MLNav:
Machine Learning-based Path Planning for Improved Rover Navigation

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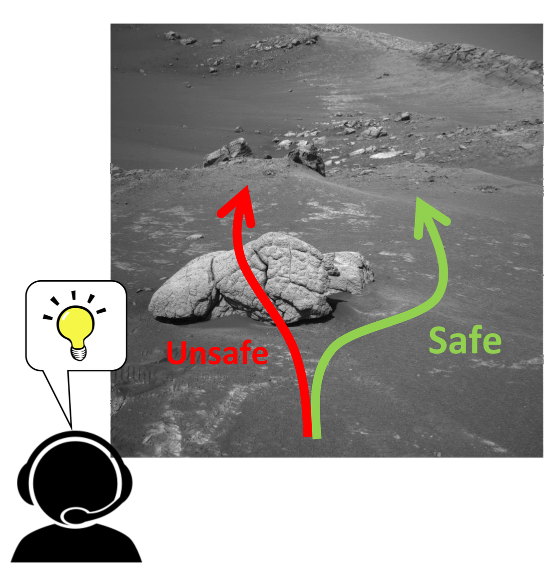
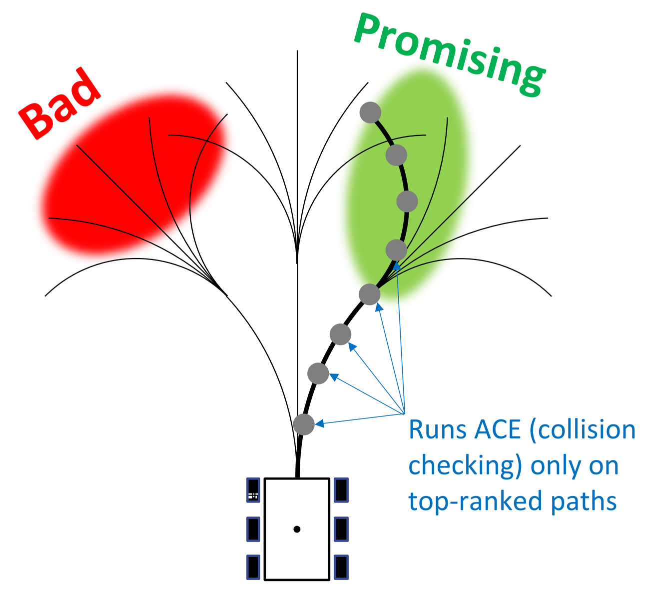
Objective: to develop a software framework to provide a machine-learning-assisted autonomous driving capability for future rovers to enhance efficiency and bring the technology to TRL4.

Core Idea: Experienced rover drivers have an intuition about which paths are safe. Our new algorithm, MLNav, mimics this intuition through a learning-based search heuristics, while guaranteeing safety by running the same, computationally expensive collision checking as ENav, called ACE, only on top-ranked paths.

