Developing Scientific Writing through In-Class Workshops

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Inquiry focus

Training a key skill: **proposal writing**
Broad focus: critical thinking, long-term learning

Target course

ME5418 Machine Learning in Robotics
Graduate, elective course (Msc)

Overview of short intervention (10-15 mins)

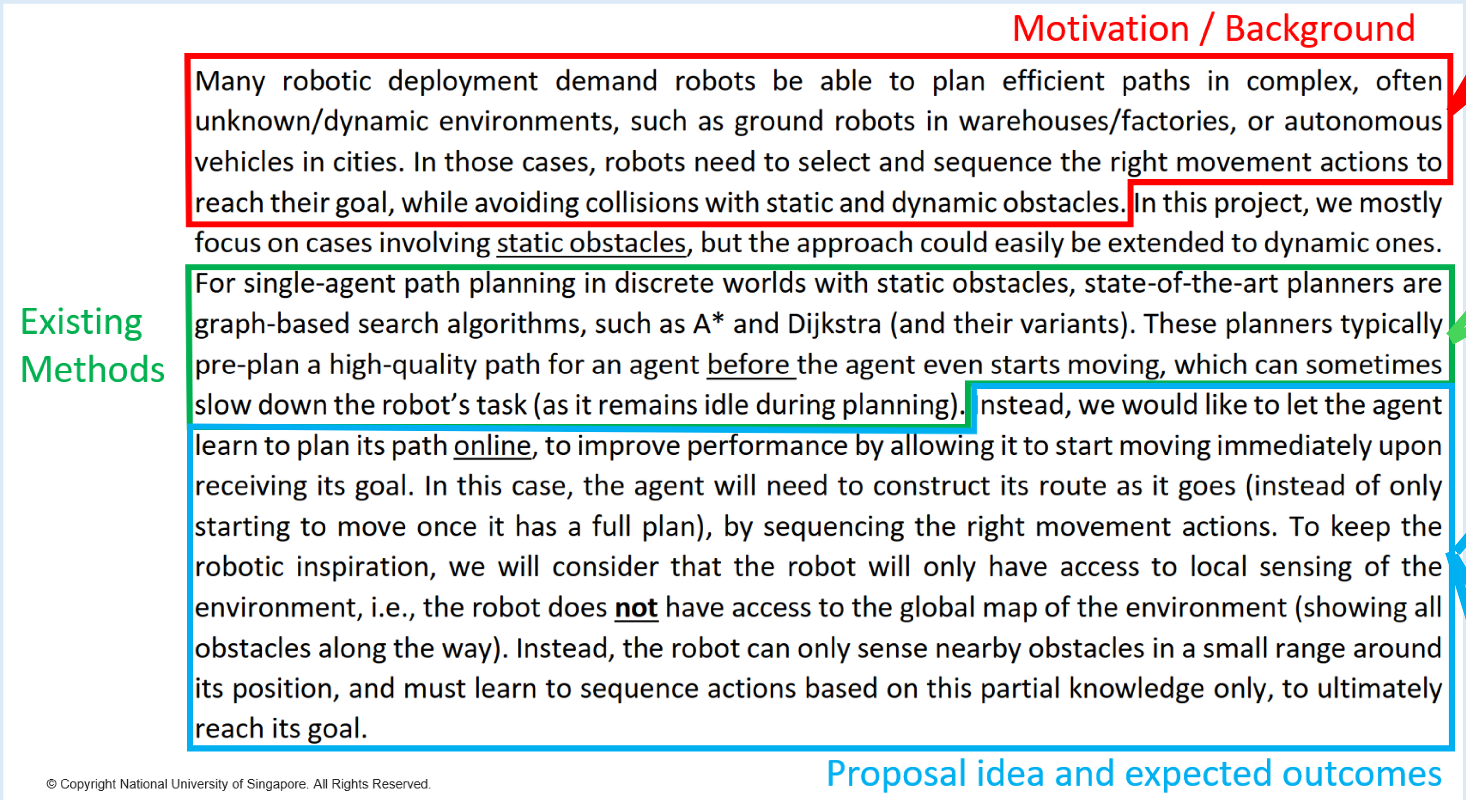
Assess **prior knowledge and intuition** via good & bad exemplars (PollEV) → **Mini-lecture** after poll results, presenting proper writing techniques

Discussion points

Proper structure of a good proposal
(rationale, background, proposed idea)

Jargon
(to avoid or define)

