Machine Learning and Optimization for Resource-Constrained Platforms

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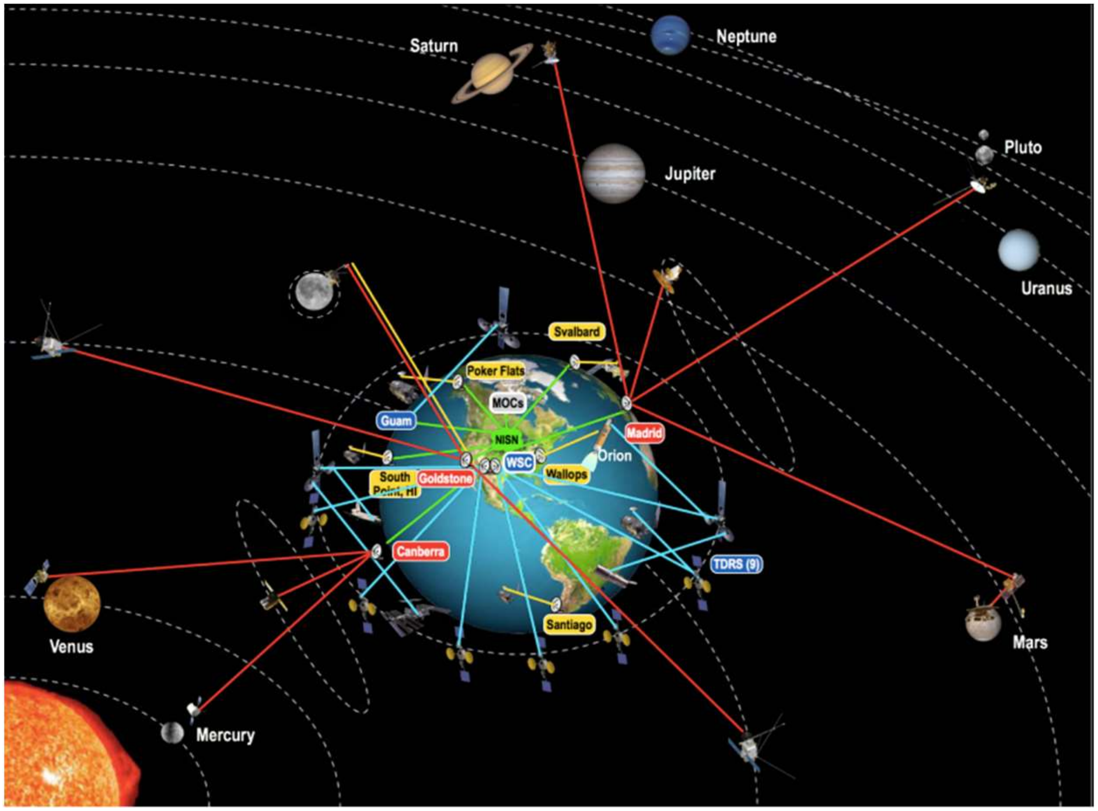
NASA Space Communications and Navigation

- Three operational networks (DSN, SN, NEN)
- Ground stations spread out all over the world
- Provide communications services to supported missions using space-based and ground-based assets
- Scheduling handled by priority, request, and collegiate bargaining

