



# Search Algorithms in the Aftermath of a Disaster

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**COPIOR-HORAF CONFERENCE ON  
OPERATIONS/AL RESEARCH TOOLS FOR THE  
AFTERMATH OF A DISASTER:  
THE MAJOR EARTHQUAKE IN TURKEY-SYRIA**

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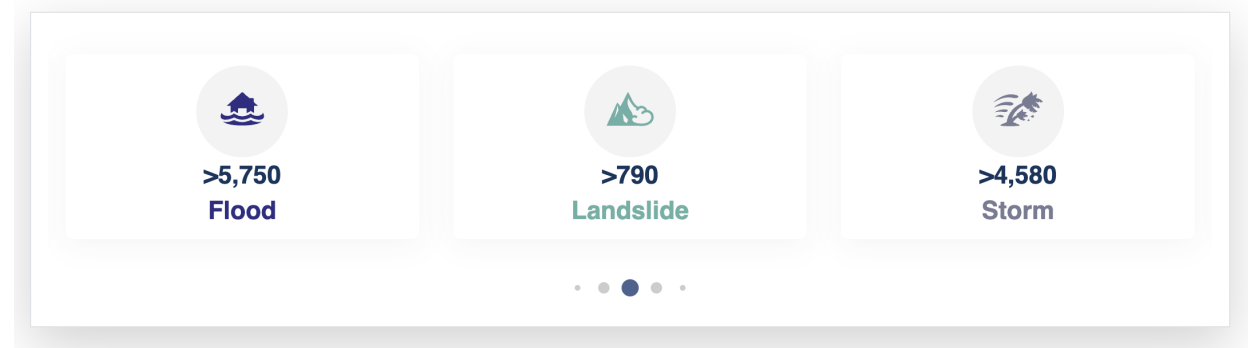
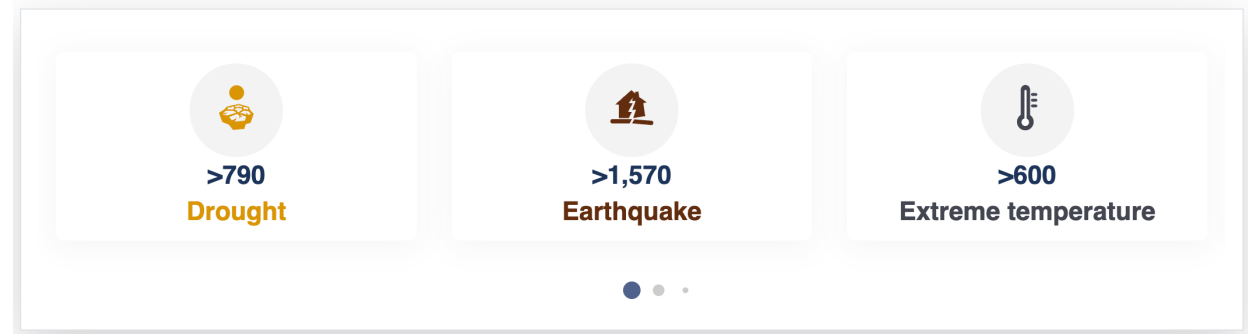
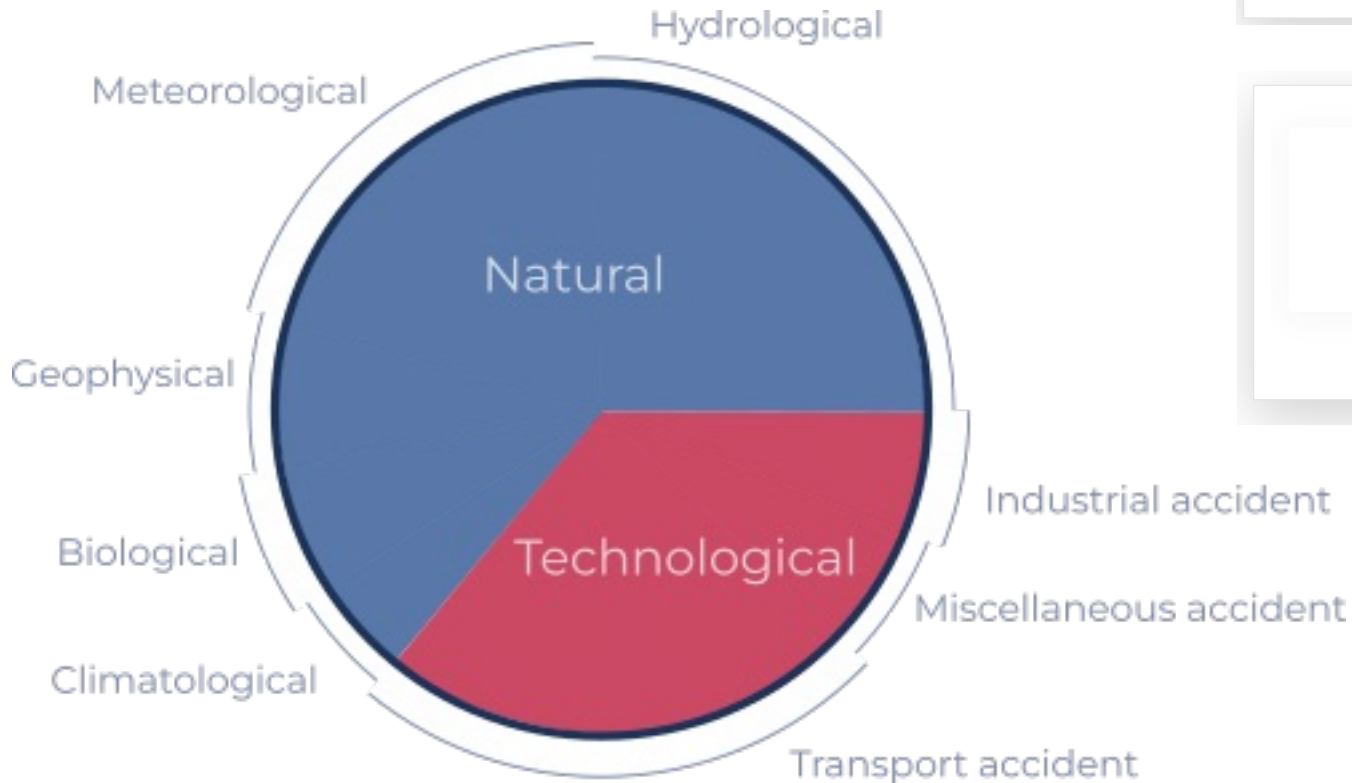
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# About 2/3 of disasters in EM-DAT ~ natural hazards



