Smart Scheduling Using Transfer of Control Strategies for Multiagent Resource Allocation in Mass Casualty Scenarios

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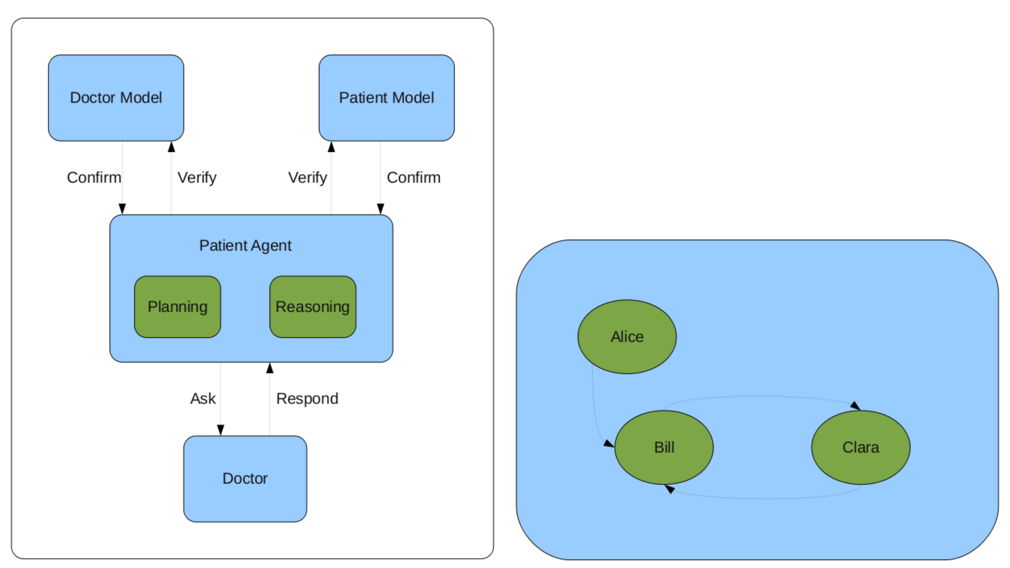
1. Introduction

- Novel approach to scheduling doctors, with a focus on mass casualty incidents.
- Based on multiagent resource allocation (MARA) and Transfer-of-Control strategies.
- Incorporation of user models and learning.

2. Patient scheduling as resource allocation

- Patient scheduling is a resource allocation problem, timeslots are the "resources".
- Patients value times based on personal preferences and their condition.

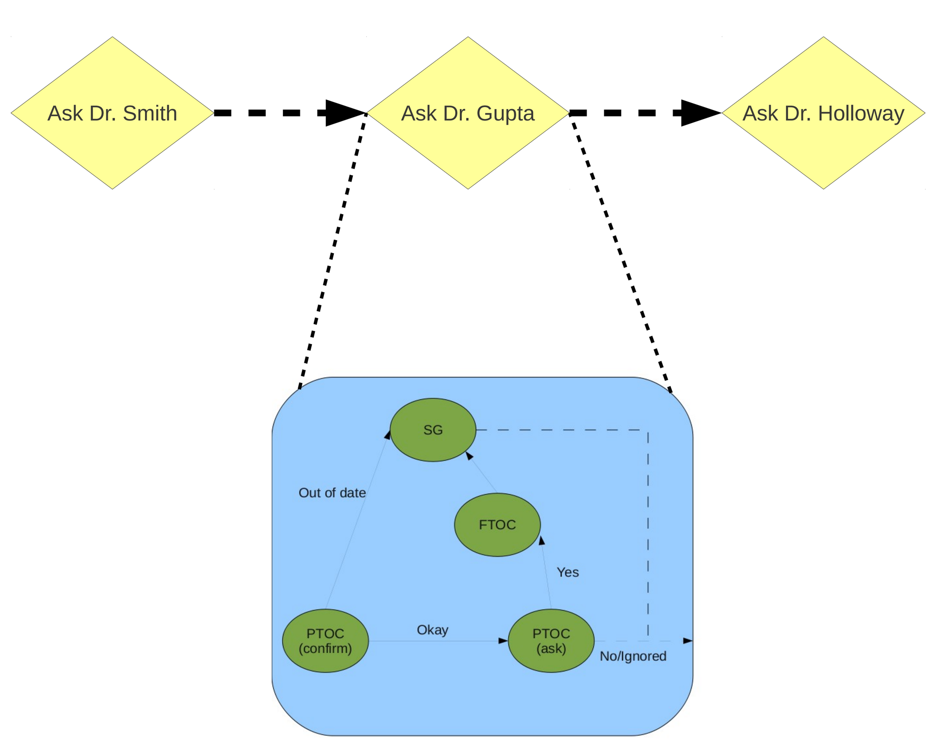
3. Multiagent resource allocation



- Each patient is assigned a software agent.
- Distributed negotiations optimize the schedule.
- Trouble estimating the cost of losing resources.

