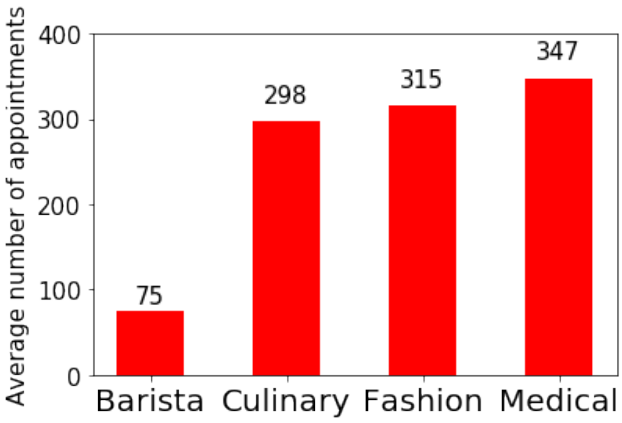

Figure 2: A bar chart comparing the number of actions (appointments) required to reach the goal in each career. Barista is much smaller because it can only go up to level 5, while the others are going up to level 10.

Career	Actions Reduction (%)	ρ / Action Save
Barista	5%	56.7
Culinary	26%	45.8
Fashion	20%	52.6

Table 1: Table showing how objects affect career progression. Here, ρ denotes in-game resources available to all players. The "Actions Reduction (%)" column shows the percentage of fewer actions required to achieve level threshold. The "ρ / Action Save" column shows the ratio between the amount of resources used, for all objects affecting that career, and how many actions less they would need to take. The Medical career objects are not availabe below level 10.

an exchange of resources. We then compared it to the number of actions needed to complete the same career goals we set out before, with no objects to use.

Table 1 shows the results of the experiment. Objects made a bigger impact on the Fashion and Culinary careers, while having little impact on the Barista. The Medical career shows no impact, since objects are only available past level 10. We also displayed the ratio of the amount of resources the players would have to exchange to acquire the objects by the amount of actions they would save. Designers analyzed the findings and changed the tuning of the object's to increase their impact and make them more accessible.

Use Case: Comparing the off-time between builds

Question: *Did gameplay change between builds?*

With major changes between game iterations, significant impact on the gameplay can be felt. The question "how much impact did the changes have" is on everyone's mind. Using our AI agent to play both builds of the game, we can create metrics for comparison. Since we are not simulating the full game experience, our approach can only make punctual statements, but those can point to the impact of changes.

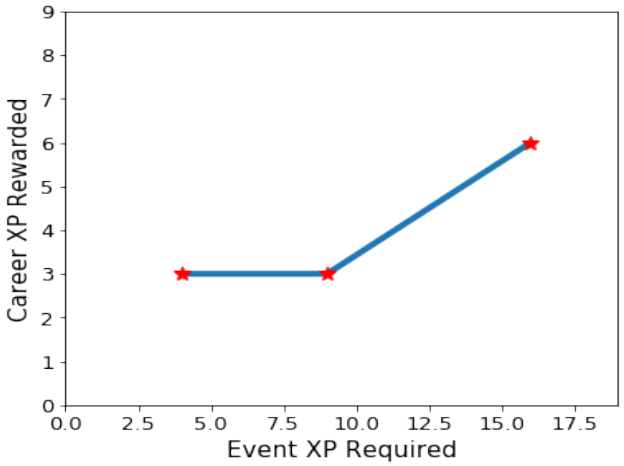

Figure 3: Line plot showing the relation between the amount of experience required to achieve each step of the event and the amount of career experience it rewards for reaching it. Each step in the event is marked by a red star. This plot evidences that reaching the second step takes more than double the effort of the first one for the exact same reward.

Career	Evt Actions	Tot. Actions	Sessions
Barista A	75	82	2
Barista B	347	381	24
Culinary A	298	327	8
Culinary B	1506	1643	94

Table 2: Table showing the comparison of the number of actions and sessions needed for Barista and Culinary careers on build A and build B. The Evt Actions column refers to how many event related actions were taken. The Tot. Actions column shows the total number of actions taken during the experiment. The Sessions column shows the number of sessions necessary to finish the experiment.

For our experiment, we compare progression through the Barista and Culinary careers between two significantly different builds named A and B for simplicity. The resource management system is the key change between these builds, as a consequence we expect a big impact in the gameplay and the goals our agents want to achieve.

Table 2 shows the results of our experiments. The difference in the number of actions performed between builds A and B is evident. For both careers, build B requires over four times as many actions to reach the target goals. We also compared builds in terms of sessions. A session is a period that starts when players log into the game and ends when no more actions are available. We saw a significant increase in the number of sessions from the build A to B, but the length of the session also changed. While in build A, players had to wait in average six hours between sessions, in build B the average wait time drops to about 45 minutes. This way, playing build A allows faster progression, but build B incentivizes players to keep checking the game throughout the day

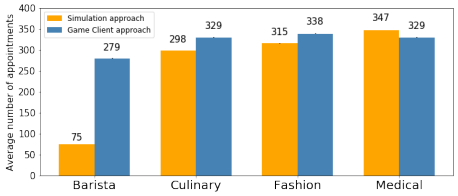

Figure 4: Bar chart comparing career progress in each approach. Numbers are the average amount of actions (appointments) to reach the goal. Our approach finds a path closer to optimal play in all but one career.

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 game client. We have also highlighted the power of this technique with four use cases proposed by the game team and

[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.

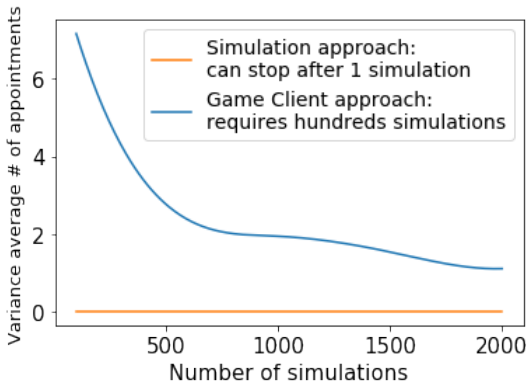

Figure 5: Comparing the variance between the two approaches. While A* on the simulation approach achieves deterministic play and has no variance, the Softmax game client approach has high variance and needs a considerable number of simulations to converge.

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.

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