A Neural Network-Based Proposal for Optimizing Battery Life and Autonomous Task Management in Nanosatellites

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LINX

Energy Efficiency Requirements

The network must ensure that the battery's state of charge (SoC) remains above 20%, avoiding long periods below 30% to ensure the satellite's longevity and effectiveness.

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Reinforcement Learning

Reinforcement learning is an area of machine learning inspired by behavioral psychology, which focuses on determining what actions a software agent should choose in a given environment to maximize some notion of cumulative reward or prize.

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DQN

Our model will be a feedforward neural network that takes the difference between the current and previous screen patches. It has two outputs, representing Q(s, left) and Q(s, right) (where s is the network input). Effectively, the network tries to predict the expected return of performing each action given the current input. Reinforcement Learning (DQN) Tutorial

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Bellman's equation

$$V(s) = \max_a \{R(s, a) + \gamma V(s')\} \tag{1}$$

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Explanation of the Bellman Equation

The Bellman equation is defined as:

$$V(s) = \max_{a} \{R(s, a) + \gamma V(s')\} \tag{2}$$

Where:

- $V(s)$ is the value of state s. It represents the maximum expected return when the agent is in state s.
- $\max_a$ denotes that we are selecting the action a that maximizes the following value.
- $R(s, a)$ is the immediate reward received for taking action a in state s.
- γ is the discount factor, balancing the importance of immediate rewards versus future rewards. It ranges from 0 to 1.
- $V(s')$ is the value of the subsequent state s', representing the expected return from that new state.

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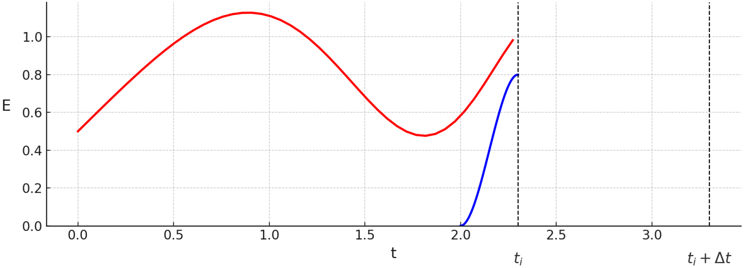
W_0



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Task Execution Model

$$\mathrm{M}_j = \left(\left[I, t'_j, \Delta t_j, P_j^R, P_j^D\right], \left[W_I^R, W_I^D\right]\right)$$

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Definitions

Where:

- I - Initial time.
- t'_j - Time at which task j is scheduled to be executed.
- Δt_j - Time duration for which task j is executed.
- P_j^R - Execution priority: indicates the relative importance of task j compared to other tasks in terms of when they should be executed.
- P_j^D - Data download priority: indicates the relative importance of task j in terms of when associated data should be downloaded.
- $\left[W_i^R, W_i^D\right]$ - Intrinsic properties.

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Status and Vectors

Status information:

$$E(t_i); \quad \frac{dE}{dt}; \quad \frac{d^2E^-}{dt^2}$$
$$W(t_i); \quad \frac{dW^-}{dt}; \quad \frac{d^2W^-}{dt^2}$$

Data vector for project:

$$D = (d_1, d_2, \ldots, d_J) \quad \text{amount of data of task } j$$

Execution status vector:

$$S = (s_1, s_2, \ldots, s_J) \quad / \quad s_j = \begin{cases} 0 & \text{if } j \text{ not executed} \\ 1 & \text{if } j \text{ is executed} \end{cases}$$

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Expected output vector

$$
\begin{array}{c|c}
 & \begin{array}{cccccc} 1 & 2 & 3 & 4 & 5 & \cdots \end{array} \\
\hline
\begin{array}{c} t1 \\ t2 \\ t3 \\ t4 \\ t5 \\ \vdots \end{array} &
\left[\begin{array}{cccccc}
0 & 0 & 1 & 0 & 0 & \cdots \\
1 & 0 & 0 & 0 & 0 & \cdots \\
0 & 1 & 0 & 0 & 0 & \cdots \\
0 & 0 & 0 & 0 & 1 & \cdots \\
0 & 0 & 0 & 1 & 0 & \cdots \\
\vdots & \vdots & \vdots & \vdots & \vdots & \ddots
\end{array}\right]
\end{array}
$$

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Implementations

Red Plus 001 –jorge vega
Red 002 –jorge vega
Red 003 –jorge vega
DQN (12 march 2024) – Carlos
Retask priorities –Jorge Vega
SoC Cycles prediction –Jorge Vega
Power Graph (09 april 2024) –ciph

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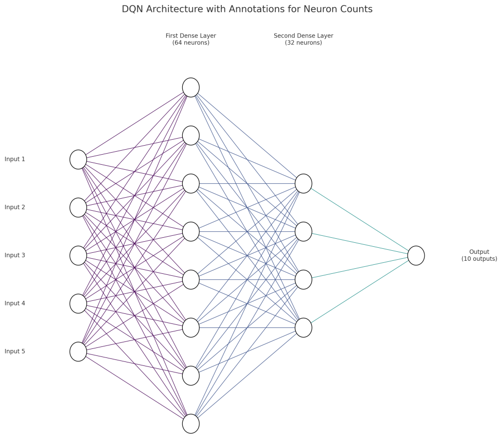
Architecture



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