Design Considerations for Creating AI-based Gameplay

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Abstract

Artificial Intelligence has been applied to many facets of the game design and development process. Though this has led to many advances in games and AI research, there remain few examples of games in which play centers around engagement with AI processes: the design space of AI-based games remains underexplored. By examining a breadth of playful experiences through different lenses, it is determined that games which forefront AI are beneficial for players, designers, and for the field of game scholarship itself. Moreover, there is evidence that symbolic approaches (rather than statistical) lend themselves to experiences with more agency, greater human interpretability, and more controlled authorability.

Introduction

Artificial Intelligence is used in many aspects of the game design and development process and is also a central part of gameplay. While there is much research in AI and games, there are aspects of game AI that are still not well understood and are critical to our understanding of games, gameplay, and design. Recently, the range of AI techniques used for game AI research clusters around machine learning and statistical approaches, and while this lead to considerable advancements in areas such as player modeling, procedural content generation, natural language interfaces, and other areas, the use of AI as a core part of gameplay is not frequently addressed in depth.

Games that make AI available for the player to interact with and also understand were have referred to as AI-based games (Eladhari et al. 2011) (Treanor et al. 2015). These games can offer representations of complex phenomena such as social dynamics, have the potential to provide customizable narratives and events that adapt in real-time based on players' predilections, and can serve as tools and authoring systems that enable and inspire users to engage in self-expression and produce creative artifacts of their own. Frequently, the successful play of these games depends on the player developing a robust and somewhat accurate model of the underlying processes of their AI systems. We envision a world with more AI-based games that challenge existing gameplay conventions and help to explore the human experience. For this world to exist, there needs to be more technical, theoretical, and practice-based research.

This paper aims to promote AI-based game design research by laying out a roadmap to the techniques and challenges within the space. We do so by first identifying where exactly AI-based game design exists within the space of AI research and application in game development. We make this step not to discourage work in the other areas of the space but to identify and emphasize that the space of AI-based game design is under-explored. In the following section, we describe several aspects of games—such as a game's agency and intepretability—in which AI influences the experience of both authors and players and how different approaches to AI influence them. The two general approaches we focus on are the broad areas of statistical and symbolic AI. We make these distinctions because we believe that symbolic approaches will promote good design, and we intend to push gently against the current focus on statistical methods. In the last section, we soften the dichotomy and present a comprehensive view of hybrid approaches that acknowledges the strengths and weaknesses of both approaches. When taken as a whole, these contributions present a vision for future research into AI-based game design.

A View on AI in Games

As much as the authors might like to refer to "AI in Games" and leave it at that, that phrase inadequately captures the diverse stages of game development and the varied ways artificial intelligence is applied to them. To focus the conversation of this paper, the authors first present a novel view on artificial intelligence in games: two axes that form a graph featuring the placement of different aspects of game design and game development. This is an extension of previous writing on AI-based game design (Treanor et al. 2015) (Eladhari et al. 2011), which we will soon see, has traditionally focused on the upper-right quadrant of this new model.

To understand this model, we must first understand the axes. One axis is the designer-centric Surface / Background axis. The other axis is the player-centric Mental Model axis. Upon this model, we place elements of the game development process that have had (or could have) artificial intelligence techniques applied to them. Note that any given individual game could occupy multiple places on this graph if AI was used in multiple aspects of its development.

The Surface / Background Axis

The Surface / Background Axis captures the notion of *where* in the artificial intelligence is applied to the game. If we think of game development as a pipeline, there are many stages to the process. Some of these stages include the initial brainstorming and ideation of pre-production, development of the game, marketing the game, and post-production upkeep and content drops (e.g., new DLC and other expansions in the currently popular "games as a service" model, maintaining servers for multiplayer components, etc.). Techniques that are considered "high-surface, low-background" are incorporated into the actual act of play itself and directly affect or influence the player experience while playing. Crucially, "high surface" techniques are also capable of being influenced by a player's play as well–thus, they can influence and be influenced in turn. Application areas considered "high-background, low-surface" are peripheral to the act of play but are indeed no less critical to the process of game development.