# Why we need search algorithms?

- It costs to find what we are searching for.
- Lives are at risk if we do not find people in time.

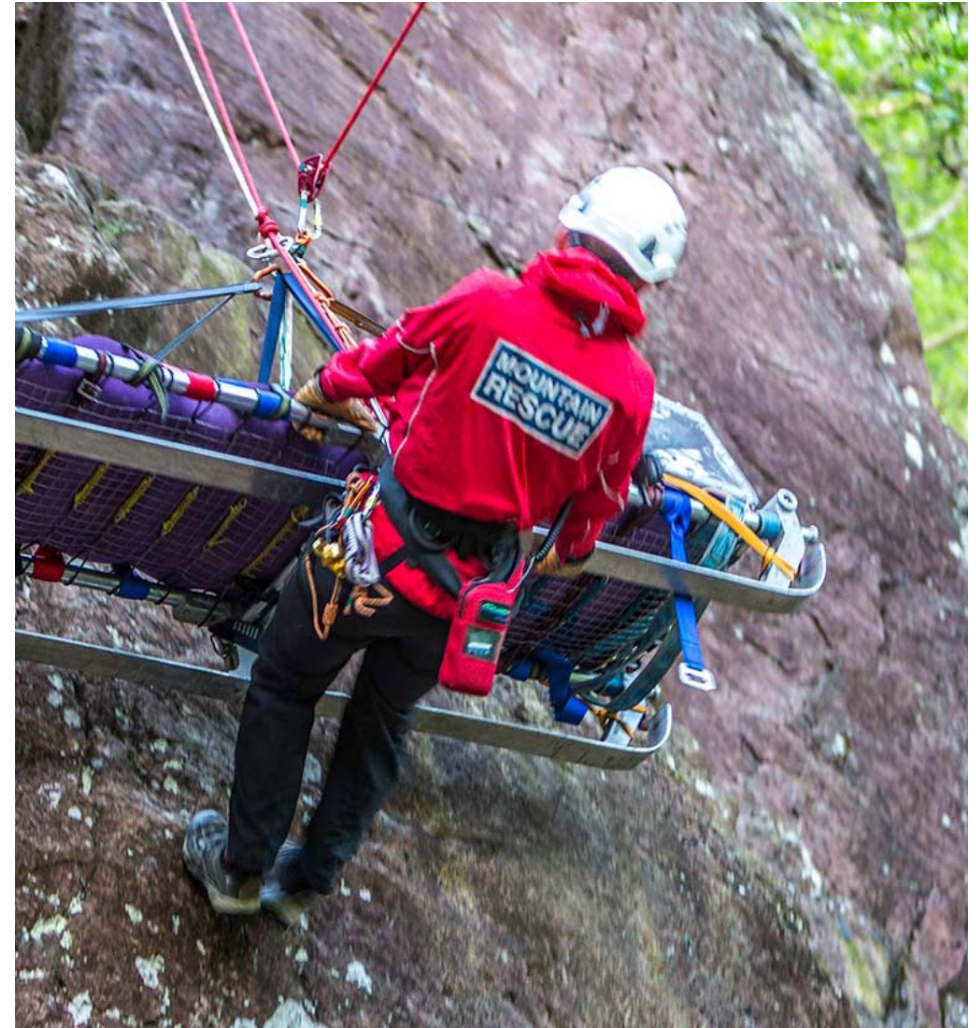
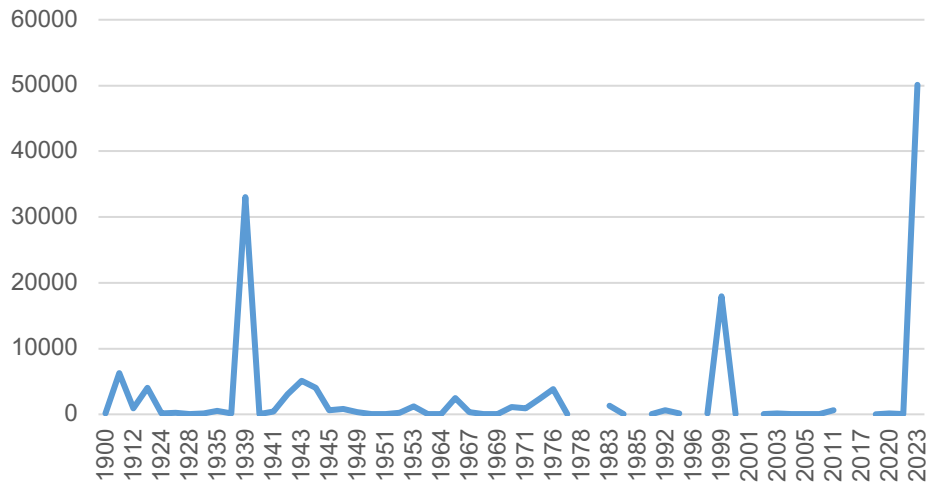