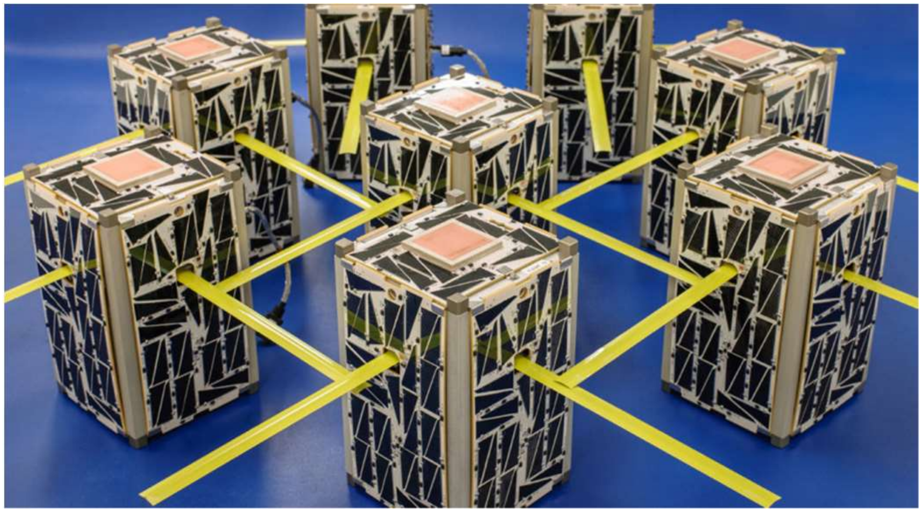


Cognitive Communications Task

- Artificial Intelligence (AI) and Machine Learning (ML) strategies for NASA communication network
- Optimization
  - Increase overall performance of the network
  - Parameter modification
    - Throughput
    - Power consumption
    - Latency
- Large networks create a scaling issue
- Overwhelming computation resources required

Resource Constraint

- Cubesats
  - Cost effective, small form factor
  - Efficient test platform
  - Science investigation, new technology demo
  - Constellation, swarms
- Hardware and power limit
- Emulation with similar constrained hardware



Network Scheduling

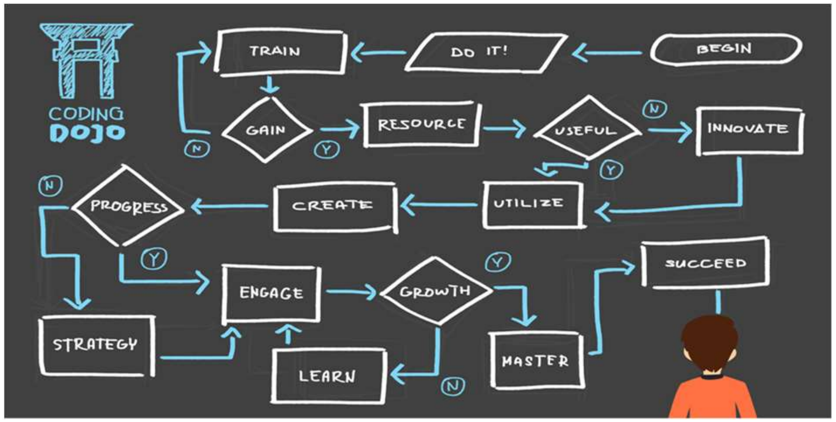
- As launch costs decrease, desire to launch missions increases
- Manual scheduling can be overburdened
- Process
  - Mission requirements, orbit patterns, ground asset availability, mission priority
  - Network-specific flavors for NASA
    - TUT time, collegiate scheduling, priority
- Anomalous events further burden manual scheduling personnel

Automated scheduling

- Centralized, Decentralized
  - Full network view vs cluster view
- Schedule analysis and deconfliction
- Route planning
  - Power consumption
  - Time variance
  - BER
  - Bandwidth
- Optimization can be run 1000s of times for optimal solution

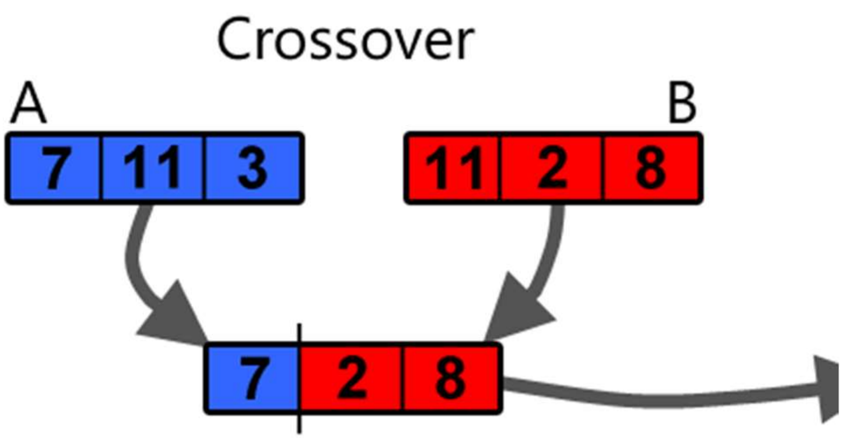
Algorithms

- AI & ML rely on algorithms to produce solutions
- Optimal vs near-optimal
  - Time tradeoff
- Many AI areas
  - Evolutionary, Swarmm Neural, Immune, …
  - All provide pros and cons for problem spaces

