# Knowledge Fusion with Polyagent Models

*Exploring Alternative Narratives and Estimating the Potential Value of New Information*

In polyagent models, multiple swarms, each representing a unique domain entity, explore alternative plausible trajectories for their entity through a shared spatio-temporal environment (illustrated in Figure 1, introduction in [1]). This advanced modeling approach first demonstrated its ability to analyze and predict complex scenarios in real time when it outperformed human experts in forecasting urban combat operations [2]. Additional applications include the creation of geospatial IED-risk profiles from past events [3], the planning of complex coordinated multi-player action sequences through swarming in hierarchical task networks [4], and the imputation and fusion of analyst models [5].

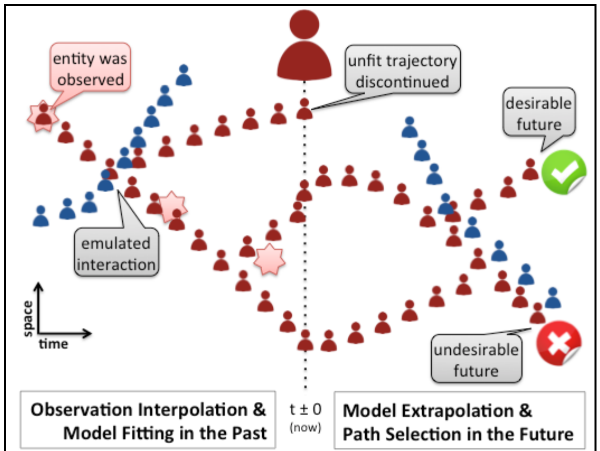


**Figure 1. The swarm of ghosts for a single domain entity (managed by their avatar at the top) evolves behavioral models that interpolate past observations (left of t±0) and extrapolates entity behavior into desirable futures.**

This White Paper focuses on two products that may be generated by polyagent models: 1) a confidence-ranked collection of alternative ways to fuse a set of facts into consistent narratives, and 2) a value-ranked set of hypotheses whose confirmation or denial significantly improves our certainty of the current or future state of the domain of interest. In support of both products we assume that there exists a polyagent model of the domain of interest that is continuously updated with new facts (e.g., entity observations, topology changes, preference updates, etc.). These facts are assumed to be incomplete, delayed, and potentially incorrect.

## Alternative Narratives from Facts

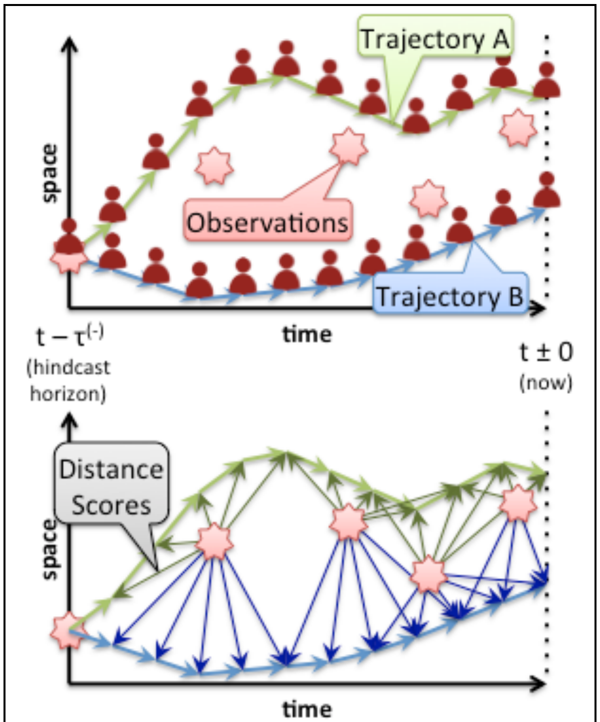


**Figure 2. Scoring two alternative ghost trajectories for their distance to entity observations.**

The left side of Figure 1 illustrates a polyagent's fusion of spotty observations of its domain entity into self-consistent narratives. Inserted into the model at the far left (time in the figure runs left to right, so the far left is the "hindcast horizon" of the model) each entity ghost executes a parameterized behavioral model that selects actions that may move the ghost in space (or emulate other activities) and in time (the duration of the activity). When the ghost's temporal movement carries it past the t±0 mark (center line in Figure 1), the ghost's trajectory in space and potentially in domain-relevant internal state (e.g., health, wealth, armament) may be scored relative to all currently available observations of the ghost's entity in the same time interval. Considering the intuitive case of location observations of the entity for instance, we could measure the distance (in the space-time volume) of each such observation to each point visited by the ghost (time-weighted distance penalty score shown in Figure 2).

