Trinity College Dublin
Coláiste na Tríonóide, Baile Átha Cliath
The University of Dublin

School of Computer Science and Statistics

Diversifying the METAs of Games by Analysing the Gameplay Data of AI

Con Óg Ó Laoghaire

September 23, 2021

Submitted in partial fulfilment of the requirements for the degree of B.A. (Mod.) Computer Science

Declaration

I hereby declare that this Final Year Project is entirely my own work and that it has not been submitted as an exercise for a degree at this or any other university.

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Abstract

"At this point the game is only about min-maxing"

-A friend of mine when referring to a game with a once-vibrant community

Min-maxing is a practice whereby a player in a game maximises specific traits and tactics, and minimises everything else. In multiplayer environments this is done by nearly all players once it is abundantly clear among the playerbase which traits and tactics are the most competitive choices.

Acknowledgements

I have great appreciation for the entities that facilitate the leeway that makes it possible for people with sporadic and tangent-prone workflows–such as myself–to be fruitful. In the case of this project they are:

- The developers and documenters of the NEAT algorithm, an incredibly flexible algorithm with a highly intuitive interface.
- The 'Cheesy AI' YouTube channel, who have created entertaining video tutorials on applying NEAT.
- My project supervisor, Mads, who gave me invaluable insights that reoriented the project at times of need.

Contents

1 Introduction

1.1 What is a game's meta

The 'meta' of a game can be understood as the acronym Most Effective Tactics Available. As such we have 'meta' as a noun, which is the set of the most effective tactics in a game. Meta may also be used as an adjective: a given tactic within a game can be said to 'be meta'. If the meta is unhealthy–i.e. that certain tactics are so effective that they rule out others from a competitive standpoint–the same tactic that 'is meta' can be said to 'be imbalanced'. Every game has a meta, from choosing an item in a video game, to making the opening moves in a board game like chess, to choosing whether to shoot for a point or go in for a goal in a match of Gaelic Football.

The meta of a game is the set of in-game tactics that are known to be viable from a competitive perspective, and so the meta is directly contingent upon the balance bestowed in the rules of the game. Following the initial adoption of a game, the way in which it ages is determined in part by the health of its meta; it is perhaps the single greatest factor that determines how long a game that is popular will remain popular. Gaelic Football has been played for centuries, and chess for millennia; both have healthy metas that stem from expertly-balanced rule sets.

1.2 What does a healthy meta look like

A healthy meta is one that allows players, and teams of players, to define themselves by their playstyles. As examples, certain early League of Legends teams were notorious for having their entire team serve as bodyguards for one 'glass cannon', and some chess masters are notorious for sequences of opening moves where they sacrifice a piece to gain superior positioning. Needless to say, the notoriety of signature strategies, and the hype leading up to the clash of two notorious strategies, are bedrocks of the culture of any game.

A longer example of a healthy meta: Quintessential to the balance of Gaelic Football is the ratio of reward for scoring a goal rather than a point. Choosing whether to shoot for a point or go in for a goal is a prime example of a low-risk low-reward tactic countervailed by a high-risk high-reward tactic. In the centuries the game has been played no one of those tactics has emerged to be generally superior to the other. That is not to say that in certain instances that one decision is not superior to the other; which decision is superior in a given instance depends on an innumerable amount of in-game variables. Hence, the set of most effective tactics available are derived from the rapidly changing state of the game. The key takeaway here is that the meta in the example is eternally intriguing because it is elusive, even to the most seasoned coaches.

A more contemporary, long example of a healthy meta: The key ingredient of the combat system in the sci-fi shooter Halo can be said to be 'the tripod' [1]. The tripod is the player's choice between firing their weapon, throwing a grenade, and performing a melee strike. Due to the tripod, at any given moment of an engagement, even for the most seasoned players, it is never entirely certain what the superior tactic is. When the dual wielding of weapons was introduced in Halo 2, the feature itself was well received, although the dominance of dual-wielding in the meta broke the tripod: Firing two weapons at once overshadowed both melee and grenade attacks. Due to firing two weapons being the best tactic in nearly any engagement where dual wielding presented itself (and it presenting itself for the majority of engagements), this led to claims that the combat felt 'flat'. During the creation of Halo 3, its development studio, Bungie, understood the value of restoring the tripod and in general in making its meta feel elusive. What resulted was one of the, if not *the*, most popular shooter game to date.

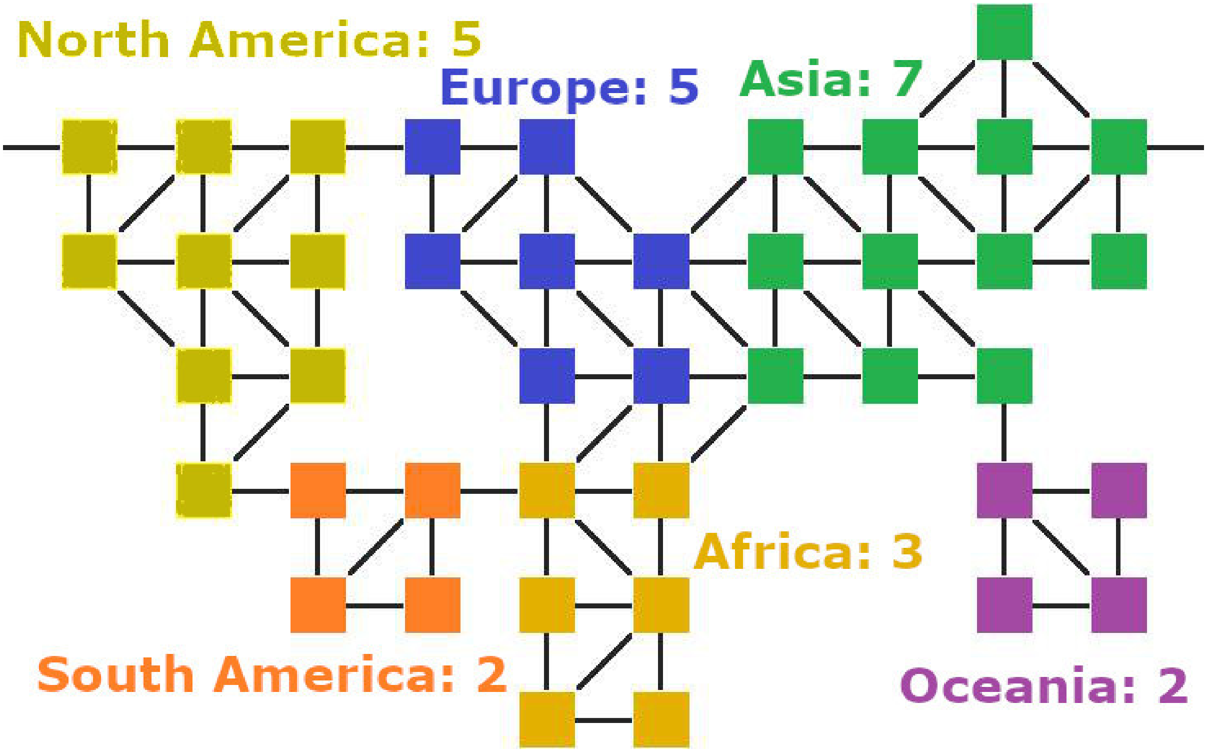
1.3 The nature of games with unhealthy metas

