Selection in 3D games and simulations is a well-studied problem. Many techniques have been created to address many of the typical scenarios a user could occupy. For any single scenario with consistent conditions, there is likely a technique which is well suited. If there isn't, then there is an opportunity for one to be created to best suit the expected conditions of that new scenario. It is critical that the user be given an appropriate technique to interact with their environment. Without it, the entire experience is at risk of becoming burdensome and not enjoyable.

In our research, we have outlined different selection scenarios, all of which were classified by their level of object density and object velocity. We then performed an initial study on how it impacts performance of various selection techniques, including a new technique we developed just for this test called Expand. Our results verified that a standard Raycast technique works well in slow moving and sparse environments, while revealing that our new Expand technique works well in more dense environments.

With the results from our first study, we sought to develop a solution that would bridge the gap in performance between those techniques tested. Our idea was a framework that could harvest several different selection techniques and determine which was the most optimal at any time. Each technique would report its effectiveness given the provided conditions. The framework was responsible for activating the appropriate technique when a selection was made. With this framework in hand, we performed two additional user studies to determine how effective it could be in actual use, and to identify the strengths and weaknesses of it. Each study compared several techniques alone to the framework that utilized them in unison, picking the most suitable. Again, the same scenarios from our first study were reused. From these studies, we gained a deeper understanding of the many challenges associated with automatic selection technique determination. The results from these two studies showed that transitioning between techniques was potentially viable, but rife with design challenges that made its optimization quite difficult.

In an effort to sidestep some of the issues surrounding the switching of discrete techniques, we sought to attack the problem from the other direction, and make a single technique act similarly to two techniques, adjusting dynamically to conditions. We performed a user study to analyze the performance of this technique, with promising results. While the qualitative differences were small, the user feedback did indicate that users preferred this technique over the others, which were static in nature.

Finally, we sought to gain a deeper understanding of existing dynamic selection techniques, studying how they were designed, and how they could be improved. We scrutinized the attributes of each technique that were already being adjusted dynamically or that could be adjusted and innovated new ways in which the technique could be improved upon. Within this analysis, we also gave thought to how each technique could be best integrated into the Auto-Select framework we proposed earlier.
The public is welcome to attend.