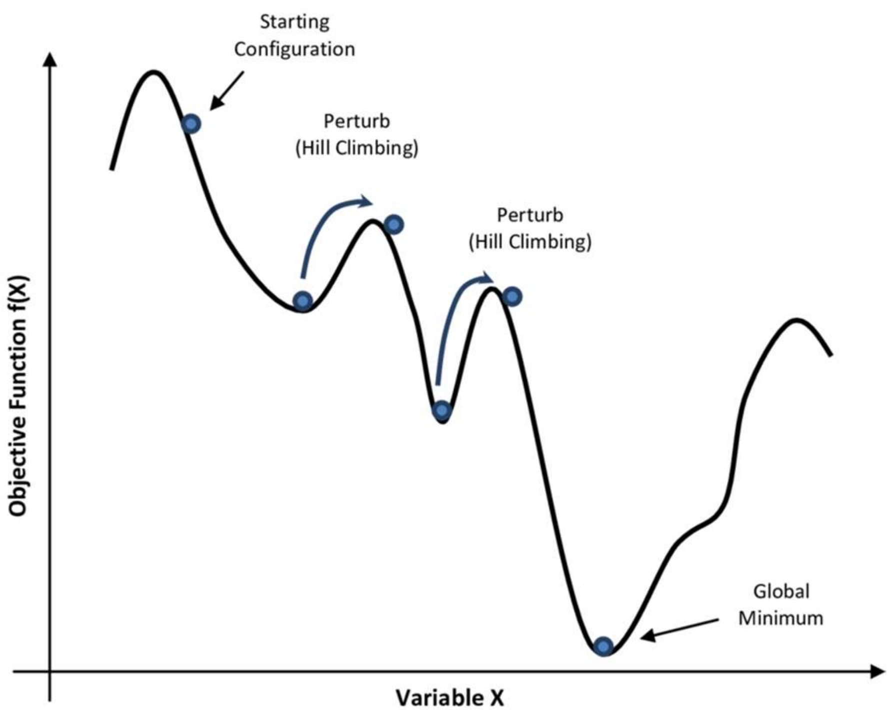


Genetic Algorithm

- Species population and genetics
- Mutation and Crossover combines "genes"
- Pros
  - Faster than exhaustive search
  - Low memory requirement
  - Simple, quick implementation
- Cons
  - No optimal solution guarantee
  - Large compute time for some spaces



