Model Minimization of Dynamic Belief Networks for Group Elevator Control (statement of interest)

Daniel Nikovski and Matthew Brand
Mitsubishi Electric Research Laboratories
201 Broadway, Cambridge, MA 02139, USA
nikovski@merl.com, brand@merl.com

Group elevator scheduling is a well known hard industrial problem characterized by unbounded state spaces and substantial uncertainty. Dynamic belief networks are an ideal representation for the complex probabilistic dynamics of the interaction between the stochastic stream of arriving passengers and the operation of elevator cars serving them. We are interested in algorithms for minimizing an intractable factored-state dynamic belief network into a simpler probabilistic model, where reasoning and planning could become tractable. The algorithm should make it possible to use a separate destination distribution for each passenger in the system, and precisely tailor the schedule of an elevator bank to the concrete passengers currently using it.

1 Group Elevator Control

Group elevator scheduling is a hard optimal control problem, which has been researched extensively due to its high practical significance. Given a new hall call generated by a newly arrived passenger at one of the floors of a building with multiple elevator shafts, the objective of an elevator group control algorithm is to decide which car this hall call should be served by. The problem is characterized by a huge state space, involving the positions and velocities of all cars, as well as substantial uncertainty arising from the stochastic nature of the passenger arrival process.

We have recently developed an algorithm that marginalizes efficiently over this uncertainty by means of dynamic programming over all possible paths of an elevator car [1]. However, this solution is only practical when the scheduler does not distinguish between the probability distributions of individual passengers, i.e. the probability that a passenger would exit at a particular destination floor is independent of the floor where this passenger boarded the elevator car. In this case, the state space of the probabilistic model can be augmented by a single variable describing the number of passengers still in the car, since the probabilities of stopping at a destination floor are completely determined solely by *how many* passengers are inside the car, and knowing exactly *which* passengers are in it does not change these probabilities. Thus, if N passengers are currently scheduled to be served by a given car, the state-space of the probabilistic model grows only linearly ($N+1$ times). Figure 1 shows the probabilistic model corresponding to a single car descending from the 13th floor of a building, with two calls assigned to it — on floors 7 and 11. In this case $N=2$, and hence the model must distinguish only 3 states of the possible number of people inside the car (0, 1, and 2 passengers).

This compact representation of the state of elevator passengers is not possible when individual passengers have different distributions over their destination floors. This situation arises, for example, when several companies occupy blocks of adjacent floors in an office building of 5 floors. Suppose that two companies occupy floors 2 and 3, and 4 and 5, respectively, and the employees of these companies make trips only to and from the floors occupied by their company and the lobby, but never to the floors occupied by the other company. Furthermore, suppose that a car is moving down with a single person inside, and we want to know

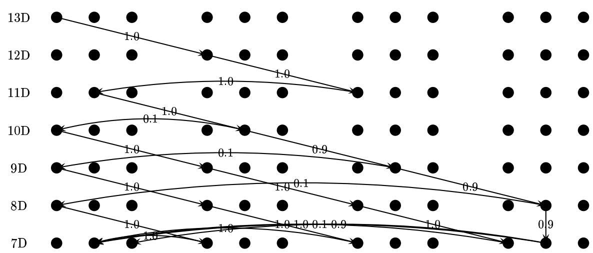

Figure 1: Simplified trellis structure for the embedded Markov chain of a single descending car scheduled to stop at floors 7 and 11. Rows signify floors; columns signify the number of recently boarded passengers; column groups signify elevator speeds.

the probability that it would stop on the second floor. Knowing that a single person is inside does not determine this probability uniquely. If this person entered the car on the third or fourth floor, the probability of stopping on the second floor, which does not belong to his/her company, would be zero. If this person entered the car on the third floor instead, the probability of stopping on the second floor would not be zero, since the two floors belong to the same company and trips between them are possible and likely.

In such cases, which are clearly very usual in office buildings, the scheduler must maintain a separate variable indicating whether each individual passenger is still in the car, or has already exited it. In order to distinguish between all possible states of the passengers, the scheduler must use 2^N passenger states. For example, the two passengers in figure 1 would require 4 state variables reflecting the possible combinations of each of them being in the car or not. While this increase is negligible for $N = 2$, it quickly becomes unmanageable, requiring models of exponential size and exponential computation time.

One possible solution to the problem of efficiently reasoning and planning in state spaces of exponential size would be to recognize that the dynamics of passengers entering and exiting an elevator car can be represented by a dynamic belief network whose state is factored among N individual Boolean state variables, or fluents, for each passenger.

2 Model Minimization of Dynamic Belief Nets

Simply using a dynamic belief network as part of our model does not reduce the exponential computational complexity of estimating passenger waiting time, unless possible conditional independence relations are identified and leveraged. Fortunately, such relations are easy to identify in our case — each of the fluents is conditionally independent of the others. (However, the motion of the car depends on the *whole* factored state). We propose to minimize the factored probabilistic model in accordance with the practice in the field of decision-theoretic planning [2, 3, 4]. Even though there is no known general solution to this problem for the case of an arbitrary independence structure of factored representations, we expect that finding and merging *reward-equivalent* states and transitions in the probabilistic model, as described in [2], is particularly applicable to our dynamic belief network. We will present our initial explorations of this approach.

References

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