The Terran player scouts the Protoss at $t = 6$, leaves for a while, then returns to scout again at $t = 10$. Figure 6 shows, for each of the key units, the model’s belief that at least one such unit will exist at each future time step, given evidence up to $t = 6$ and $t = 10$.

We first examine our model’s predictions with evidence up to $t = 6$. The Terran player has just scouted the Robotics Facility, but the Support Bay and Reaver have not been built yet. Belief that an Observatory or a Support Bay exists begins to increase at $t = 8$. The Observatory is the “standard” continuation, so it receives more belief. Belief that a Shuttle exists increases in step with belief in the Support Bay because the Support Bay is strongly associated with the Reaver drop strategy, which always features a Shuttle. Belief that a Reaver exists increases more slowly than belief in the Support Bay because a Support Bay must be completed before a Reaver can be built. In the game, the Support Bay and Shuttle were actually built at $t = 9$, and the Reaver was built at $t = 11$.

We now examine how the model’s predictions change when more evidence arrives. At $t = 10$, the Terran player scouts the Support Bay. This should unambiguously signal that a Reaver is going to be built, since there is no other reason to build a Support Bay. As expected, belief that a Reaver is coming increases considerably compared to the prediction with evidence through time 6. Belief that a Shuttle exists has also increased.

4 DISCUSSION

Our model generally performed well in comparison to the baseline for both count predictions and 0/1 predictions. The fact that our model is stationary while the baseline is non-stationary appears to account for most of the cases where the baseline was equal to or better than our model. Whereas the baseline can exploit the fact that certain patterns of production events are associated with particular time periods, in our model the Markov property of the hidden state erases information about how much time has elapsed. In the early game, our model begins predicting production events too early because it models the first several epochs, which all look the same, with a single state that has a high self-transition probability. Later in the game, uncertainty about the time means it has trouble capturing time-dependent “pauses” in production. On the other hand, our model can in principle be extended to full-length games, while our baseline method is too coarse to be useful much beyond the opening.

Another weakness of our model is that it incorporates no explicit prior knowledge about configurations of unit counts. For example, there will almost never be two Observatories, but our model can only account for this by designing the state transition matrix to visit the Observatory-producing state only once. Accuracy could be improved by making production of a unit at time $t$ ($P_t^i$) dependent on the count of that unit at time $t-1$ ($U_{t-1}^i$), with a corresponding increase in the complexity of the latent variable portion of the model. The situation worsens if we want to incorporate prerequisite relationships, as these cause the counting processes for different unit types to become coupled, destroying the conditional independences that we leveraged for efficient inference.

5 FUTURE WORK

A significant future challenge is to devise a model that can perform well in a full-length game. The space of possible strategies expands greatly as the game runs longer and the actions of the opponent begin to influence one’s own decisions. Naively extending the current model by adding states is likely to prove intractable. One possibility is to try to exploit hierarchical structure in strategies to reduce the strategy space. We suspect that strategic decisions take place on multiple time scales—broad objectives at the top level, and smaller steps necessary to achieve them at the bottom. A model of a full game will need to incorporate a model of resource flow in order to reason effectively about production rates. It will also need to account for changes in the opponent’s strategy in response to our actions.

We are also interested in applying opponent models to optimize scouting policies. As we saw in Figure 2, human players have converged on at least one time period in which the tradeoff between probability of scouting success and expected information gain is at an optimum. An agent could use our model to determine when important information is likely to be available. Modeling the probability that a scouting action will succeed in acquiring information, assuming that the information is there, is a challenging problem in itself.

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