# Handling Unforeseen Failures Using Argumentation-Based Learning * **

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In our paper published as [1], a new argumentation-based learning technique is proposed to handle unforeseen failures for a robot. The method is in the category of online incremental learning techniques that uses argumentation theory for modeling the support and attack relation between arguments in the knowledge base of the robot, which itself is constructed in an online incremental manner.

The elderly population is rising in Europe [2] and General-Purpose Service Robots (GPSR) can assist this fragile group of people in the future. Such robots should operate in a home-like environment with a dynamic nature where even the robot's programmer cannot predict what kind of failure conditions the robot might confront during its task executions. Unforeseen external failures can occur because of an unexpected change in the environment around the robot, for instance, a new type of obstacle blocking the way. It is important to note that confronting unforeseen failures is mostly the default state for GPSRs, rather than an exceptional state as often described in the literature.

Consequently, GPSRs need to efficiently handle unforeseen failure conditions. Since the robot has never seen these kinds of failures before, it cannot be simply pre-programmed to handle them. Therefore, the robot should use a learning mechanism to test different recovery behaviors and figure out how to recover from each failure state.

In this research, we have proposed to use a new approach that incorporates argumentation frameworks for online incremental learning. This method uses a bipolar argumentation framework [3] to generate a set of related hypotheses out of the robot's observations and then models the defeasibility relation between the generated hypotheses using an abstract argumentation framework [4]. The support relations in this model are related to the number the observations of the robot. Whenever the robot observes a state with some specific feature-values that supports one failure recovery behavior, it adds all the subsets of the feature values as support nodes to the model. The model gets updated when a new data instance is observed.

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We evaluated the performance of our method by conducting a comparison with state-of-the-art online incremental learning methods chosen based on the recent survey [5]. A new robotic scenario has been developed as a case study to evaluate the performance of the methods. In this scenario, the robot should enter a room using one of three doors. However, it might confront different types of obstacles of different colors on its way. Depending on the type and color of the obstacle, there is only one randomly selected successful recovery behavior that the robot should detect by learning.

The result of this experiment (Figure 1) not only showed that the ultimate classification precision of the proposed method is higher than other methods but it also emphasized that the learning speed of the argumentation-based learning approach is higher than other methods. This means that the proposed method can learn with higher precision and less number of observations.

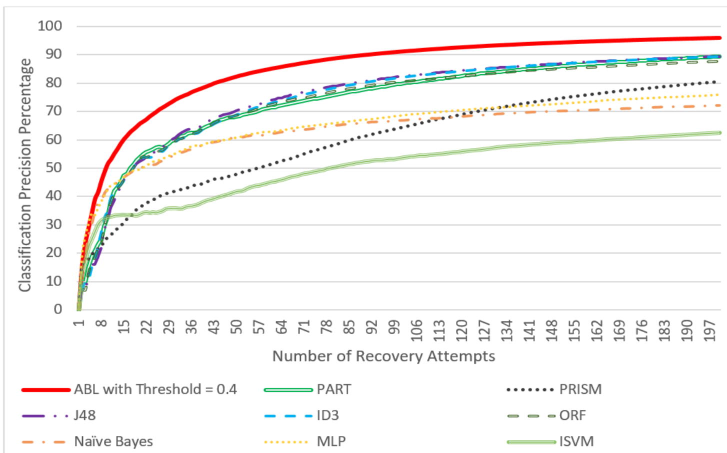


**Fig. 1.** The comparison of the Argumentation-Based Learning (ABL method) with key methods for incremental online learning [5] using the test scenario.

## References

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