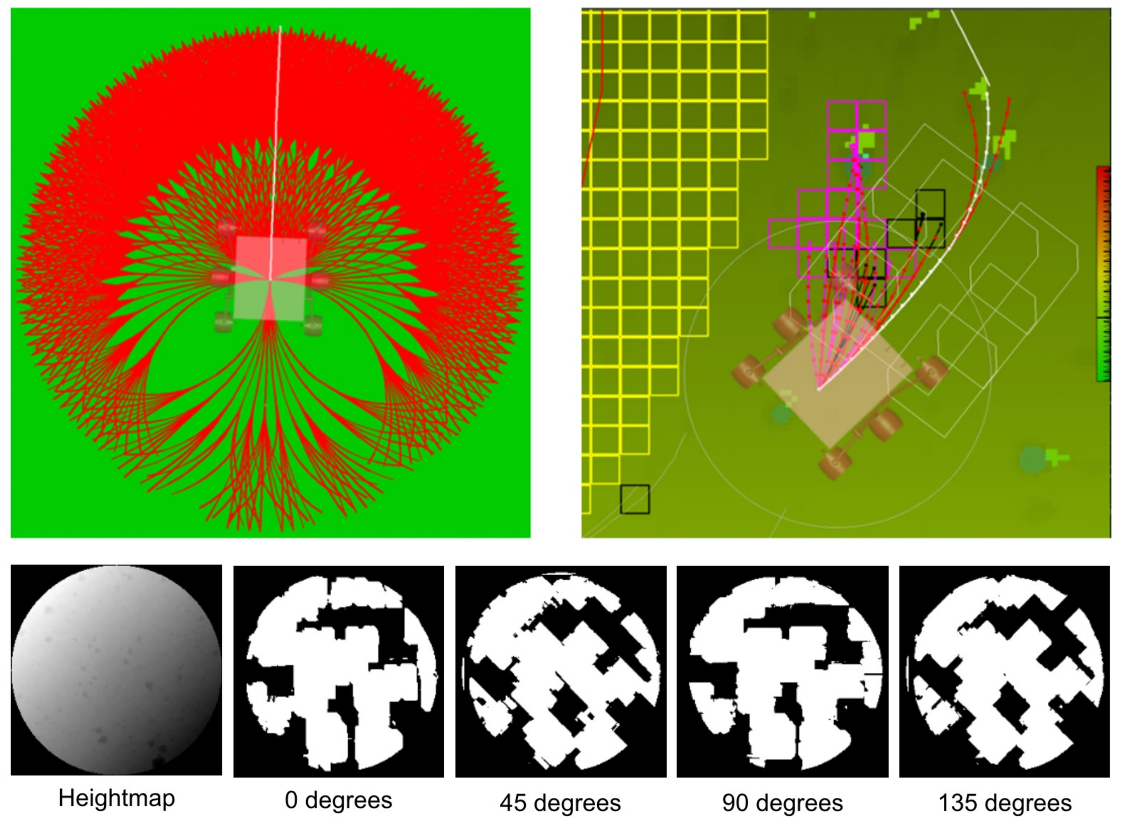
Human driver's intuition

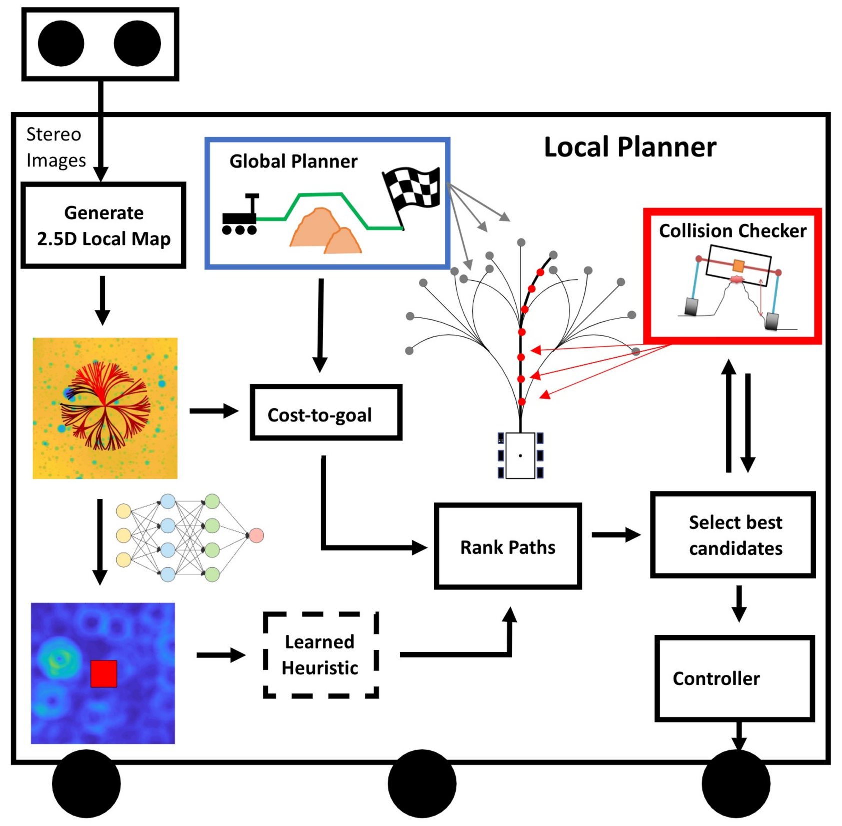


MLNav's learning-based heuristics

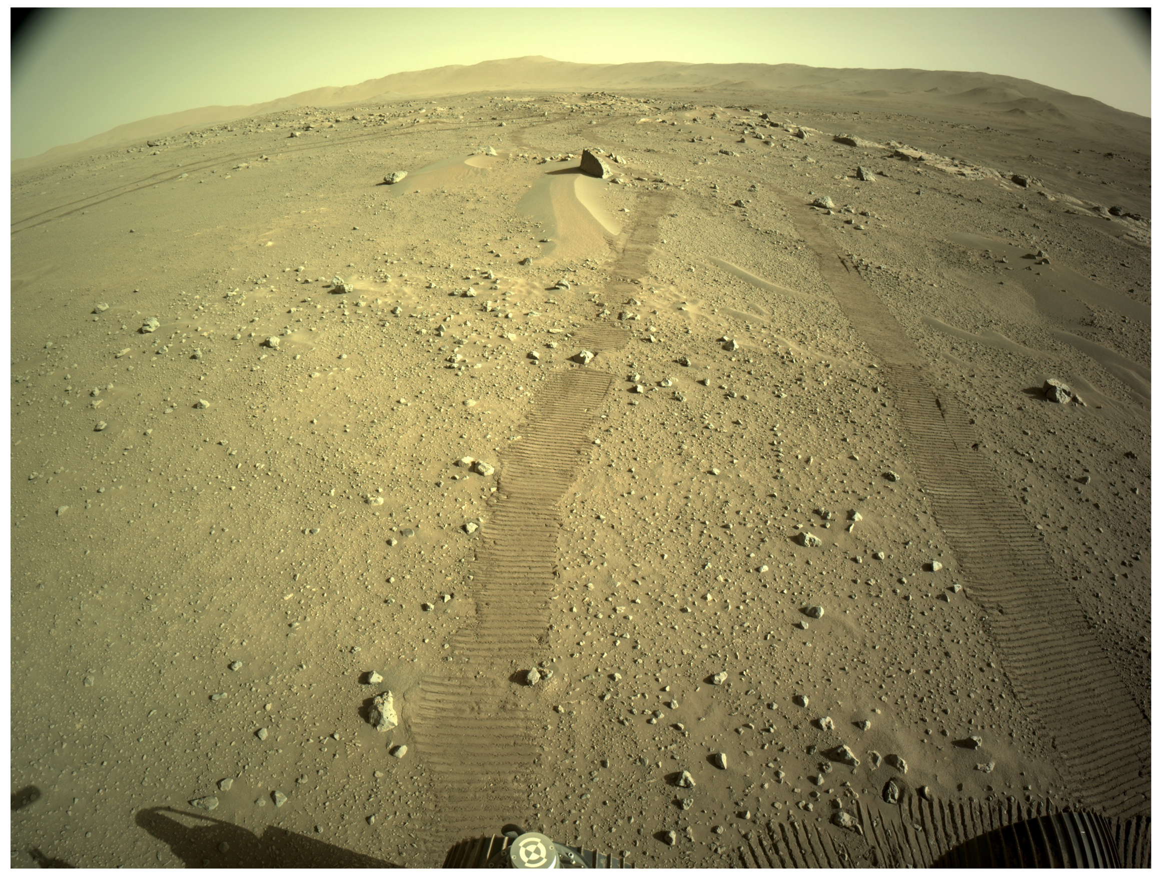


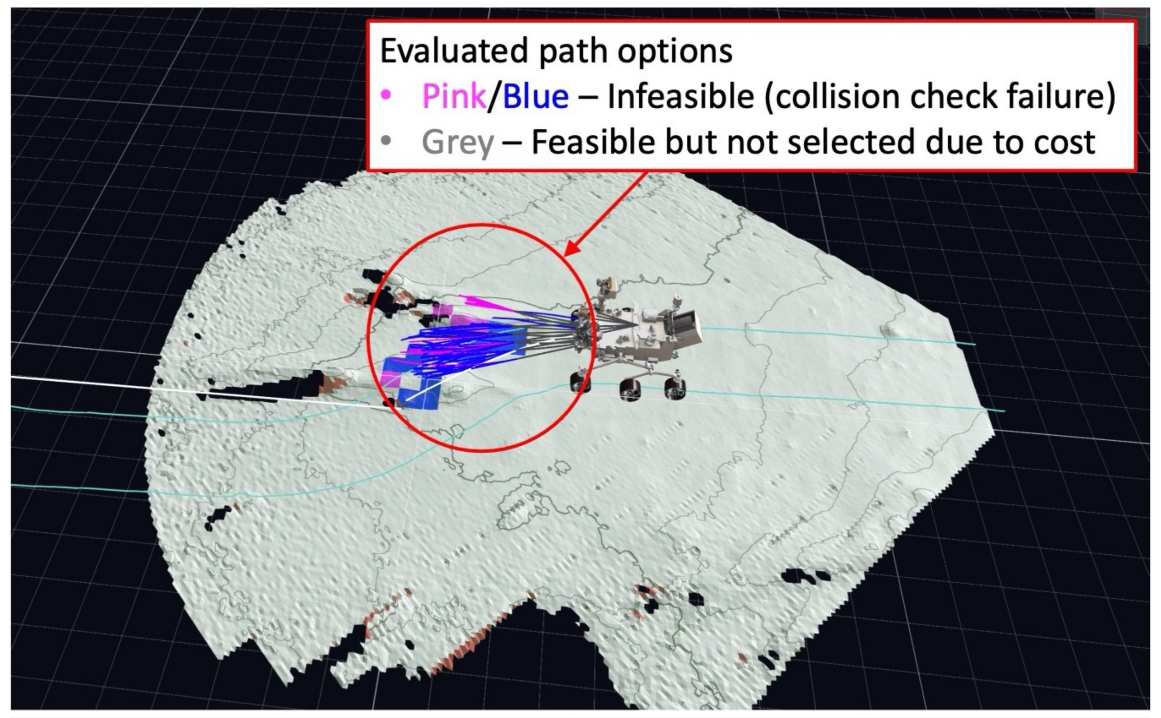
Approach: In a nutshell, MLNav is a search-based path planner that uses learned heuristics, where the safety of the chosen path is guaranteed by running a model-based collision checker. A single run of the MLNav heuristic takes a heightmap of terrain as an input and outputs the predicted outcomes of ENav's computationally demanding collision checking, ACE, at every cell of the map for multiple headings. It employs the U-net model, trained in a supervised manner with a training dataset collected by running ACE numerous times on synthetic terrains in ENav Sim. The path options are ranked by MLNav heuristics and other cost metrics, where ACE is run only on the top-ranked paths until a feasible path is found.