To illustrate this, let us look at the game Left 4 Dead (South 2008). The AI systems of Left 4 Dead (Booth 2009), and in particular, its AI Director, would rank highly on the surface dimension. Every time the player plays, it actively shapes their experience, modulating the number of enemies and equipment in the scenario to evoke a continuously tense-but-fair match. An element ranked lower on the surface axis is the game's matchmaking system (or, indeed, matchmaking systems of multiplayer games in general). Certainly, the other players that a player is matched up with (or matched against, in competitive multiplayer games) will directly influence the game playing experience (i.e., 'high surface'). However, it is a decision made at the outset of the match and then statically set in stone for its duration, outside of player influence (beyond the player's accumulated MMR, ELO, or other scores that the player has garnered through previous play sessions (Suznjevic, Matijasevic, and Konfic 2015)). A low surface / high background aspect of these games would be player telemetry (Nguyen, Chen, and El-Nasr 2015): capturing, logging, and analyzing button clicks, menu navigation, etc. This work has applications at several levels of the game development process, from user and player research for game design (Gagné, El-Nasr, and Shaw 2011) to ensuring player retention for monetization (Weber et al. 2011). Though the financial well-being of a developer undoubtedly indirectly affects and influences the player experience, these 'behind the scenes' measures do not directly affect the player's gameplay experience.

The Mental Model Axis

The first axis roughly corresponds to applications of artificial intelligence on different parts of the game development production process. The Mental Model Axis shows how different forms of artificial intelligence might be present in the player's mind. We refer to this as the mental model axis to speak to how much the player's experience of play is affected—and, more specifically, rewarded—by devoting the energy required to construct a mental model of how the underlying AI systems of the gameplay experience work.

The presence of an AI system in a playable experience is insufficient to guarantee that a player will be incentivized to develop this mental model. Wardrip-Fruin's Sim City Effect (Wardrip-Fruin 2009) discusses the process of a player discovering the contours of a system through play. Though they may never fully learn all of the intricacies of the underlying system (nor learn enough practical city management for an actual mayoral bid), they might slowly piece together small connections of the greater system. Examples of these effects are industrial zoning and police stations on crime or the relative impact roads and railways have on pollution. These small revelations accumulate into the player being able to design cities that achieve their own particular goals. This is in contrast to Wardrip-Fruin's Tale-Spin effect, which describes experiences with rich and complex underlying systems that are manifested via a surface layer presentation so simple it dissuades players from believing a sophisticated system even exists.

A visualization of these two axes is featured in Figure 1.

Quadrant Descriptions

The upper-left corner describes applications of artificial intelligence that directly affect the gameplay experience but require minimal mental modeling by the player. Many procedural content generation systems, in which the generator is run once and then left to explore, fall under this heading. Examples include Minecraft and other mining games (Kreminski and Wardrip-Fruin 2018), the map generation, procedurally generated sound, and many other applications (Togelius et al. 2011).

The lower-left corner describes applications of artificial intelligence that do not affect the player, nor do they directly influence gameplay. Uses of AI in this quadrant are concerned mainly with the business of game development. As previously referenced, gathering user data for player retention purposes and monetization would fall into this quadrant (Weber et al. 2011). This is undoubtedly an exciting and lucrative application area for many artificial intelligence techniques but is not the focus of this paper.

The lower-right quadrant contains application areas of artificial intelligence that could potentially reward the astute player but are designed not to be interactive. One example of this is the Matchmaking system that exists in many games. Systems of this type are a means to an end; they ferry the player to the next match. However, even an innocuous system can lead players to intentionally throw matches to artificially lower their matchmaking ranking, thus enabling them to face the strings of easier opponents. Similarly, MOBAs and other team-based games have had to find solutions to draft dodging. Telemetry and analysis of user play traces have been conducted to help inform the development of matchmaking services (Véron, Marin, and Monnet 2014). Non-AI mediated ranking measures in eSports face their own challenges (Carter and Gibbs 2013).

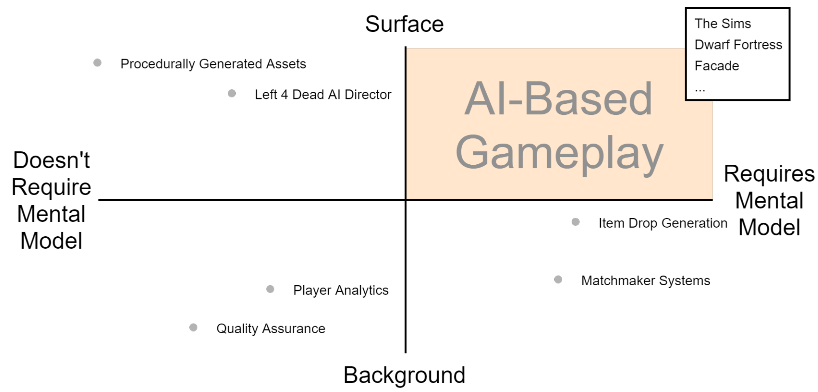

Figure 1: A view on the use of artificial intelligence in games. In the top right quadrant are games that use AI to directly affect gameplay and also require a mental model of how the AI operates in order to play.

