shifts

Conclusion – What We Achieved

- Shortest path performance gains on static and dynamic graphs; centrality still needs optimization
- MASS-enabled features significantly improved performance
- Multi-agent training → 190% reduction in training time
- Distributed reward window → faster convergence
- Dynamic hyperparameter tuning → self-optimizing agents

Conclusion - Challenges & Future Work

Challenges:

- Scalability of centrality metrics
- Long training time for large graphs
- Necessity of hyperparameter fine-tuning for different graph types

Future Work:

- Graph Convolutional Networks (GCNs)
- Improved agent communication
- Online Q-learning for real-time updates

Q&A

Questions?

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