Players and teams being able to define a competitive style for themselves within a game is not only crucial to their experience, but to the experience of their fans. An unhealthy meta requires competitive players to conform to playing the game in a restrictive way, which does not make the competition intriguing to the player or, if there is one, the audience. While games with unhealthy metas are usually short lived, many popular games, past and present, exist that have unhealthy metas. Games that have remained popular over the years despite significant meta issues have various qualities that redeem them. On the other hand, most games that are popular today, and that have issues with their metas, often do not have redeeming qualities, but rather prolong themselves by creating a torrent of new content that means that no unhealthy meta has long to sour. Before we talk about this contemporary torrenting model, let us first explore how games from the past have endured the years despite health issues with their metas:

The sorts of games that manage to remain popular despite balance issues are those that are fun despite their simplicity, those that are played infrequently by an often entry-level playerbase, those that are accommodating for players who play in a casual-competitive manner, and those that have a strategy that orientates around understanding the other players. For those reasons many renowned board games, card games, and video games are popular, despite glaring imbalances in their metas.

For example, the strategy involved in the board game Monopoly can be completely ruined by a statistical analyses that reveals which sets of properties have the best risk-reward ratio [2]. However, despite this comprehensive dismantling of the game's meta, it has not caused the game to fall out of favour, due to the infrequent and casual audience of the game.

Another example of a traditional game that can be dismantled–albeit not quite to the same degree as Monopoly–is Risk. When I was sixteen years old I made the below image, which represents the "strategical essence" of the original Risk map.



In a failed bid to explain to a friend how "South America is the same as Oceania except it has two entry points" I found the motivation to create this map, which strips away the "cosmetic smokescreen". Without any algebra, a number of imbalances are apparent: such as the strategically superior continent of North America yielding the same bonus as the strategically inferior continent of Europe. The game that followed the explanation of my analysis of the continents to my friends was perhaps the most intriguing game of Risk I have played: now that I had revealed the true territory meta to everyone, players sought to predict the adherence of others to that meta. The ability of players to punish other players for being predictable revealed to me the true genius of Risk, and how it had stayed intriguing to players over the years despite such strategic imbalances.

While the cases of the two aforementioned games lend interesting insight into the conditions under which metas can retain an audience in the longterm despite imbalances, these games have past the test of time, and as such do not need balance. On the contrary, the many games that are popular today, only for them to lose practically all traction after a brief period, do need a solution for their meta issues.

1.4 Meta health: A neglectable issue in existing business models

The rifeness of meta issues in video games today is, for the most part, a byproduct of contemporary video game business models. An icon of the meta health issues that are endemic among video games today is the Call of Duty shooter game franchise. The business model of this franchise is emblematic of many other contemporary, mainstream games. The franchise is famous for releasing a game a month before Christmas every year to great financial success–twice selling more than 30 million copies. About a month after the release of one of these games and a handful of the game's guns occupy most of players' game time. There is considerable disdain among the game's community for the guns that comprise this narrow meta, although they continue to use them so as to optimise their competitiveness. Most indicative of how sour the franchise's metas can be is how its community refers to the period following release, but before a meta formulates, to be the 'honey moon period'.

So how is it then that the franchise remains so popular? The fast pace of release–not only of the games, but of in-game content–means there is little time for the imbalances in the games to form into decrepit metas, and for these metas to subsequently sour the game’s community. Patches containing new content, as well as balance changes to existing content, are frequently added to the game. When these are added, there is a fleeting period of intriguing play, where it is not yet certain which guns are meta. Before long however the meta stagnates again–at least in a somewhat different stagnation to the previous stagnation. As the meta stagnates again, so too do the community sour. But before long the next game is released, and relative to the stagnancy of the current game, new is sounding very good to the franchise’s community.

While addressing balance issues in Monopoly would be a once-off fix, addressing the meta of a game that is constantly being updated with new content would require a very dynamic solution. There is little imperative for such a fundamental solution within the business model of serial releasing. This is not to say that meta health is a matter that franchises like Call of Duty do not address. Indeed several patchwork solutions have arisen:

To address players engaging with new in-game content, they are made grossly competitive so as to ensure players engage with it upon release. This gross competitiveness addresses the risk of new content being eclipsed by an existing meta, albeit in such a way that perpetuates imbalance. To address the meta of the game stagnating, the game’s balance is continually ’given a shake’, so as to stop any one broken meta becoming sour.

1.5 The imperative for healthy metas in evolving business models

Side note on the use of the word ’episode’: In this section I will use ’episode’ to reference a stand-alone title in a series of games (e.g. Super Speed Racers 3), although at other points in this paper I use the same word to reference a measurable section within a game (e.g. a single car race within a car racing game).

The material circumstance that has derived the notion of games as a series of distinct episodes (e.g. Halo 1, 2, and 3) is largely that hard disks were the meta of video game resale. For the past few decades this trend has prevailed, and it was still dominant up until quite recently. Now, as the product of a number of technological advancements, such as in cloud computing, the meta of video game retail is changing, and no single business model has emerged to captivate the vast majority of the market yet. What is clear however is that all of the new business models are diskless. As such, the notion of a game as a series of distinct episodes, is now usually either a choice or a tradition, and very rarely a hardware convenience.