The upper-right quadrant is the quadrant that the authors call for more people to explore; the type of game previously discussed as AI-based games. These are aspects of gameplay informed or enabled by artificial intelligence that players interact with directly, and for which the experience depends upon the player developing a mental model of these systems through play. Game experiences such as The Sims (Maxis 2008), Dwarf Fortress (Adams and Adams 2006), and Façade (Mateas and Stern 2002) all reside here. Though previous quadrants represent applications of AI within a game, here we are referring to games as a whole. These are playable experiences whose AI Systems are core to their character; the line between the overall game and the underlying AI system is blurred. It is the vision of the authors that this quadrant needs significantly more research devoted to it to be fully explored.

The following section presents a comparative approach to different AI techniques and how the same 'underlying' experience might be radically different based on the AI technique employed to enable it.

Comparative Analysis of the Use of Different Approaches to AI in AI-based Games

The overall goal of this paper is to advocate for and facilitate the creation of games that use AI within the surface-level/requires a mental model quadrant described above (i.e., AI-based games). Such games involve players directly engaging with the AI as part of their aesthetic experience, and this section lays out several ways that the use of AI influences that experience. Throughout the section, we compare two broad categories of AI: statistical and symbolic. We realize that these categories can be blurred (the next section goes into more detail), but we found it useful to consider each approach at this level. Overall, this section is meant to push against the current in AI research and explain why we believe there is ample opportunity to create novel and satisfying games by employing symbolic AI in AI-based games.

Interpretability

While both creating and playing games with targeted representations or experiences, the ability to interpret a game's behavior is an important factor. Game designers have framed this as the ability to learn the rules of the game system (Koster 2004), creating Meaningful Play (Zimmerman and Salen Tekinbaş 2003), and avoiding arbitrary and "meaningless" choices (Romero and Schreiber 2008). Each of these game designers advocates that a player should be able to reason about the operation of the game system and make informed choices toward their goals. This is especially important with AI-based games, where all interaction is framed by the player needing to read meaning into the AI's actions (Mateas 2003), as the systems are often complex and dynamic.

In games that use AI that does not require mental models in order to intentionally interact with, interpretability is less important. For example, while understanding how the landscape of a planet was generated in No Man's Sky (Games 2016) is arguably not particularly relevant, understanding the connection between a Sim's (Maxis 2008) "needs meter" and their action is relevant.

Statistical Approaches Interpretability is a well-recognized issue in machine learning (Gunning 2017). Limited interpretability is inherent in most statistical methods as the content of a learned model is not represented in human-interpretable ways. However, statistical methods often still produce results that adhere to expectations and are very powerful for many applications in which the output is more important than process (e.g., texture generation, speech to text, and computer vision).

However, this obliqueness can be an issue for AI-based games that prioritize the player's ability to build a mental model of the AI's operation. From a player's perspective, the interaction loop (listen, think, speak (Crawford 2003)) is a process of learning. Every output of a system gives the player material to build an understanding of how it operates. When a player concludes the operation of a system that primarily relies on statistical methods, those conclusions necessarily cannot map to the actual operation of the system, as the operation of the system is not internally represented in human-understandable terms.

That is not to say that players of these games can not build mental models that are useful for attaining desired ends. However, such mental models are limited in that their primary ability is to anticipate how a system will behave, but not why. Though from a player-centric perspective, this will only be a problem if the output of the system significantly violates the player's model without providing enough evidence to update the model or descriptions of why different behavior occurred (which, typically referred to as explainable AI (Gunning 2017), is one of the core challenges of statistical methods).

Symbolic Approaches Since symbols are the words used to refer to representational entities, symbolic approaches are highly interpretable as humans can ascribe meaning to them. When a theorem prover makes a proof, the step-by-step process is available for humans to inspect. Likewise, when a system enacts a plan for an agent, the system's rationale is available. While the "reasoning" of symbolic systems is not always the most obvious to a human, they are valid and justified. This mechanical or "alien" manipulation of symbols might be considered aesthetically good or bad depending on the game, though it can negatively affect the believability of agent behavior.