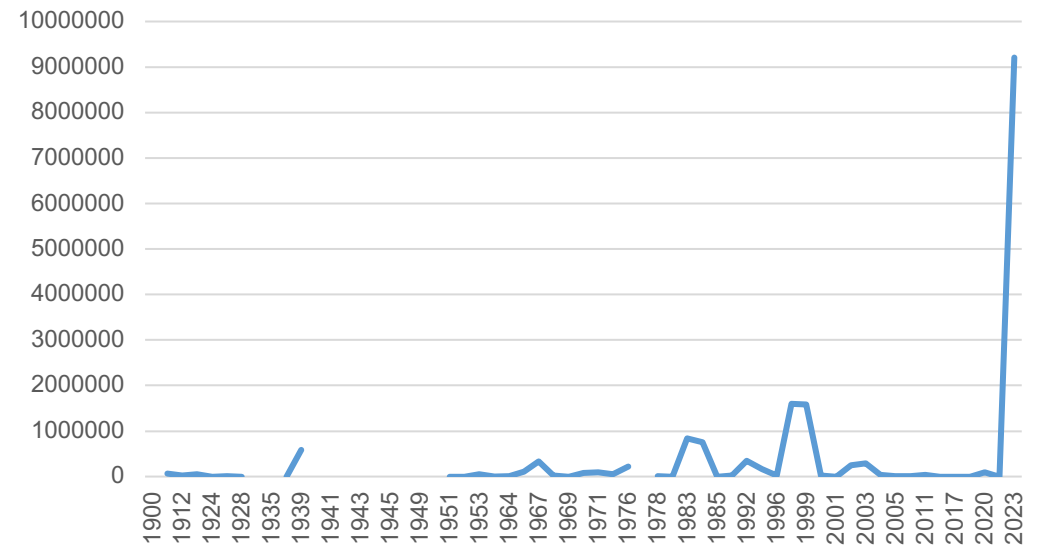
Image credit: <https://www.mountain.rescue.org.uk/>