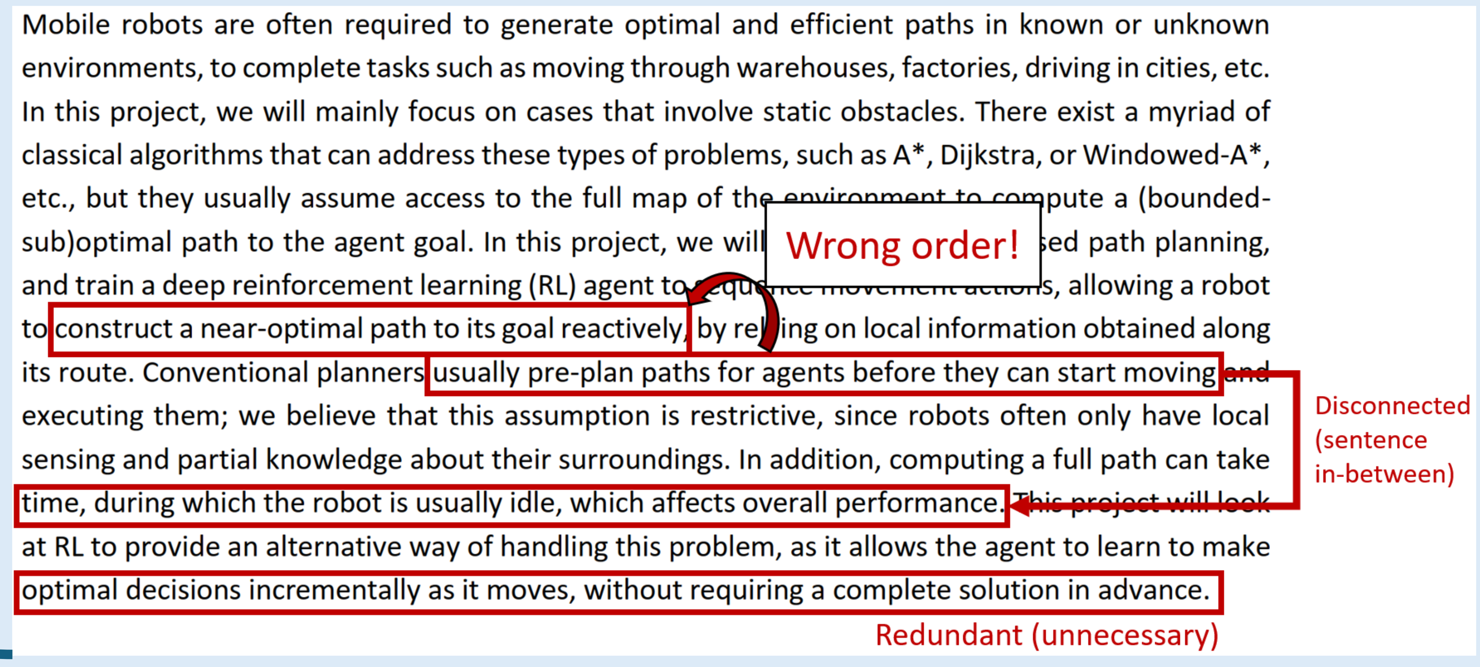
Proper content


Motivation / Background

Many robotic deployment demand robots be able to plan efficient paths in complex, often unknown/dynamic environments, such as ground robots in warehouses/factories, or autonomous vehicles in cities. In those cases, robots need to select and sequence the right movement actions to reach their goal, while avoiding collisions with static and dynamic obstacles. In this project, we mostly focus on cases involving static obstacles, but the approach could easily be extended to dynamic ones. For single-agent path planning in discrete worlds with static obstacles, state-of-the-art planners are graph-based search algorithms, such as A* and Dijkstra (and their variants). These planners typically pre-plan a high-quality path for an agent before the agent even starts moving, which can sometimes slow down the robot's task (as it remains idle during planning). Instead, we would like to let the agent learn to plan its path online, to improve performance by allowing it to start moving immediately upon receiving its goal. In this case, the agent will need to construct its route as it goes (instead of only starting to move once it has a full plan), by sequencing the right movement actions. To keep the robotic inspiration, we will consider that the robot will only have access to local sensing of the environment, i.e., the robot does not have access to the global map of the environment (showing all obstacles along the way). Instead, the robot can only sense nearby obstacles in a small range around its position, and must learn to sequence actions based on this partial knowledge only, to ultimately reach its goal.

Existing Methods

Proposal idea and expected outcomes


Mobile robots are often required to generate optimal and efficient paths in known or unknown environments, to complete tasks such as moving through warehouses, factories, driving in cities, etc. In this project, we will mainly focus on cases that involve static obstacles. There exist a myriad of classical algorithms that can address these types of problems, such as A*, Dijkstra, or Windowed-A*, etc., but they usually assume access to the full map of the environment to compute a (bounded-sub)optimal path to the agent goal. In this project, we wil Wrong order! sed path planning, and train a deep reinforcement learning (RL) agent to movement actions, allowing a robot to construct a near-optimal path to its goal reactively by relying on local information obtained along its route. Conventional planners usually pre-plan paths for agents before they can start moving and executing them; we believe that this assumption is restrictive, since robots often only have local sensing and partial knowledge about their surroundings. In addition, computing a full path can take time, during which the robot is usually idle, which affects overall performance. ~~This project will look at RL~~ to provide an alternative way of handling this problem, as it allows the agent to learn to make optimal decisions incrementally as it moves, without requiring a complete solution in advance.