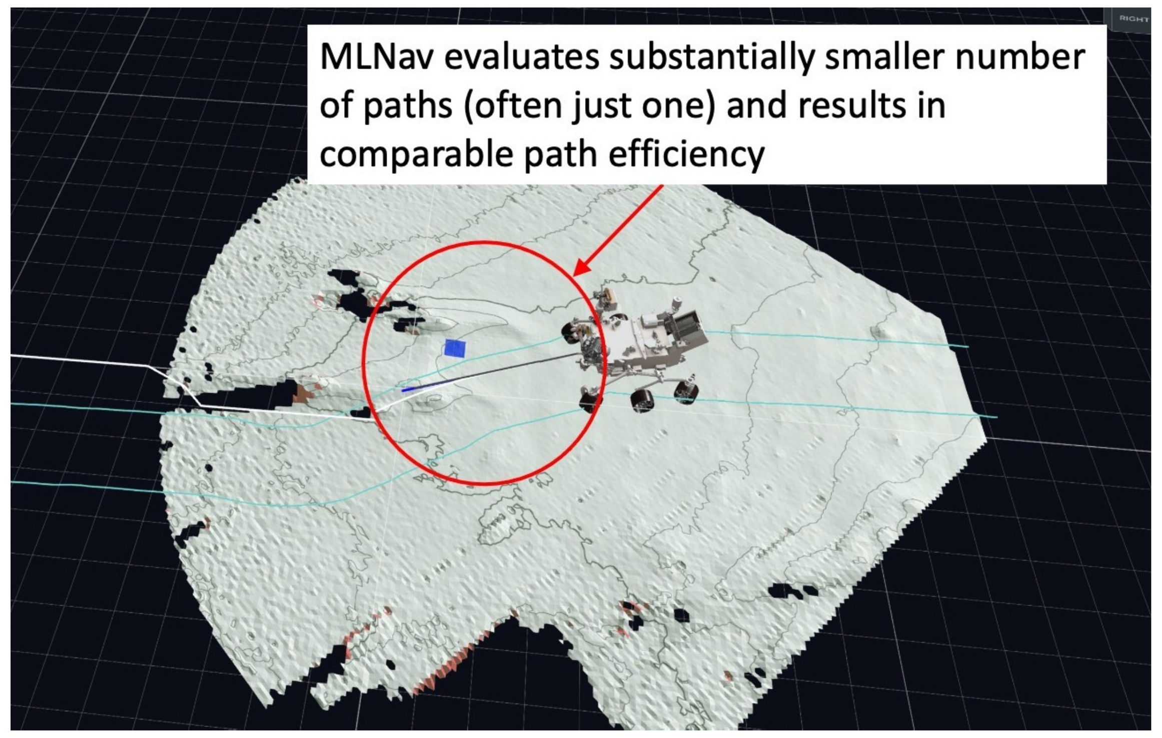




Simulation on M2020's Sol 122 terrain







Results: The table shows quantitative results, evaluated by 1,500 Monte-Carlo runs each. Improvement in success rate on complex terrains from 69.9% to 78.8% was achieved together with 31% reduction in path inefficiency and 36% reduction in overthink rate. MLNav successfully ran on real Mars terrain data from Perseverance on Sol 122 and 178. This result is particularly remarkable because the training data that we used for this experiment was produced solely with synthetic terrains before the landing of the rover.

PERFORMANCE EVALUATION OF MLNAV FOR MARS ROVER NAVIGATION. WE COMPARE MLNAV TO THE BASELINE ENAV, AND STUDY ITS SENSITIVITY TO KEY PARAMETERS (MLNAV†) AND TREE DESIGN (MLNAV†(*BT*), MLNAV†(*DT*) AND MLNAV†). SEE IV-C(C) FOR MORE DETAILS.

Metric	Terrain	Baseline	MLNav	Baseline†	MLNav†	MLNav† (BT)	MLNav† (DT)	MLNav† (VLT)
Success rate (%)	Benign	100.0	99.5	99.4	99.9	99.9	98.5	99.7
	Complex	69.9	72.5	69.0	69.3	73.9	59.9	78.8
Path Inefficiency (%)	Benign	4.4	3.9	3.95	3.3	3.2	3.7	3.0
	Complex	25.4	20.4	22.1	19.5	17.6	19.1	17.6
Number of Collision Checks	Benign	275	262	74	39	58	78	70
	Complex	377	283	216	90	142	164	317
Overthink Rate (%)	Benign	5.3	2.2	4.7	1.2	2.7	4.4	2.98
	Complex	20	7.1	19	6.5	10.3	15.6	12.6

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