# Earthquakes in Turkey

Sum of Total Deaths



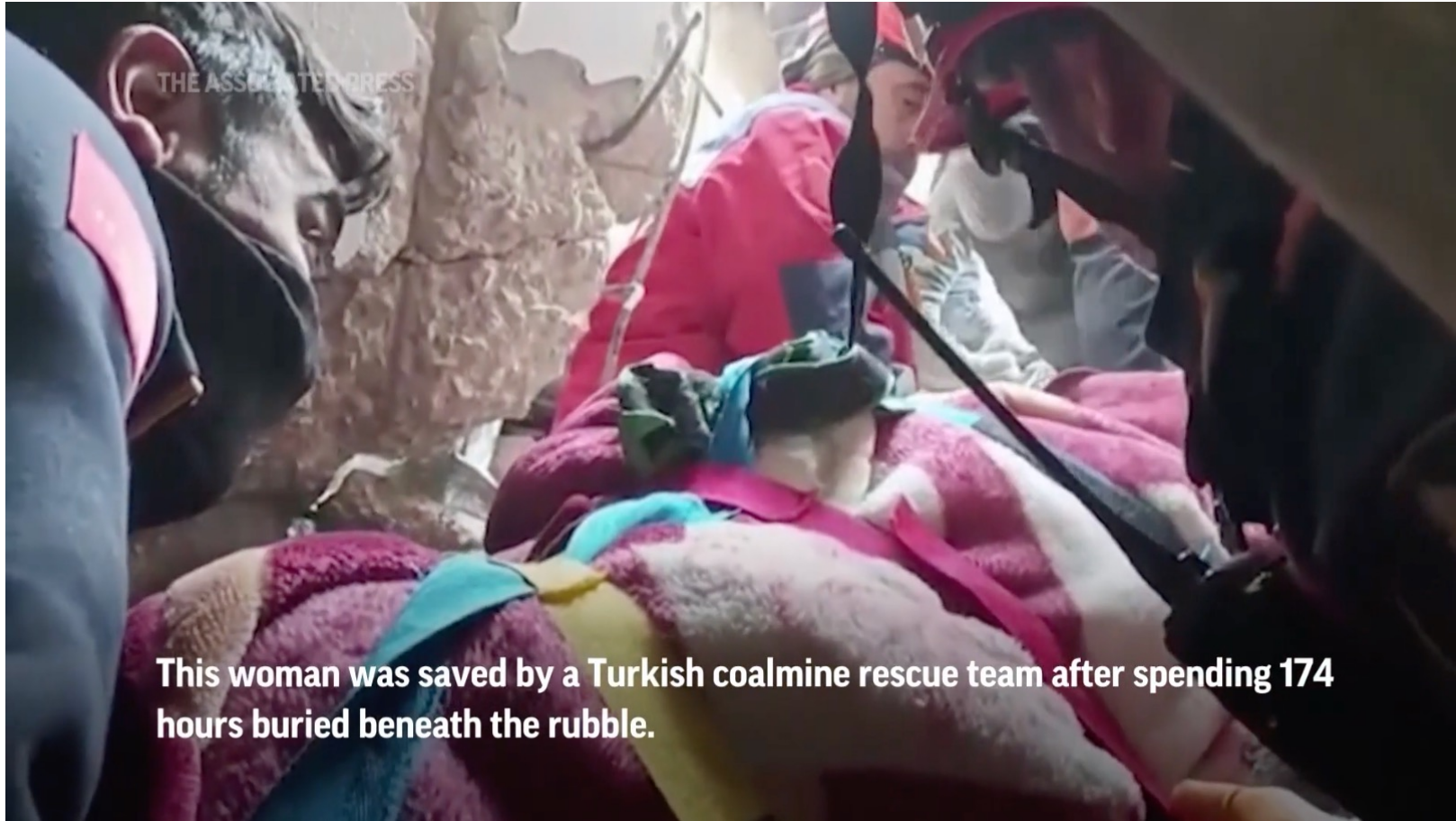
Sum of Total Affected



Source: EM-DAT



<https://www.theguardian.com/world/2023/mar/06/turkey-earthquake-victims-families-still-search>



**This woman was saved by a Turkish coalmine rescue team after spending 174 hours buried beneath the rubble.**

<https://apnews.com/article/disaster-planning-and-response-2023-turkey-syria-earthquake-earthquakes-a7ae0cf86757d238dc0dd5f6a5dd96ce>





# Optimal Search and Stop Problem

 JOURNAL ARTICLE

## A Periodic Optimal Search

David Matula

*The American Mathematical Monthly*, Vol. 71, No. 1 (Jan., 1964), pp. 15-21 (7 pages)

<https://doi.org/10.2307/2311296> · <https://www.jstor.org/stable/2311296> 

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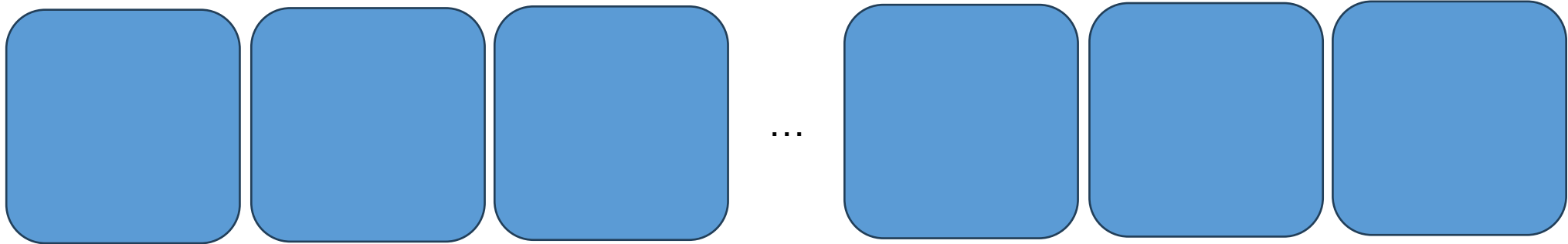
## A Problem in Optimal Search and Stop

