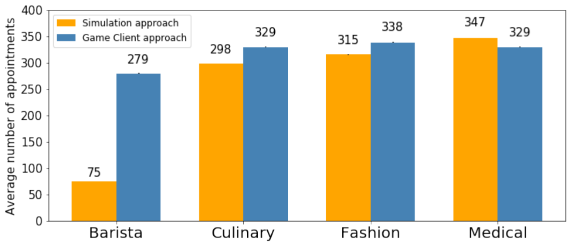

Figure 4: Bar chart comparing career progress in each approach. Numbers are the average amount of actions (appointments) to reach the goal. Our approach finds a path closer to optimal play in all but one career.

to steadily improve their progress. The two different builds provide very different experiences. It is up to the designers to decide which experience they prefer.

Comparing Approaches

Earlier, we identified some of the limitations of running an agent on the game client. We now compare the results of the two different approaches, simulation based and game client based, using the career experiment as the basis of our comparison. We are looking to compare how many actions each approach needs to achieve the career goal. The agents of each approach use different algorithms: while the simulation uses A*, the game client approach uses Softmax.[1] Figure 4 shows the comparison between the two approaches. The simulation based approach reaches a style of gameplay closer to optimal in all but one case. Optimal in this case would be using the minimum amount of actions. The Barista stands out for the large difference. For the medical career, the 2000 node A* cutoff could be moving the algorithm into a local optimal, while the game client Softmax was closer to optimal play.

We can also compare the number of simulations needed for significant results. We ran 2000 simulations for each approach, and the conclusion is obvious. The simulation with A* agent achieves a deterministic playstyle, having no variance. In contrast, the game client Softmax agent has high variance requiring numerous simulations for convergence. Figure 5 compares the variance between the two approaches. A single run of A* already achieves our goals, which balances the time spent re-implementing the mechanics.

Discussion and Conclusion

We illustrated the advantages of AI-based playtesting in game development and how it can help designers to validate their work. We have shown the limitations of trying to implement an AI agent on the game client and proposed the approach of building a simulator of the game mechanics. Our approach gives us full control over the experiments and avoids the difficulties of coupling with an instrumented

[1]Namely, we used Softmax over utility of valid actions, trained with stochastic gradient ascent to optimize linear weights of the action parameters. During the model execution, lower temperature reduced the variance of the results.

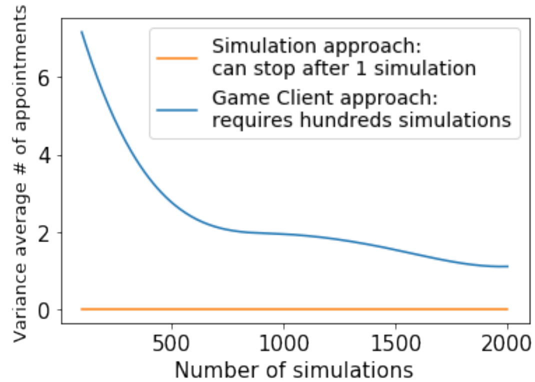

Figure 5: Comparing the variance between the two approaches. While A* on the simulation approach achieves deterministic play and has no variance, the Softmax game client approach has high variance and needs a considerable number of simulations to converge.

game client. We have also highlighted the power of this technique with four use cases proposed by the game team and which results were later presented to the designers, informing decisions they took to make changes.

Because most games keep their data in a standard format, it is becoming easier to write a simulation outside of the game client. These tools may come in existence even before a playable game client is built, even as the game is being designed. AI can then have an even bigger impact in playtesting, assisting from early stages in the game development, helping speed up the production cycle, saving time and efforts while achieving more balanced gameplay. We have shown that our approach produces overall stronger results by empowering search-based algorithms. A basic algorithm such as A* achieves more precise results than agents running within the limitations of the game client.

A* delivered convincing results, but for the price of developing and tuning the heuristic function. The Monte Carlo Tree Search algorithm could be a viable alternative eliminating this overhead of making a new heuristic in favor of a custom win condition for each experiment. MCTS Agents were proven successful at gameplaying, and we believe it would be no different for a game such as The Sims Mobile. Veritatis ad modi recusandae ea at, enim laborum obcaecati adipisci, illum fugiat eveniet itaque autem doloribus cumque praesentium, iste harum quam et perspiciatis incidunt cumque maiores eaque a reiciendis, ab perferendis iusto obcaecati laboriosam error praesentium eos magni eum veritatis voluptatibus?Autem facilis error recusandae ad facere repudiandae temporibus optio pariatur minus accusantium, exercitationem deleniti perferendis quod minus nostrum quae iusto non blanditiis, voluptatibus quo facere cumque repudiandae voluptatem reiciendis?Dolorum praesentium accusamus esse quaerat, cum sequi odio voluptate dolorem fuga?Earum magni ab at porro harum facere laudantium facilis, nulla sequi nesciunt tempore.Iusto dolore quibusdam animi inventore nesciunt doloremque nisi nihil aperiam, quasi illo ullam ab