The intent of running ghosts from the past to the present is to fit the parameterization of their behavioral models to the observations of the entity the ghosts represent. Thus, the more observations a ghost's trajectory is close to (lower aggregated distance scores for Trajectory A in Figure 2), the fitter we consider the ghost's chosen parameterization of the behavioral model. Closing the model-fitting loop, that avatar's generator of new ghosts receives a reinforcement to re-use the parameterization of the ghost that was just scored proportional to the fitness of this ghost's trajectory. As ghosts generate their trajectories much faster than real-time, the polyagent model quickly converges on one or a few sets of pa-

**Mark Slonecker**, President
mark.slonecker@axonai.com

**Dr. Sven A. Brueckner**, Chief Scientist
sven.brueckner@axonai.com

rameterizations for each polyagent that, collectively replicate the currently available observations. Extrapolating these parameterizations through ghosts past the current time into the future (right side of Figure 1) has shown to produce accurate scenario forecasts.

Here, we focus on the fact that for a given set of observables, more than one ghost-behavior parameterization may lead in the fitness ranking. The less-interesting explanation for such an outcome is that external constraints effectively eliminate the impact of some or all parameters and thus different parameterizations result in the same trajectories and fitness scores.

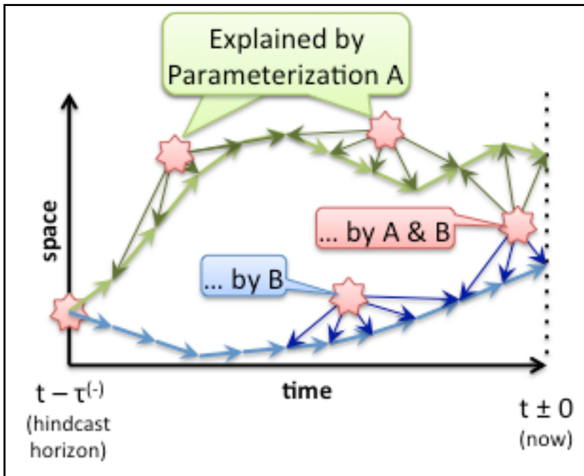

Figure 3. Alternative Narratives for one Entity.

More interesting is the case where these different parameterizations receive their high scores from different subsets of the observations (Figure 3). Here the polyagent converged on alternative narratives that explain some of the observations but none that explains them all (otherwise the one that explained all observations would have a significantly higher score). Identifying these alternative narratives, ranking them by likelihood and importance, and bringing them to the user's attention creates a unique opportunity for human judgment to refine the model (e.g., prune narratives that the user disagrees with) or modify observations.

## Value-Ranked Information Needs

Providing alternative narratives for a collection of facts can guide the ranking of all available facts by the importance of the narrative they support. In adversarial reasoning for instance, alternative narratives may be an indicator of deception, with one narrative showing the true intent and others the intent the adversary is trying to project. In that case, facts that support narratives that are most dangerous to us should have the highest priority to be confirmed.

In addition to ranking existing facts for re-confirmation, the polyagent model can also generate ranked hypotheses that may guide the search for or active collection of additional facts. Consider the example of the bifurcation of (red) ghost trajectories on right side (future) of Figure 1 triggered by the emulated interaction with another entity whose presence was predicted by its ghost population (blue). As a result, one outcome of this interaction leads to a desired future, while the other set of ghost trajectories points to an undesirable outcome. Since this interaction still lies in the future, we may have the opportunity to put information gathering assets in place such that we can rapidly learn of the actual outcome of the interaction and take response actions. Thus a polyagent model may prioritize information gathering activities.

Finally, similar analysis methods applied to ghost trajectories in the hindcast volume of the polyagent model as the potential to generate search queries into data stores that provide additional facts to refine the model fitting results.

## References

[1] S. A. Brueckner, "Predictive Modeling with Polyagents." AxonAI, LLC, 01-Dec-2014.
[2] H. V. D. Parunak and S. Brueckner, "Concurrent modeling of alternative worlds with polyagents," in Multi-Agent-Based Simulation VII, Springer, 2007, pp. 128–141.
[3] S. A. Brueckner, "Swarming Geographic Event Profiling, Link Analysis, and Prediction," in Self-Adaptive and Self-Organizing Systems, 2009. SASO'09. Third IEEE International Conference on, 2009, pp. 71–81.
[4] S. Brueckner, T. C. Belding, R. Bisson, E. Downs, and H. V. D. Parunak, "Swarming Polyagents Executing Hierarchical Task Networks," in Self-Adaptive and Self-Organizing Systems, 2009. SASO'09. Third IEEE International Conference on, 2009, pp. 51–60.
[5] L. Sappelsa, S. A. Brueckner, and H. V. D. Parunak, "The Generic Narrative Space Model as an Intelligence Analysis Tool," American Intelligence Journal, vol. 3, no. 2, pp. 69–78, 2013.

**Mark Slonecker**, President
mark.slonecker@axonai.com

**Dr. Sven A. Brueckner**, Chief Scientist
sven.brueckner@axonai.com