Disconnected (sentence in-between)

Redundant (unnecessary)

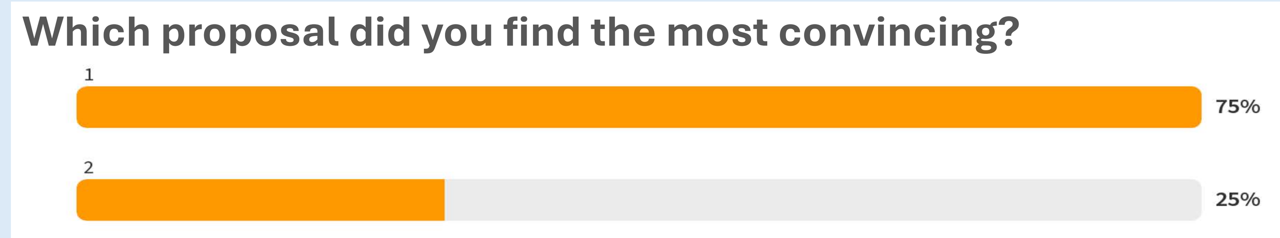
Critical Thinking Value Rubric

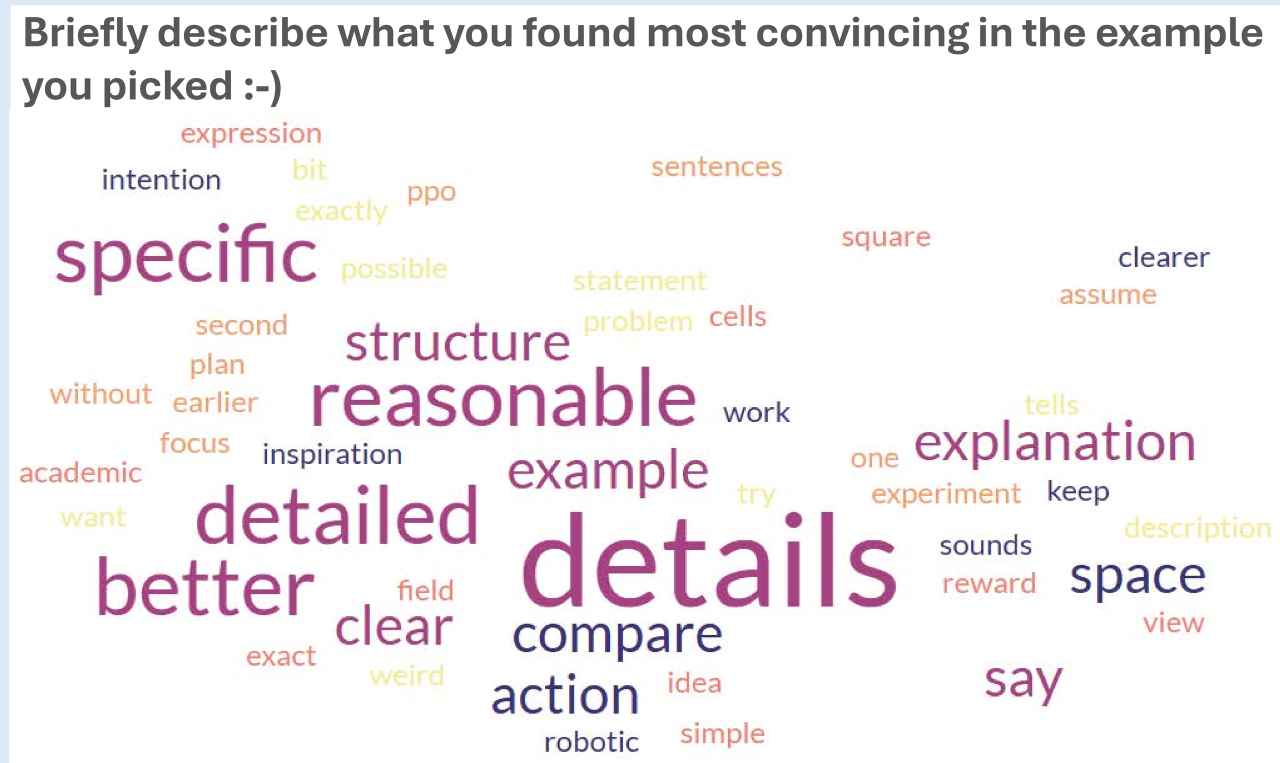
- Topic selection
- Existing Knowledge, Research, and/or Views
- Explanation of issues
- Design Process
- Analysis
- Evidence
- Influence of context and assumptions
- Team's position (perspective, thesis/hypothesis)
- Problem Solution and related outcomes
- Limitations and Implications

Approach

- Compare end-of-course group proposals (n = ~33 per class) between AY2024 and AY2025.
  - **Quantitative analysis** (Critical Thinking Value Rubric + direct approval (yes/no))
  - **Qualitative description**: reflection over proposal quality (TA feedback); random sampling by Instructor

Cross-sectional findings (N = 100 students in class)





Pre- post evaluation: change in proposal quality

- **Hypothesis:** proposals' structure and content will show quantifiable, significant improvement
- **Quantitative analysis:** *pending* (data available)

Limitations

- **Potential confounders**: language skills; proposal's topic
- **Sample**: small size; different pre and post students

Implications & next steps

- Complete the quantitative analysis
- Extend intervention to future iterations of the course