Often, symbolic systems make use of sophisticated architectures to select content or choose agent behavior. Symbolic AI-based games involve the player acquiring a rough model of these architectures to achieve their desired ends. For example, in The Sims 4 (Maxis 2008), the player can associate a Sim's need for hygiene meters with the degree of hygiene a Sim has because to a human, a low amount of "hygiene" is symbolically associated with not being clean. The system architecture and the authoring support this with its behavior in other game areas. Furthermore, there can be a strong relationship between authored content and what is presented to the player.

However, it should be emphasized that a human's interpretation of a game (and its symbols) and even their perception of what symbols are available for interpretation can, and likely will, be different than what the system uses or the author intends. In order for a game to symbolically represent an author's intent, a game needs to be carefully designed and delivered to a receptive audience (Treanor and Mateas 2013).

Agency

Most often, game designers strive to give the players of their games the experience of high agency. Generally, having a sense of agency involves the feeling of one having the power to take specific action in a situation toward a desirable end. In games, it is theorized that agency is achieved when the formal and material affordances of a system are in balance (Mateas 2001). In other words, when the game leads a player to consider doing something (the formal), it can also respond to it (through the material). In many games, these criteria are not met, and games do not provide high agency experiences. This is most prevalent in narrative games. For example, the story and cutscenes in a game like Grand Theft Auto V (Games 2013) present detailed characters with personalities and things to say, but in gameplay, characters mostly serve as targets and ragdolls and do not respond to the player's actions or the resulting dynamics.

Much work has been done in academic game and autonomous agent research to address this, and it is a difficult technical problem. However, it should be noted that agency can also be achieved through design choices. For example, lower fidelity character content (graphics, dialogue, etc.) arguably suggests to a player that the game is not meant to respond to everything that you would expect a human-like agent to respond to. Genre convention also informs what players will expect and thus their sense of agency. The degree to which a game can be said to provide agency results from a combination of technical, design, and cultural factors.

Statistical Approaches A purely statistical approach to physical behavior in a game would inherently present a problem for agency, as part of what a player expects from a game is tied to their experience of reality (object permanence, consistent laws of physics, etc.). However, other areas of behavior are perceived as less static, and statistical methods can significantly alleviate authorial burden and provide surprising and interesting experiences. For example, learned models can drive animation in unanticipated environments, and dialogue can be generated dynamically.

However, for AI-based games, the player is intended to understand how and why the system performs as it does, and statistical methods are black boxes that the player has little access to understanding. Because agency is tied so closely to what a player perceives and expects, this is another area where a system's processes are more important than its output, and because statistical methods are generally not interpretable, they can impede how much agency a game can provide.

Symbolic Approaches On the other hand, more symbolically oriented systems provide a structure that players can discover. Symbolic systems arguably have more consistent "hooks" that a player can ascribe meaning to and extrapolate about the system's overall operation.

As an example, consider the 2013 version of SimCity (Maxis 2013). In order to grow their city as desired, the player must be roughly cognizant of the operation of the underlying Glassbox system (Willmott 2012). Generally, Glassbox simulates the flow of resources between buildings via agents traversing player-designed paths. Because the system is symbolic, the game can directly present select aspects of the Glassbox engine, and the player can take directed action and thus potentially achieve agency (depending on their level of understanding). This version of SimCity could be contrasted with an imagined city-building simulator that evolved based on a model based on large data sets from real-world cities. In this game, the player would layout roads, zones, etc. (just as in SimCity), but how the city evolves would be generated from the model. While this game is arguably a more accurate simulation of a real-world city and its growth, players would not have the same sense of agency, as the system's output would not map to a mental model, but rather the opaque learned model, which would most likely invalidate the player's fledgling mental model.

Symbolically represented systems contain a theory of what they represent and are prescriptive, rather than just descriptive. Experientially, this lends symbolic systems a degree of legitimacy when the system does not behave as a player might expect. Without this, a player experiences a sense of helplessness and distrust that their actions or experience are meaningful to gameplay (i.e., a loss of agency).