There are many imperatives for diskless games other than the convenience of not having to use a physical disk. Continuous games (those which are a continually evolving game, rather than a series of episodic games) offer a much more steady revenue stream to games studios and their holders. When developing episodic games, developers are often restricted by an allocation of time and money, which has led to a phenomenon of unfinished games being released, only to receive a stream of hotfixes post-release. This scenario tells that the will of the industry is towards more continuous models. In many cases the will of capital is also towards continuous models: Traditionally the purchasing of a game had been the primary source of revenue, although in-game purchases and subscriptions have seen phenomenal growth as a portion of the industry's revenue. While these in-game purchases can be found in both episodic and continuous games, they would seem to see better sales in continuous games, where the player's in-game content is sure to be relevant beyond the shelf-life of an episode.

Already, the two most popular games on PC (ranked by monthly active users), Minecraft and League of Legends, are continuous games. Some games are evolving towards a hybrid of these models, by increasing the intended shelf life of their games. For example, Microsoft's newest Halo game, Halo Infinite, which they are soon to release, is intended to be the newest Halo game for the 10 years that will follow its release. Another emerging phenomenon that can be observed through Microsoft's

Halo series is reviving the old games of a series and bundling them together into one continuous game. All of these new video games models demand serious solutions with regards to meta health. The type of meta that suffices for games with 1 year shelf-lifes does not suffice for more continuous games.

2 | Approach

2.1 Aims of this project

The aim of this project is to address the issue of meta health at a fundamental level, so as to escape the cycle of non-comprehensive balance changes that serve only to reshuffle the meta so as to stop it stagnating. The constant reshuffling of metas in contemporary video games means that even long term players are alienated if they take a brief break from the game; this is the opposite to chess, where an old time player can return to challenge newer players and often be as relevant as ever–which is part of what makes the chess community so deeply rooted. While there are many more factors to balance in contemporary video game than there are in chess, indeed orders of magnitude more, there is no excuse, as the tools available when the essential balance of chess was crafted were orders of magnitude more limited. The aim of this project could also be said to be to use AI-driven analytical approaches to see if it is possible to optimise the essence of what makes a game's strategy intriguing; in other words, to test the bounds of how diverse a meta can be.

2.2 The leaps and bounds of AI in gaming

It is only in very recent years that AI have come far enough to be able to be competitive, and even dominant, in in-depth video games. The AI, Deep Blue, won against the chess world champion in 1996. Despite this outstanding performance, many remarked that AI would struggle outside of areas such as chess, where there are a finite set of decisions. Many perceived, and still perceive, that Deep Blue had merely rote-learned the different outcomes of the game, and that such a technique could not be applied outside of chess, in environments where the decisions are less discrete. Although since then the range of games and tasks that AI have shown competence in and been able to dominate in has only grown. In 2018 a team of AI, OpenAI Five, defeated the world champions of Dota 2 team. Dota 2 is commonly regarded to be one of the most in-depth popular strategy games. As such, it is probable that many other games can be mastered with the same deep Q-leaning technology employed by OpenAI.

2.3 Human data driven analytical approaches

'Out of episode' refers to the parts of a game that occur outside of the section which we are trying to measure–e.g. choosing a car before a race, where the race is the section we are trying to measure. 'In episode' refers to the parts of a game that occur within the instances which we are trying to measure–e.g. driving around a corner during a race.

Some development teams have developed substantial analytical approaches to optimising their multiplayer experiences. Although at times the techniques employed by these teams to address balance are well developed—such as in the case of Bungie—they have not yet incorporated newer technological advancements into their approach. These existing approaches are focused solely on data collected from player gameplay. That being said, many issues can be discovered and corrected through analysing player behaviour. Most popular games studies fail to do this, let alone incorporate the newer approach I will be exploring.

When Bungie–who were the developers of the Halo shooter games at the time–employed analytical approaches to player behaviour in Halo, many great adjustments were made. For example, mapping player deaths in a multiplayer map called Valhalla brought to light the fact that the side of the map one team spawned on had an inherent advantage over the other side [1]. This allowed the level designers the knowledge to make the appropriate adjustments. This map went on to become perhaps the most iconic team multiplayer map in video game history.

2.4 Merits of an AI driven approach

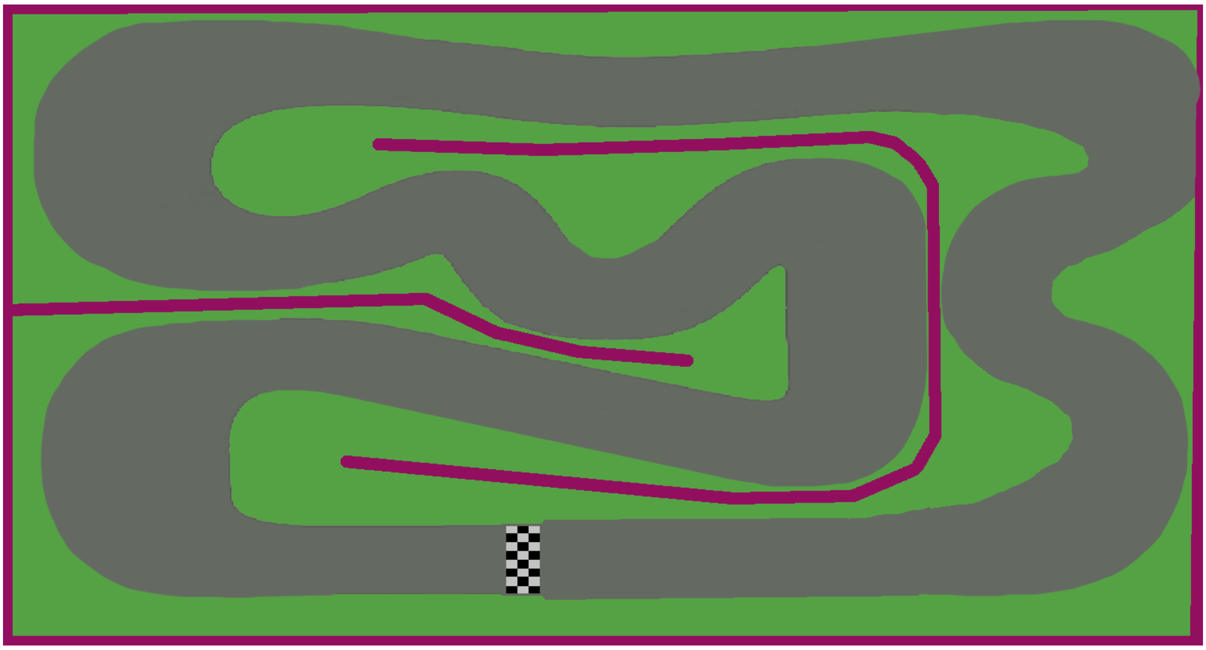
Human data driven analyses make a lot of sense for analysing player activity within specific player vs player setting and broadly within player vs computer settings, such as the campaigns of games. However, in the context of multiplayer balancing, human data based approaches are limited in their potential. I will explore a scenario that human-data only approaches cannot address: Balancing the viability between adopting different choices in a multiplayer environment. For example, an overview of player time spent bearing different weapons, that factors out the availability of these weapons, could not be used as a comprehensive indicator of whether these weapons were overly competitive. Although frequent use of a given weapon by players, relative to the availability of the weapon, is an indicator as to whether the weapon is over-competitive or under-competitive, using this as a metric would have unintended consequences. If we advantaged less-used weapons based on player data, we would likely end up pushing players towards adopting less fun game content in their effort to be competitive. This is because player decision are based on more than raw competitive opportunity cost; the frequency of players making a given decisions does not necessarily correlate with how competitive that decision is.