4. Planning

- Agents use pre-planned strategies in negotiation, called "Transfer-of-Control" (TOC) strategies[4][3].
- Strategies are made to maximize expected utility for a patient, and minimize the bothering doctors.
- An example TOC strategy:



- **F**ull **T**ransfer **O**f **C**ontrol (FTOC): Request that the doctor take over treatment.
- **P**artial **T**ransfer **O**f **C**ontrol (PTOC): Ask the doctor a question or confirm that the plan is still valid.
- **S**trategy **G**eneration (SG): Generate a new TOC strategy.

5. Estimating Costs using Transfer-Of-Control strategies

- The cost of preemption is the expected value of a contingency plan, less the benefit of the resource.
- This is a high quality estimate of the costs of changes in wait times and quality of care.
- Similar to micro-economic "Opportunity Costs".

6. Learning

- Circumstances change with time, but agents can adapt by learning.
- Let $c(x)$ be an interaction cost, $t(x)$ be an interaction time.
- Bother Costs estimates [4]:

$$BSF = \sum_{i \in I} c(i)\beta^{t(i)}$$

Where i is an interaction, β is the learning rate.

- Plan Length estimates:

$$k = \frac{1}{1 + \sum_{r \in R} c(r)\alpha^{t(r)}}$$

Where r is a regeneration, α is the learning rate.

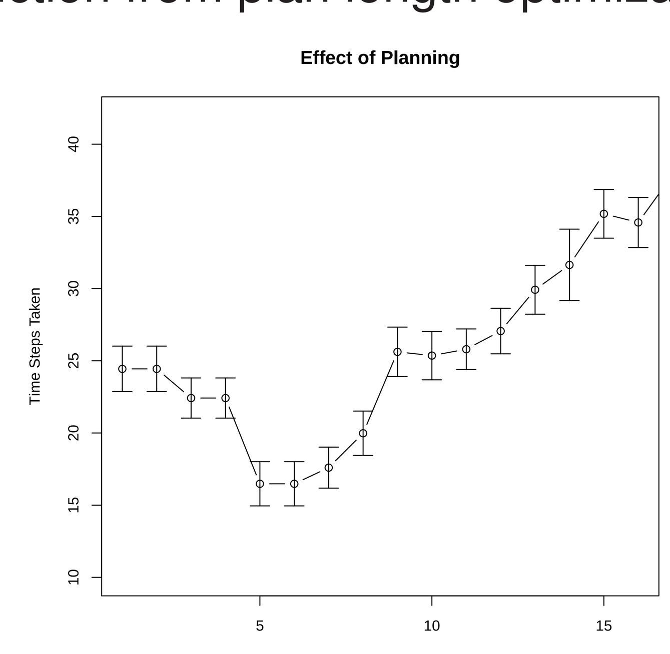
- Congestion estimates:

$$EU_{plan} = \frac{1}{1 + \sum_{p \in P} c(p)\gamma^{t(r)}}$$

Where p is a preemption, γ is the learning rate.

7. Effects of Learning

- Bother models improve resource utilization.
- Congestion and Plan length estimate prevent deadlock.
- Cost reduction from plan length optimization:



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7. Benchmarking

- We simulated the system to measure its performance.
- The scenario is a mass casualty incident, where many patients arrive simultaneously at a hospital with few doctors.
- This is not intended to accurately model every detail of a real-world scenario, but to provide an initial characterization of the system.