Sheldon M. Ross

Published Online: 1 Dec 1969 | <https://doi.org/10.1287/opre.17.6.984>



# Problem Description



A finite set of possible locations,  $I$

$p_i$ : probability that the object is in one of these locations

$c_i$ : cost of searching each location

$a_i$ : probability of finding the object during the search when it is in  $i$

Minimise the expected cost of finding the object

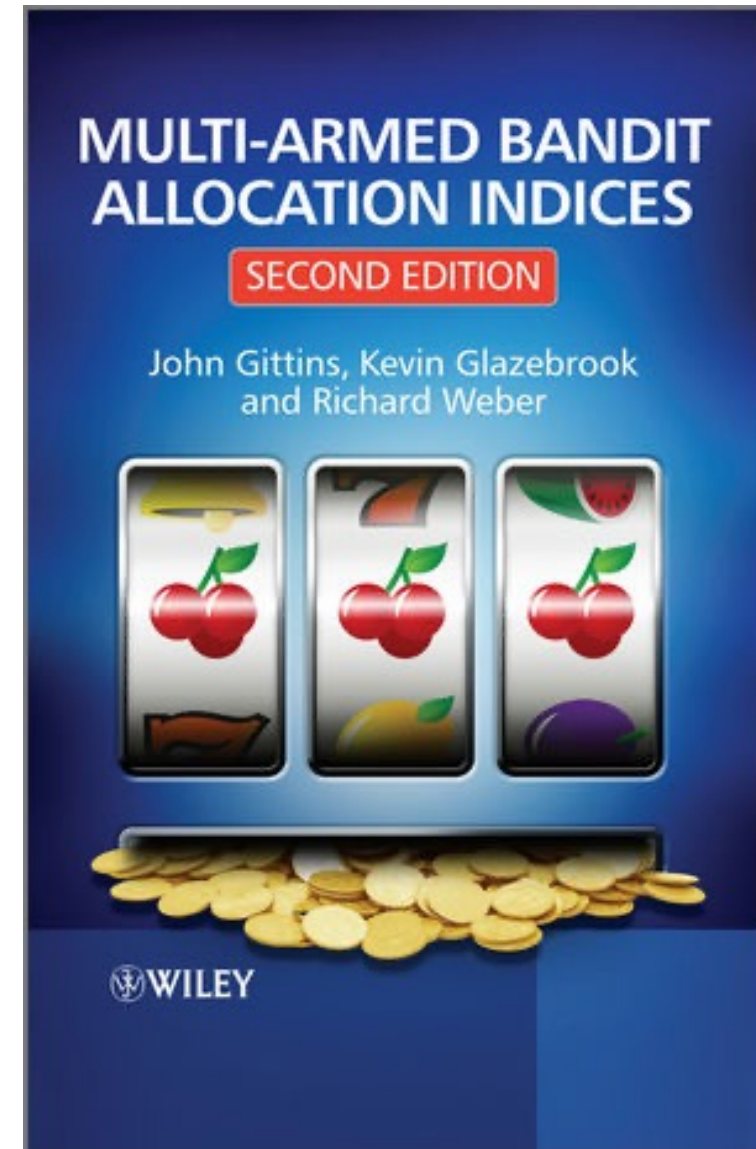
A strategy: when to search, and, if so, which box?

# Multi-Armed Bandit Problem

A decision-maker (“**gambler**”) chooses one of  $n$  actions (“**arms**”) in each time step.

Chosen arm produces random payoff from unknown distribution.

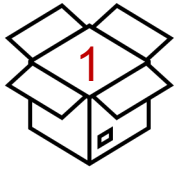
**Goal: Maximize expected total payoff.**



## Where else do we see MAB applications?

- Crowdsourcing
  - assigning the right tasks to right users (Lin et al., 2022)
- Sequential clinical trials in medicine (Aziz et al., 2021)
  - finding the optimal dosage in early stage clinical trials
- Ad placement
  - allocating the budget of an advertiser across multiple surfaces optimally when both the demand and the value are unknown (Avadhanula et al., 2021)
- Price experimentation
  - deciding on real-time prices for a large number of products with incomplete demand information (Misra et al., 2019)
- Search
  - Fast and slow (Clarkson et al., 2020)
  - With multiple sensors (Song and Teneketzis, 2004)

# An example



$p_i: .3$

$p_i: .2$

$p_i: .2$

$p_i: .3$

$c_i: 6$

$c_i: 3$

$c_i: 10$

$c_i: 2$

$a_i: .9$

$a_i: .5$

$a_i: .6$

$a_i: .4$

Search the location that maximises  
 $p_i * a_i (1 - a_i)^m / c_i$

Gittins Index from Multi-Armed Bandit

[0.045, 0.033, 0.012, **0.060**]