Seeing as we know for sure that AI's decisions are solely based on competitiveness, and not fun, or whatever else we humans base our in-game decision on, we *could* assume that the frequency of a given weapon's use (with availability factored out!), relative to the mean weapon use, correlates directly with imbalance. The use of AI would also mean that changes would not need to be tested on players to see their outcome, and so a multi-dimensional continuum of ai-driven metas could be generated, which would correspond to a multi-varied different balance changes. At present the most cumbersome part of these analysis is player testing.

3 Experimental Methods

3.1 Conceptualising a scenario for my theory

To test my theory, I had to conceive some game scenario with some in-game coefficient to perform an analyses on. While a more proper demonstration of my concept would be extracting data from an existing game with a player base, there is, imaginably, many more steps involved in getting started with such. A scenario I felt I could handle, and that was relevant to many existing games (e.g. Mario Kart), is whether to try and cut across the grass of a corner or adhere to the road in racing games. My coefficient to analyse would be the degree to which travelling across grass caused cars to slow down. Of course, it should be that it is usually most viable to stick to the road, but I thought it would be fun if it is often nearly as viable to cut across the grass, and on occasion equally or even slightly more viable. To get the ball rolling I appropriated a car game written in Python using pygame. I made maps that are composed of a road that forms a loop, and for there to be grass, and at times walls, on either side of the road.

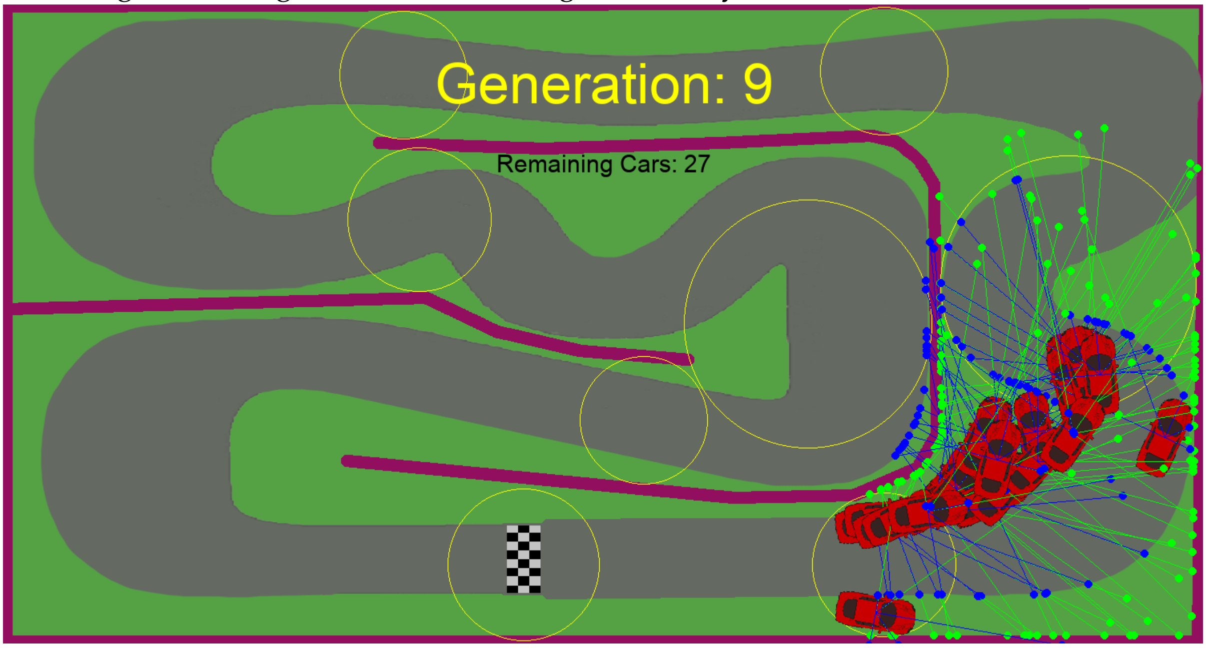


3.2 Choosing a machine learning approach

NEAT is an algorithm from the early 2000s that is now popular among academics. It is an acronym for NeuroEvolution of Augmenting Topologies. It involves mutating generations of neural nets (or 'genomes') based on the various rules(or 'hyper parameters') and rewards you set, which determine how each generation evolves into the next, and how mutation is applied to the evolution. Initially I had looked into a deep q-learning approach, although after some research it became apparent to me that a more traditional algorithm, like NEAT, would suit my ends more. From what I understand deep q-learning can be harnessed to develop more acute solutions, but that approaches like NEAT generally see tangible results sooner; anything that can be solved with NEAT can be solved in a matter of hours or minutes on a contemporary retail computer. As a novice to machine learning, NEAT seemed like the more forgiving approach, particular insofar as I could rapidly see the effects changes to various hyper parameters were having upon the evolution. As the goal of my machine learning is not particularly nuanced, deep q-learning seemed to me to be unnecessary for my ends, particularly where a more documented means presented itself.

