# Sample article to present `elsarticle` class[☆]

Author One[1,1,1,], Author Two[1], Author Three[1,1]

[a] *Address One*
[b] *Address Two*
[c] *Some University*

**Abstract**

Text of abstract. Text of abstract. Text of abstract. Text of abstract. Text of abstract.

*Keywords:* foraging, active learning, template or
*2008 MSC:* code, code (2000 is the default)

## 1. Introduction

1. Why did I do the work? Robots exploring the world right now either depend highly on their controllers to give them objectives or they are planning with some global knowledge. Operating in these kinds of conditions puts constraints on robot exploration opterations by relying on either humans to make decisions or a significant amount of scouting.
   Relying on humans to make decisions means that remote operators require considerable bandwidth to acquire sufficient situational awareness. Conducting sufficient reconnaissance to make good decisions often obviates the need to send a robotic agent.
   What is lacking in the literature are robots that make decisions about what to investigate *in situ* without reliance on humans and without necessarily having global knowledge.
2. What were the central motivations and hypotheses? Animals, e.g. human geologists, make decisions about investigating phenomena in the world without necessarily having access to high resolution satellite imagery. Despite this lack they are able to chose between sampling from materials in front of them and moving on to determine more profitable sampling locations.
   While these decisions may not be globally optimal they do demonstrate an ability that is lacking from exploration robots: to make decisions to stop and engage with the environment or to continue travelling in the hopes of finding more informative sampling locations.

[☆]This is only an example
[*]I am corresponding author
[1]I also want to inform about...
[2]Small city

## 2. Background

Who else has done what?

- Work in the 1970's about foraging. About making value judgements. - Evidence that humans make (approximately) rational decisions (we over and under estimate low and high probabilities)

- Design of experiments has led to (amongst other things) multi-armed bandit models of sequential experiment design. - See also maximum entropy sampling - See also mutual information sampling. - Also consider active learning solutions (they all end up being the same anyway)

- Robotics research has made robots that conduct exploration, but the only ones that make decisions about whether to investigate something or not do one of three things: 1. match templates. 2. seek improbable things. 3. Engage in opportunistic science - they do something if they have the time. They don't override human mission objectives.

1 and 2 say nothing about the information content of the material under investigation. 3 does not have the level of autonomy that we need for truly long-term or remote operations.

How?

What have we previously done: - D.R. Thompson's work - Only looking at satellite imagery. Good but not sufficient. - Trey's work - Using POMDPs not scalable to a planet. - Mine. Where does my previous work fall short? - Not bayesian (not a big deal?) - Still has the problem on knowing the number of sampling opportunities remaining.

## 3. Method

The experiment builds on prior work.

- Combining foraging models with bandit literature - Previous work had a limit on the number of samples it could take - This experiment models a type of prospecting where the number of samples isn't limited but they do take time. - To that end we are looking at productivity.

- This experiment is more akin to contextual bandits. - The image represents a context, the NIRVSS - Apply texturecam classification of a scene, as the context - the choice is to sample or continue

- Productivity

## 4. Results

## 5. Conclusion

## Appendix A. Section in Appendix

Sample text. Sample text. Sample text. Sample text. Sample text. Sample text. Sample text. Sample text. Sample text. Sample text. Sample text. Sample text. Sample text.