Consistency and Coherence

Whether a game aims to immerse the player in a fictional environment or engage players through strategic problem-solving scenarios, it is crucial that players accurately learn about its operation is consistent. Common consistent features might include object permanence and gravity in representational worlds, and in abstract games, the features might be the game's rules or win conditions. This is not to say that players must always have perfect information about how the system operates, that is seldom the case, but very often, good game design involves players feeling like they are learning about how to play the game better as they play (i.e., learning how the system operates). When a game presents players with information that invalidates player beliefs too often without convincing justifications, players can begin to feel that the game is choosing behavior randomly and ultimately feel that their input does not matter.

Statistical Approaches AI Dungeon 2 is a text-based game that has the player control an avatar by typing any command into a prompt (Walton 2019). Using a variant of GPT-2, the system generates a description of what happens when the player takes that action and then gives the player a chance to give another command. While the powerful underlying natural language interface model generates surprising and amusing results, the game arguably does not give the player meaningful choice (Zimmerman and Salen Tekinbaş 2003). This is evidenced by the fact that most often a game ends when some unexpected event kills the player. This happens because the underlying learned model does not have the ability to maintain a consistent representation of the game world. Generally, statistical approaches only excel at maintaining local coherence (e.g., sentence level) and fail at broader levels of resolution (e.g., story). That said, the pleasure of AI Dungeon 2 is exploring its opaque model. While players may not rely on the game to be fair or consistent, it can still be amusing to wonder what is going on inside the black box.

Symbolic Approaches Unlike statistical methods, symbolic approaches can explicitly track context and consistently react to it while in operation. This allows for the system to enforce hard preconditions and to better ensure that appropriate content is presented. A downside of this is that the higher-order context needs to be supported through architecture and often requires more authored content. In other games, the system's reaction to player choice is critical, and invalidating a player's mental model can ruin the experience. AI Dungeon 2 is an exception to most interactive fiction games, as most interactive fiction games make use of heavily symbolic systems such as Inform 7 (Nelson 2006). Inform 7 roughly represents the fictional worlds as objects, containers, and actions that can be performed upon them. State change and descriptions of actions are chosen based on a rule system. As a result, games based on Inform 7 are deeply strategic and puzzle-like.

Authorability

An AI system's authorability depends on how well it supports the creation or addition of content. As the design and development of other video games, authoring is an act of creation that players ultimately judge subjectively. It is also subject to hard constraints imposed by the game's systems and by soft constraints from existing and future content. Additionally, authors have a limited ability to create even when obeying those constraints. Not only do authors have to work with these constraints while being judged by players, creating content for AI-based games requires interfacing with complex technologies.

To create, authors need a channel to communicate design decisions with the AI system. Meaningful communication to the AI system is central to these aspects, varies widely, and includes text, reactive planners for character behavior (Mateas and Stern 2002), bespoke tools (Isla 2005), data sets or even mixed-initiative tools (Smith, Whitehead, and Mateas 2010). At a high level, this communication impacts the ease of content creation, the complexity of artifacts, creation with contextual appropriateness, amplification of authorial power, reduction of the authorial burden, and the ability to modify complex artifacts.

We will focus on asset creation and narrative design to explore how statistical and symbolic approaches intersect with authorability. Each of these areas brings a different aspect of authorability into perspective. Asset creation, such as generating textures or geometry, focuses on ease of creation, amplifying authorial power, and reducing authorial burden. Narrative design requires contextual appropriateness and creating and modifying complex artifacts.

Statistical Approaches With plenty of examples and the algorithms explored by the computer vision community, statistical methods are well-suited to the needs of generating visual (Li and Wand 2016) and audio assets (McDonagh et al. 2018). On the other hand, authoring stories or social behavior relies heavily on context, temporarily disconnected information, and consistency as judged by the player. Even the current best natural language generation models and dialogue systems have difficulty keeping consistent context or answering questions that require small amounts of reasoning.

Symbolic Approaches Asset authoring with symbolic approaches works well with tasks that can be abstracted into portions and annotated with descriptors like puzzle design (Smith et al. 2012) or procedural music composition (Brown 2012) but perform poorly in generating textures and sound files. The contextual nature of, and through lines required for, social (McCoy et al. 2014) and story games (Reed et al.

2014) plays to the strengths of symbolic approaches, and its application to this space has a rich history.

