In dynamic environments crowded with people, robot motion planning becomes difficult due to the complex and tightly-coupled interactions between agents. Trajectory planning methods, supported by models of typical human behavior and personal space, often produce reasonable behavior. However, they do not account for the future closed loop interactions of other agents with the trajectory being constructed. As a consequence, the trajectories are unable to anticipate cooperative interactions (such as a human yielding), or adverse interactions (such as the robot blocking the way). We propose a new method - Multi-Policy Decision Making (MPDM) for navigation amongst pedestrians in which the trajectory of the robot is not explicitly planned, but instead, a planning process selects one of a set of closed-loop behaviors whose utility can be predicted through forward simulation.

MPDM provides powerful framework for autonomous navigation among uncertain dynamic agents by choosing from amongst a set of closed loop policies - {Go-Solo, Follow, Stop} (Slide #4). Dynamically switching between the candidate policies allows the robot to adapt to different situations (Video #1). For instance, the best policy might be to Stop if the robot’s estimation uncertainty is large. Similarly, the robot may choose to Follow a person through a cluttered environment. This may make the robot slower, but allows it to get a clearer path since humans typically move more effectively in crowds.

E lecting the best policy depends on sampling initial conditions with influential (very high costs) outcomes. Without enough samples to find influential outcomes, the quality of planning suffers. Since the dimensionality of the space of all possible initial configurations is very large, discovering these configurations through random sampling may require drawing many samples, which becomes a performance bottleneck. Addressing this issue is crucial for reliable systems in applications such as autonomous cars, navigation in social environments, etc. We developed a risk-aware approach which augments this sampling with an optimization process that helps discover those influential outcomes. A key advantage to the risk-aware framework is that the evaluation of a policy can now be seen as an optimization problem, as opposed to the computation of a probabilistic expectation. (Video #2)