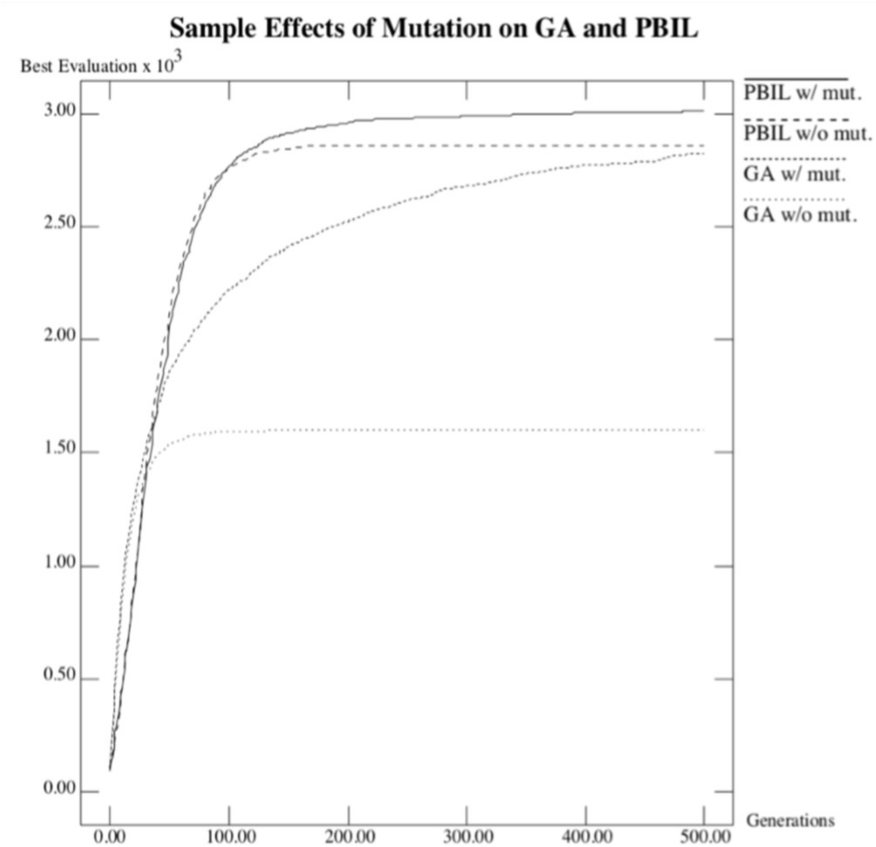
Simulated Annealing



- Inspired by metallurgy
  - Metal heated and slowly cooled to reduce defects
- Pros
  - Always converge to global optimum
  - Simple implementation
- Cons
  - Convergence to optimal solution may require oversampling
  - Time tradeoff

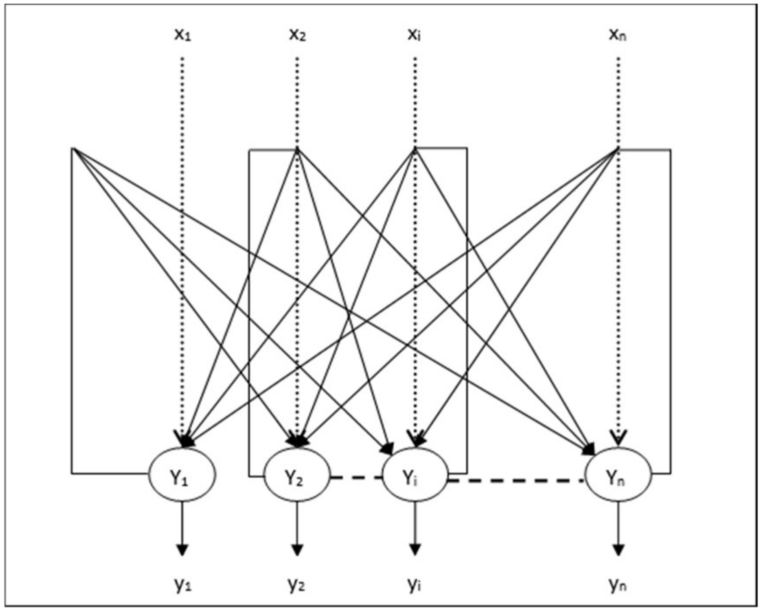
Population-based Incremental Learning

- Evolutionary like GA
- Attempts to reduce memory footprint of GA
- Mutation occurs at attribute
- Pros
  - Smaller memory footprint than GA
- Cons
  - Not guaranteed to find optimal solution