Other Challenges

Aside from the comparisons made in the previous section, there are many intersections and differences to be explored, each with its impacts on game AI. One with the most impact on games is how the AI system encapsulates design. In data-driven approaches, the act of creating and employing the system is wholly design-free, and the design knowledge is implicit within a trained model or policy. Other systems are dependent on design either in their construction(Adams and Adams 2006) or in their deployment. Where data is abundant, solutions can often be found by applying engineering and computation. Symbolic approaches are less able to leverage data to find solutions. When data is scarce or absent, the ability of each area to solve the task is reversed: statistical approaches tend not to find acceptable solutions, and symbolic ones can leverage human-derived domain knowledge to solve problems.

Environmental impact and reproducibility are problematic for both approaches to varying degrees. Deepmind's AlphaStar Final serves as an example for both because it required an enormous amount of power to train (though a large portion of that energy was offset renewably (Porat and Hölzle 2019)) and consequently expensive to reproduce[1]. Additionally, work done on this scale by corporations often contains proprietary techniques that are not sufficiently described, and the data required for recreation is not made available. Even though these costly results are extremely impressive, they set a strong example for future research that independent and academic institutions cannot sustainably or practically adopt. On the other hand, symbolic approaches have yet to achieve success at this scale and leave their environmental impacts and reproducibility unknown.

There are many other challenges ready for future analysis, including using learning as a hammer when not every problem is a nail; impacts of AI-based game design on the knowledge level (Newell 1982); and the function of hierarchy in reasoning and learning on game design.

Hybrid Approaches and Future Directions

As argued above, symbolic methods in AI-based games help achieve meaningful play, trust, and other important factors that involve the player interacting with the AI processes themselves. Such methods provide the interpretative affordances needed to build actionable mental models and are conducive to high agency experiences. Statistical methods tend to be successful when AI is used to produce content where the process involved to create it is not central to the player experience and authoring. When statistical methods are used as part of the gameplay loop, such as with generating dialogue, there is a risk that the system will present information that invalidates a player's mental model. However, this is not always a problem when surprise is central to the desired aesthetic (as with AI Dungeon 2). Ultimately, designers should carefully choose what techniques they employ for what task they are trying to solve.

That said, these two approaches need not be considered entirely separate. Connections between symbolic and statistical systems (i.e., hybrid intelligent systems) have taken forms like fuzzy logic (Zadeh 1988) and fuzzy neural networks(Lin and Lee 1991). These systems represent a pipe-lined approach to problem-solving where a neural network and a fuzzy logic system send information between themselves but exist within their islands of algorithmic and knowledge representation. While useful for some tasks, connecting these systems does not advance our collective understanding of AI techniques in a true melding of two approaches. Techniques such as probabilistic soft logic (Bach et al. 2017), Markov logic networks (Richardson and Domingos 2006), and Bayesian logic (Andersen and Hooker 1994) represent aspects of symbolic logic and connectionist approaches in a single algorithm and mode of knowledge representation. Even with these capable mixed systems, AI-based game design presents many AI challenges simultaneous with mixed representations, scales, and evaluation criteria. To comprehensively address these challenges so that systems can reason about and impact one another, a systematic approach or framework that allows for the types of reasoning necessary for each of the related challenges while allowing for inter-system communication may be necessary. While other fields have developed promising solutions to this problem (Quigley et al. 2009), game AI could leverage integrated systems (Aamodt and Nygård 1995; Langley 2006) or perhaps artificial general intelligence (Perez-Liebana et al. 2016) as potential solutions.

While evocative, comprehensive solutions to game AI may not be possible. Each subproblem has its domain and representation needs that may not generalize or be legible by other problems. Because they all could have this quality, designers should deeply consider their approaches in each subproblem and use the technique that is the best fit for that space.

Conclusion

We believe that games that place AI in the forefront by requiring the player to build a mental model of their operation are beneficial as they expand our conception of what games can be and are meaningful cultural artifacts in themselves. This paper was written to promote this AI-based game design research and to lay out a roadmap to the techniques and challenges within the space. We specifically compared and contrasted statistical and symbolic approaches to using AI in this space and concluded that symbolic approaches are more conducive to player understanding in AI-based games.

Making games, especially with AI, is a complicated process with many technical challenges. While symbolic approaches may assist with mental model building, the design considerations addressed above can indeed be broken into subproblems where statistical problems can be beneficial. Furthermore, hybrid systems show great promise.

[1]Estimated training coast of approximately $13,000,000 based on Google Cloud prices taken from 21 May 2020 from https://cloud.google.com/tpu/pricing and 44 days each for training 12 agents on 32 3rd generation TPUs (Vinyals et al. 2019).

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