[**0.045**, 0.033, 0.012, **0.036**]

$m=1$

A search policy is an ordered list of locations to search

Find the policy that minimises the expected search time

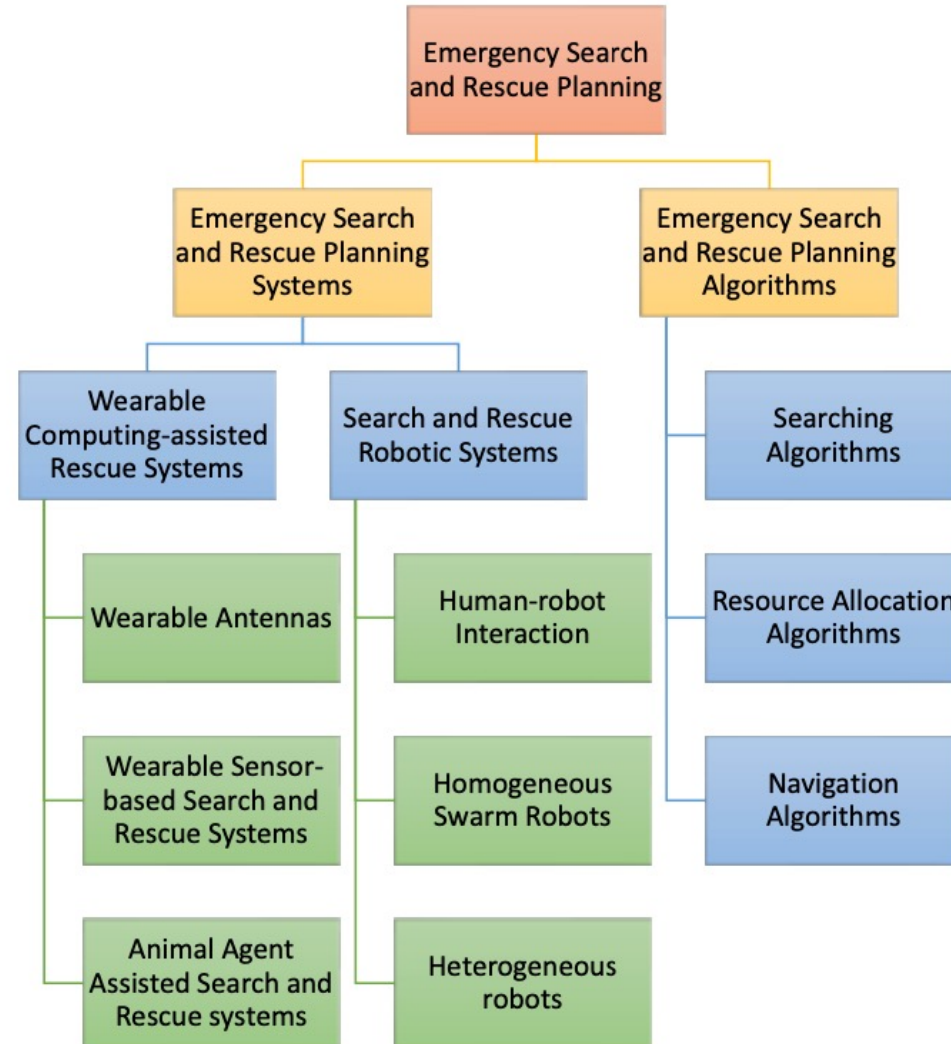
4, 1, 4, 2, 4, 2, 4, 3, 2, ...

## Extensions

- Search and rescue missions: Find an object before a crucial deadline
  - Lost at sea: hypothermia
  - After an earthquake: survivors underneath collapsed buildings
  - A bomb squad: find a time bomb before it explodes
- In many cases, the crucial deadline is not known to the search team.

*Lin and Singham (2016) propose a randomized search strategy that simultaneously maximizes the probability of finding the object by any deadline.*

# Concluding Thoughts





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