3.3 Building the game and training the AI

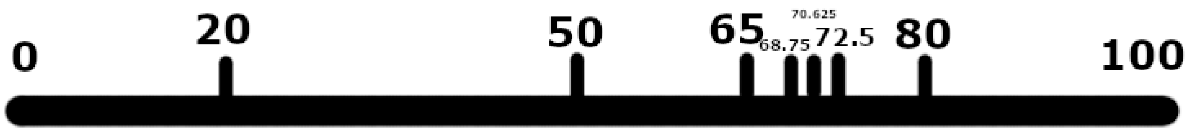
Pic: 9th generation genomes encounter grass as they come around their first corner



I first needed to implement some rules for the game. The initial game I co-opted was so that deviating off the road caused the car to go extinct; I changed that functionality to apply to the purple walls instead, and for the grass to now only slow the car. The next major feature to set up were the radars for the car. The blue radars are the 'roadedge_radar's and the green ones look for the walls. The bulk of the programming was in tweaking the reward function and hyperparameters depending on what I saw the genomes doing with their cars, setting up new ways to measure the performance of the cars, and creating a file system to store and retrieve genomes. When I became somewhat competent in orchestrating the learning, I changed my program so that as the AI are training, they are faced with a random map every generation. Before long I realised this was probably not a reasonable goal considering my novice degree of knowledge and retail-grade hardware. Instead I opted to train AI who's expertise were solely in solving a particular map.

3.4 Quantification of the AI data

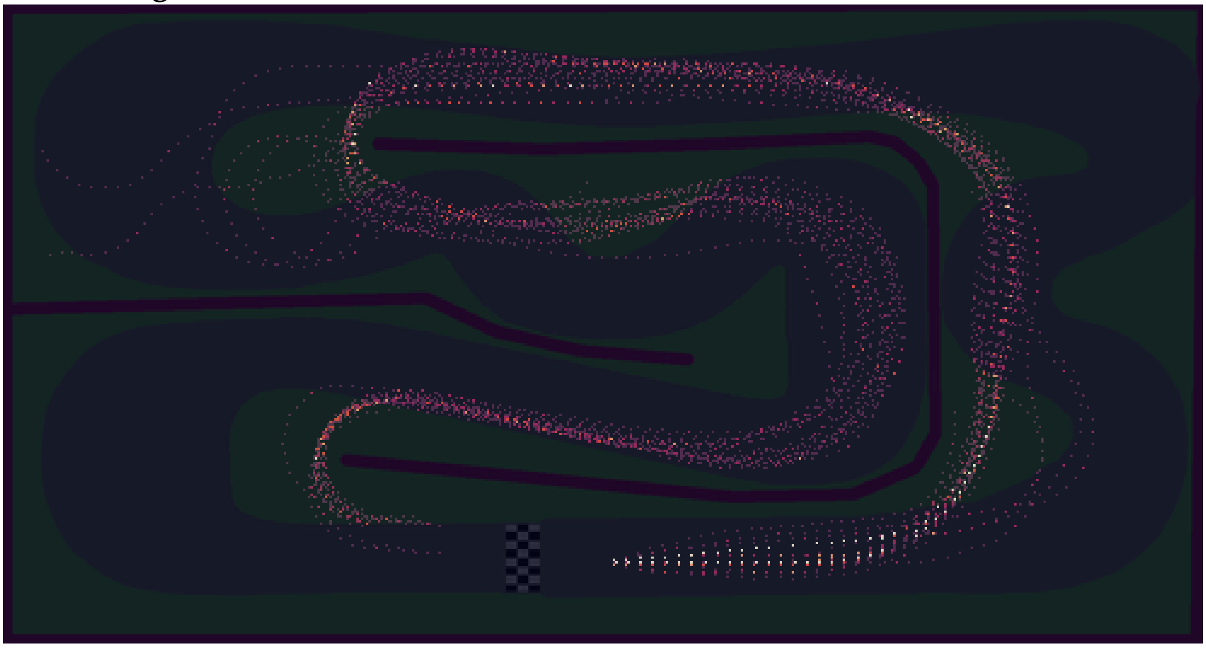
I assessed that the best way to quantify the way the cars and the grass were interacting was by visualising the movement of the cars in a heatmap. I began to produce heatmaps to get a better understanding of my results. As I became more proficient at training the cars, the heatmaps produced when the cars were trained with different grass slow factors eventually began to make sense: when the grass slow was greater the cars would adhere more to the road and vice versa. The heatmaps of my final AI are presented in the following section. I first produced heatmaps for 20, 50, and 80% slows. Based on my analyses of these, I knew the ideal coefficient lied between 50 and 80. I trained AI and produced a heatmap for 65, then 72.5, then 68.75, and finally 70.625.