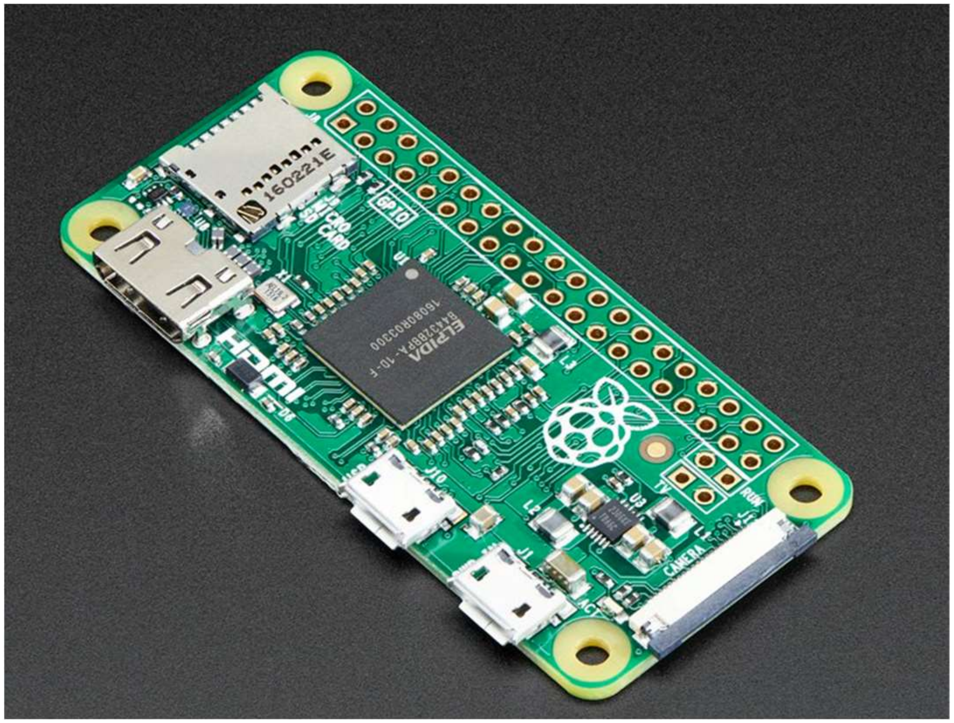


Hopfield Network

- Neural networking
- Nodes and edges
- Edges consist of weights which determine optimal paths
- Pros
  - Stored patterns can increase search time
- Cons
  - Edges may only evaluate one criteria at a time
  - May converge to wrong local minimum



Test strategy

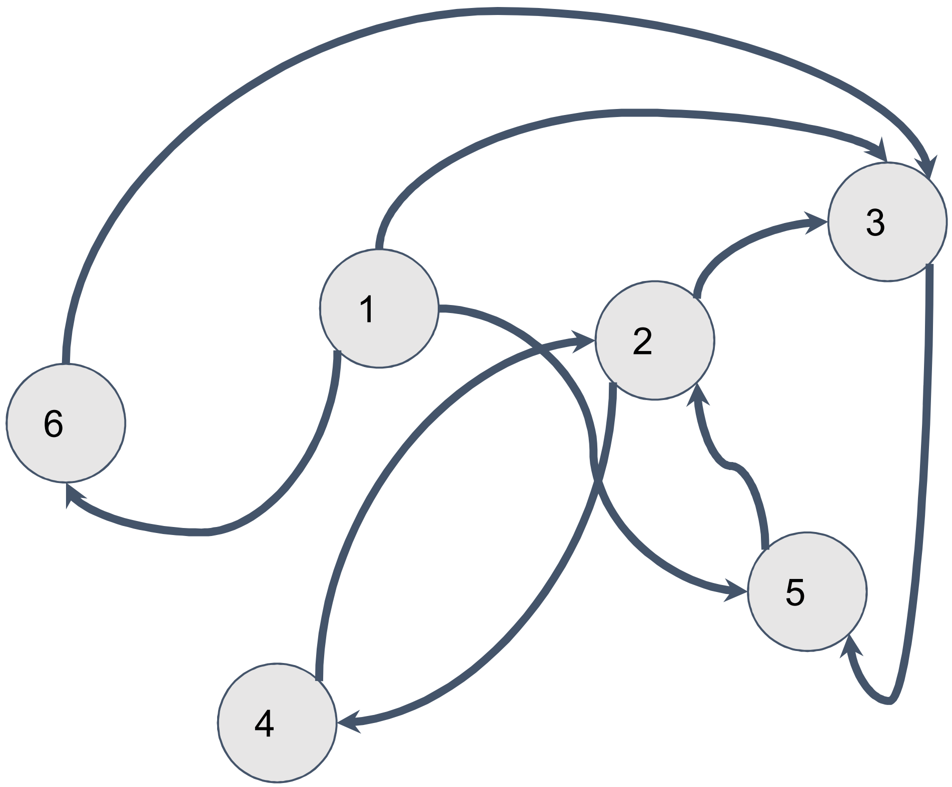


- C++ simulation of network graph
  - Nodes, edges, requests, routes
  - Metadata held at edges and nodes
    - Data rate, power, schedule
- Hardware emulation replaces software nodes
  - Raspberry Pi Zero, resource constraint

Project status

- Current
  - C++ Network Graph setup and can be imported
  - Schedule requests in place (Manual or automatic)
  - Genitor (GA) transferred to C++ and running appropriately based on one criteria (data rate)
  - Simulated annealing transferred to C++
  - Hopfield network placeholder code in place
- To do
  - Add time varying parameters to optimization
  - Increase node/edge count
  - Add power requirement as paramter
  - Implement PBIL and HN
  - Create GUI

Network Graph



Thank you

- Patrick Barnes - MTI Systems, Inc

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