8. Example Experiment: User Modeling

- Patients are modeled by a deterioration rate $D(c)$ and criticality (c).
- Scenario goal: Minimize the costs (T(c)), suffering (S(c)) and percentages of 'problem patients'.
- Total cost incurred by a single patient between T1 and T2 is:

$$Cost(T_1, T_2) = \int_{T_1}^{T_2} S(c_t) + T(c_t).dt$$

with $D(C) = \frac{dc}{dt}$, so

$$c_t = c_{t_{init}} + \int_{t_{init}}^{t} D(c).dt$$

9. Example Experiment: Doctor Model

- Following [3] doctors are modeled with a type and degree of busyness.
- A bother model [4] tracks the impact of previous system interactions on doctor willingness to respond.
- Types capture the differences between, say, an intern and a heart specialist.

10. Example Experiment: Algorithm

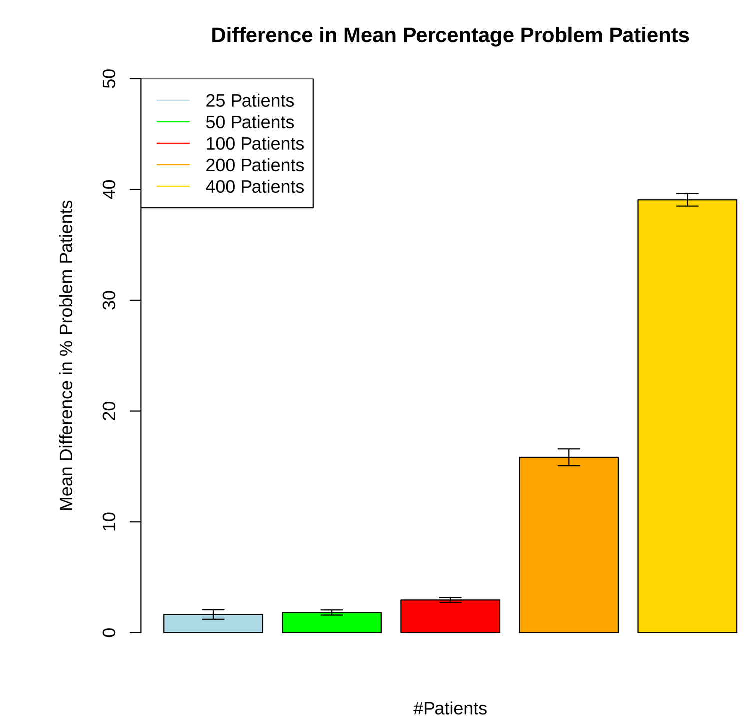
```
WHILE( there are still untreated patients )
  FOREACH Agent A
    //Let each agent take the next step in its TOC strategy
    execute_plan(A)
  ENDFOR

  //Patients deteriorate based on their conditions,
  //Doctors treat assigned patients
  update_simulation()
ENDWHILE

//Subroutine for executing the next step in a plan.
SUB execute_plan(Agent A)
  IF( A has no plan)
    generate_plan(A)
  ELSE
    execute(A->plan->next()) //execute the next TOC world.
  ENDIF
ENDSUB
```

11. Example Experiment: Strategy Generation

- Strategies are generated using a new dynamic programming approach.
- This approach requires improves upon those of prior authors ([3][4]), requiring only $O(2^n)$ steps instead of $O(n!)$.
- A linear time algorithm can also produce good approximations of the correct answer.

12. Results

- We compared our method to an implementation of the algorithm from [1].
- The systems were evaluated against 100 randomly generated sets of patients and doctors for each parameter setting.
- This graph shows the performance differences between the new algorithm and [1] in a low-critically scenario with 15 doctors.



13. Conclusions

- Learning agents adapt to changing circumstances, and provide considerable efficiency gains.
- Using contingency plans improves performance.
- More work to be done:
  - Further ablation studies
  - Comparisons with real-world data
  - Distributed implementation (e.g. on smart phones)

Bibliography

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[3] Robin Cohen, Hyunggu Jung, Michael Fleming, and Michael Y.K. Cheng, *A User Modeling Approach for Reasoning about Interaction Sensitive to Bother and its Application to Hospital Decision Scenarios*, Special Issue on Personalization in e-Health, User Modeling and User-Adapted Interaction, January 2011.

[4] Robin Cohen, Michael Y.K. Cheng and Michael W. Fleming, *Why bother about bother: Is it worth it to ask the user?*, AAAIâ05 Fall Symposium on Mixed-Initiative Problem-Solving Assistants, 2005

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