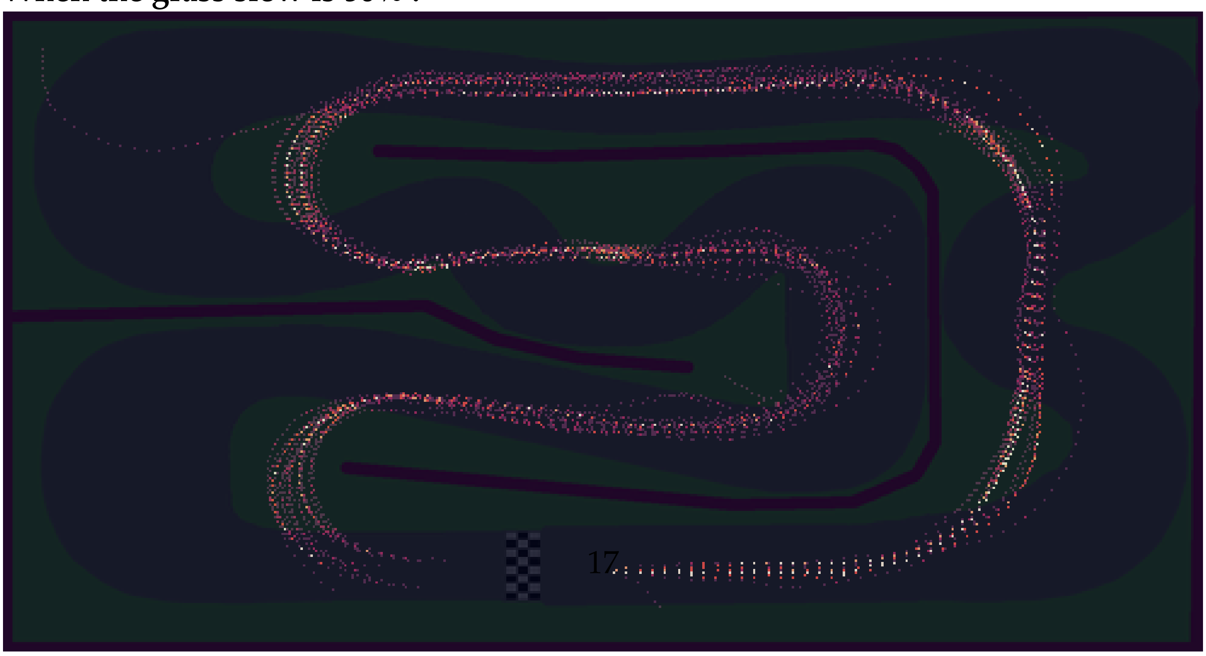
4 Results

4.1 Map 1

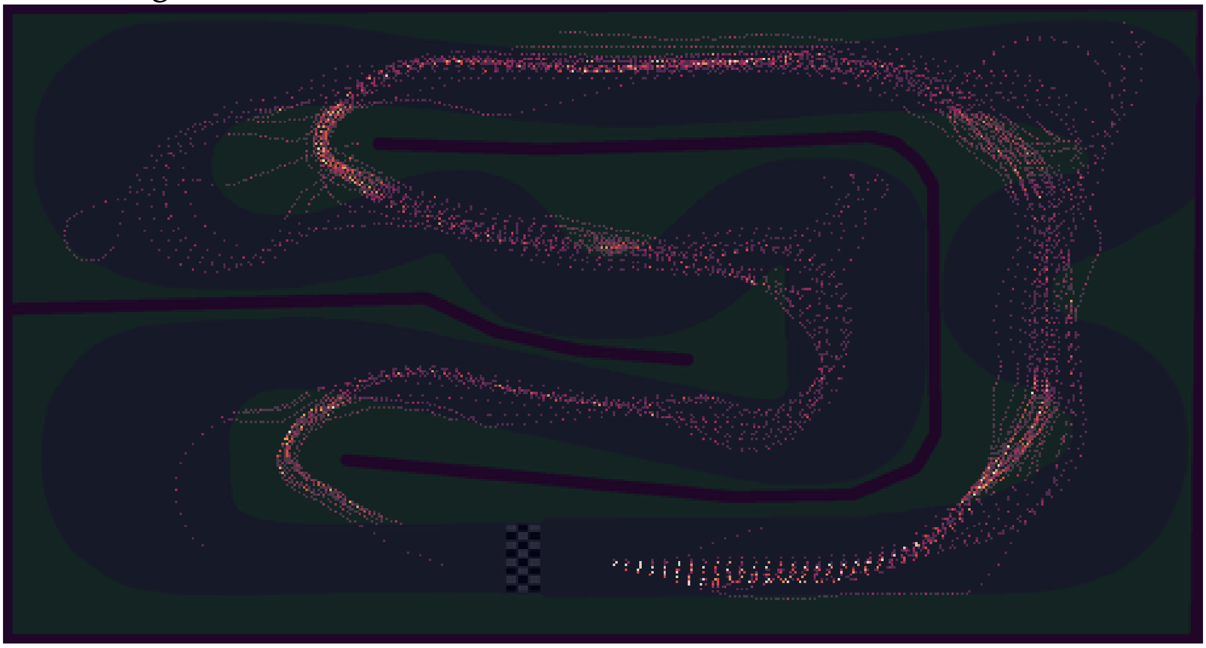
When the grass slow is 20% :



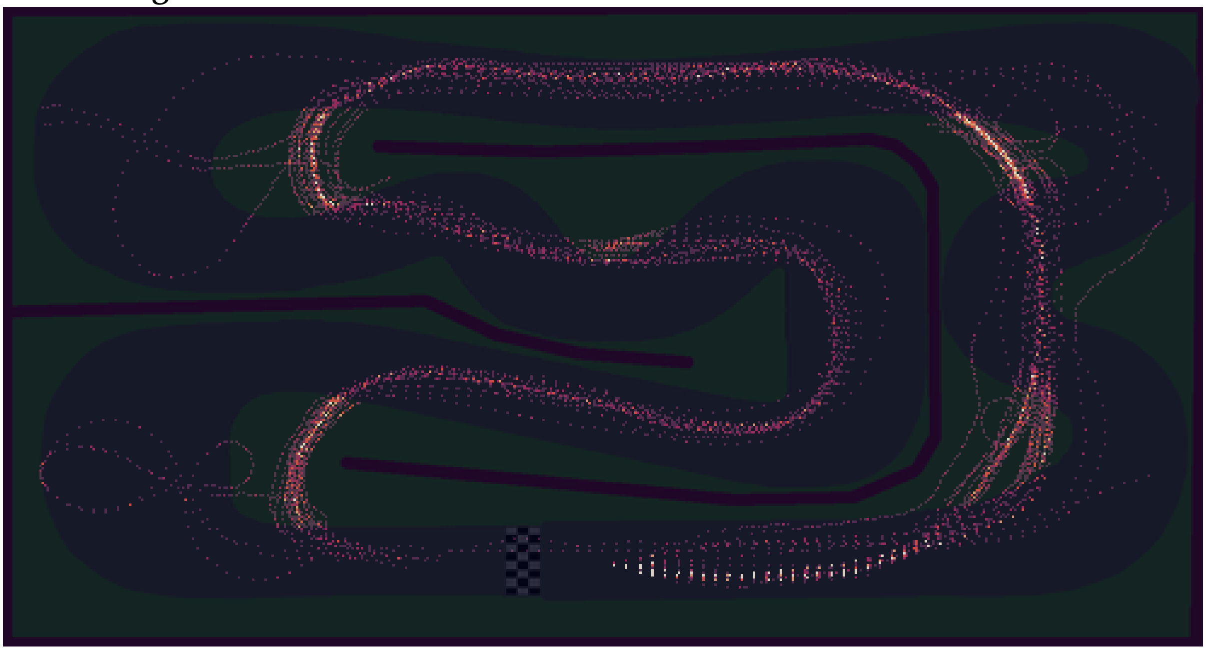
When the grass slow is 50% :



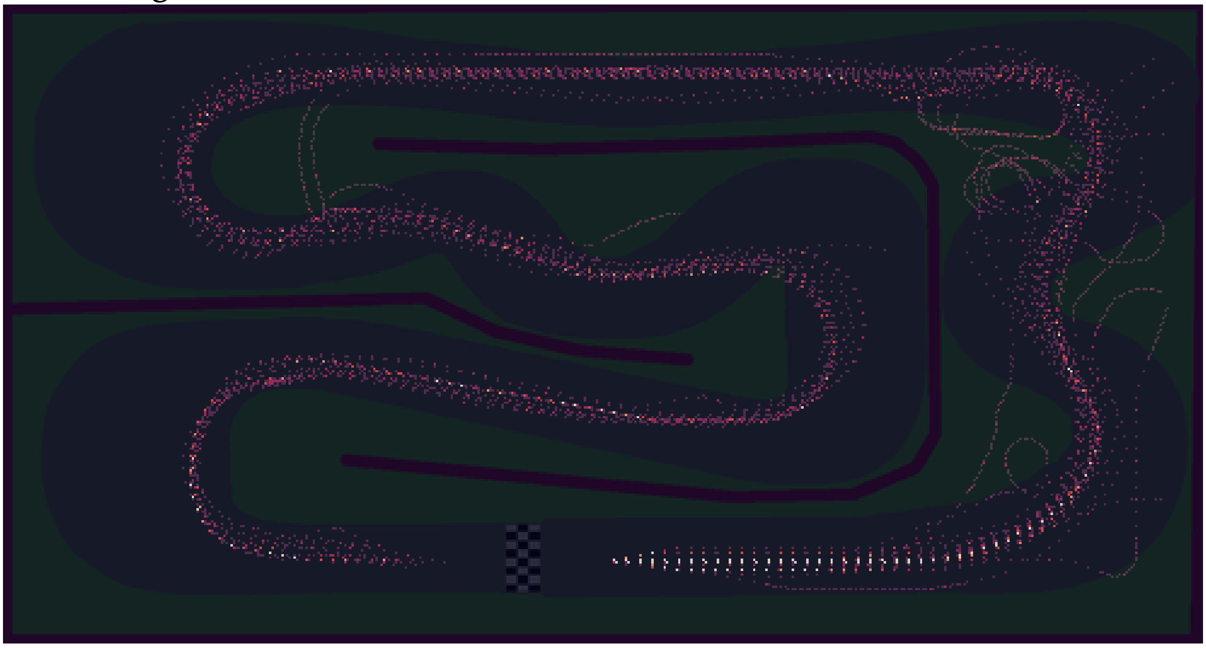
When the grass slow is 65% :



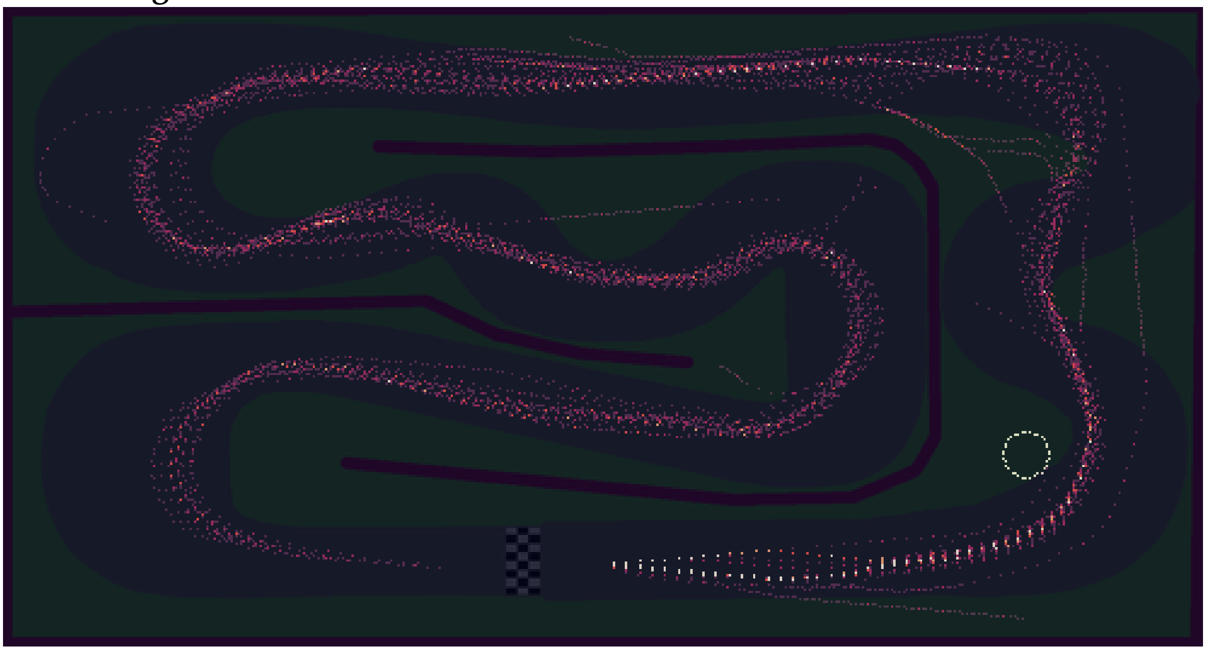
When the grass slow is 68.75% :



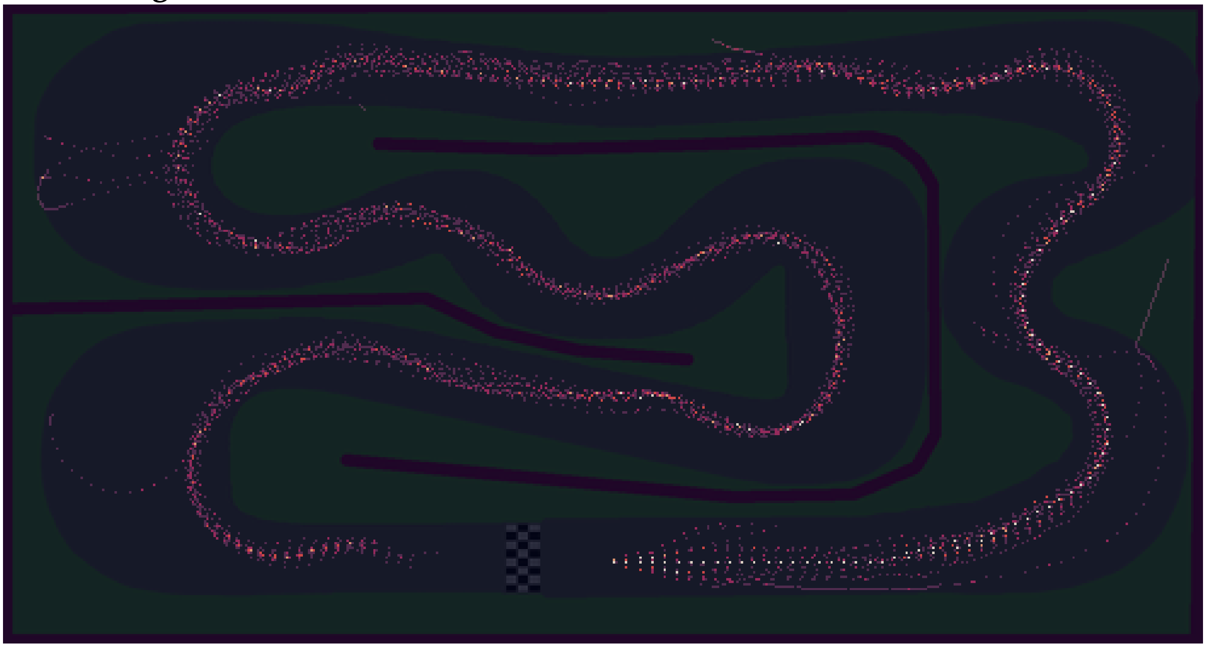
When the grass slow is 70.625% :



When the grass slow is 72.5% :

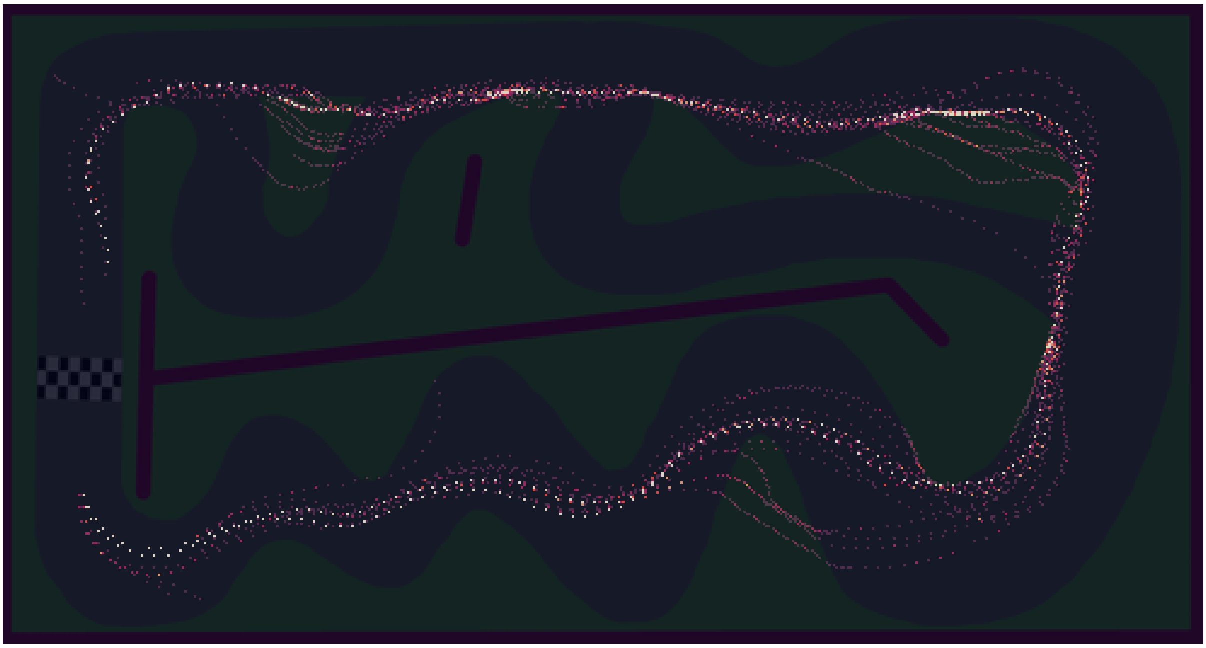


When the grass slow is 80% :



4.2 Map 2

When the grass slow is 70.625% :



5 | Conclusion

5.1 Digest of results

For the most part I failed to find a value for our coefficient that split the cars between travelling across the grass and travelling along the road at corners. However, I think this is because of how I was training the genomes: once going across the grass, or not going across the grass, became the the majority decision among the most fit genomes, the entire group eventually adopt this choice for the most part. Though I did not find a single value that splits the decisions of the genomes, I found two very close values, 68.75 and 70.625, that produce very different results despite their closeness: When the grass slows the car by 68.75 percent the cars find that it is optimal to cut the majority of the corners, while at 70.625 the cars adhere to the road for the majority of the corners. Therefore I conclude that a grass slow coefficient between these two values would be conducive of a healthy meta for this game's hypothetical player base.

There is the matter of considering the grass slow coefficient with regards to multiple maps, as would plausibly be the case in a game. It would not seem reasonable if the same type of grass slowed to different degrees on different maps. As such, some universal value must be settled on. An approach that could be taken would be to look at a 2d grid of heatmaps, that vary by map in one dimension, and by different coefficients in the other, and to decide based on that. Alternatively, the grass slow coefficient could be tailored to one map (a more generic one probably being ideal) and other maps with the same grass could be tweaked to synergise with the coefficient. In my case applying the 70.625 value, which produced results on Map 1 which I found to be desirable, also produced desirable results on Map 2. Perhaps the 70.625 value even applied more desirably on Map 2, as there a number of corners that *some* of the AI choose to cut.

5.2 Remarks on my project

Had I had more time I would have like to develop a choice for the AI that is made outside the episode(i.e. before the race begins). What I had in mind is that there could be two types of cars the AI can choose before the episode: one that is the existing car, and another that is faster but that has more restrictive turning. The coefficent to balance could be the bonus speed of the new type of car. Not only would it have been interesting to have an out-of-episode coefficient to analyse, but it would be interesting to see what a multi-varied analyses of the in-episode and out-of-episode coefficients would bear.

I am glad however that I did at least manage to complete a full analyses for one coefficient in a game. I think this alone suffices to demonstrate my concept.

5.3 Future forecast for AI-driven analytics in video games

Data analytics is exploding into all walks of life, and an area as conveniently quantifiable as video games is certain to have its part in this. Going forward I imagine unimaginable potential lies in optimising the metas of games by using AI-data driven analytics. However, I do not imagine that the human touch will ever not be a part of this process; while analytics–both human and AI derived–serve to offer great insight, I do not think the fun of a meta can ever be directly quantified, and so the human touch may always be needed to make the final decisions based on the insights.

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6.1 Bibliography

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