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Master Thesis Project

Artificial Intelligence Adaptation in Video Games

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Abstract

One of the most important features of a (computer) game that makes it memorable is an ability to bring a sense of engagement. This can be achieved in numerous ways, but the most major part is a challenge, often provided by in-game enemies and their ability to adapt towards the human player. However, adaptability is not very common in games. Throughout this thesis work, aspects of the game control systems that can be improved in order to be adaptable were studied. Based on the results gained from the study of the literature related to artificial intelligence in games, a classification of games was developed for grouping the games by the complexity of the control systems and their ability to adapt different aspects of enemies behavior including individual and group behavior. It appeared that only 33% of the games can not be considered adaptable. This classification was then used to analyze the popularity of games regarding their challenge complexity. Analysis revealed that simple, familiar behavior is more welcomed by players. However, highly adaptable games have got competitively high scores and excellent reviews from game critics and reviewers, proving that adaptability in games deserves further research.

Keywords: artificial intelligence in games, adaptability in games, non-player character adaptation, challenge

Preface

Computer games have become an interest for me not so long ago, but since then they have turned almost into a true passion. Unfortunately, there is really no place where one can choose a path of game creator, so the only way to enter the game industry is to enter it by yourself. While playing some outstanding games (they will be mentioned in the work more then one time, as will be seen), I always had in mind how I would like the characters in the game to behave and how they could possibly behave as if they were a real ones. And here I have got a chance to explore all the possibilities of creating interesting and challenging opponents and discover advanced challenge in modern video games.

So I would like to thank the Linnaeus University for giving this opportunity to study a relatively new field in computer science. Especially, I want to express my gratitude to my supervisor Aris Alissandrakis, who helped me along my way through the artificial intelligence in games with support and advices, setting meetings for discussions and revisions, shaping up the idea and work, despite busy times. Also, I would like to thank the course manager Narges Khakpour for guiding us through the scientific aspects of the research and Maria Ulan, who carefully reviewed given work and whose comments and ideas helped to improve this thesis. Finally, I want to thank my family and friends for a great support and patience during these difficult and challenging journey.

Contents

Glossary

Adaptability (in video games) is the ability of the game AI controls to adapt according to the player's actions and/or changing game context.

AAA games is an informal classification used for video games produced and distributed by a mid-sized or major publisher, typically having higher development and marketing budgets. [wikipedia]

Non-player character (abbreviated NPC) is any character in the game not controlled by the player(s).

Antagonist/opponent (in game) is a non-player character (NPC) who is hostile to player.

Game AI control is an intelligent system used in games to control the behavior of NPCs, in particular, main antagonist.

Independent video game/indie game is a video game that is often created without the financial support of a publisher, although some games funded by a publisher are still considered "indie".

Non-scripted behavior is a behavior of the NPC that can alter through the game-process. Usually implemented using AI technologies.

Scripted behavior is a behavior of the NPC that is strictly defined by in-game scripts and does not change according to player's actions.

1 Introduction

Every game has its set of rules and restrictions, that guide and limit a player's behavior, so the player cannot achieve the game goal directly. The player is meant to find ways to solve the given problem, which means to take some risk: take this turn rather than the next, preferably hide in this place, or choose a certain dialogue option.

These restrictions and rules create conflict between player and game system. Any conflict within the game gives experience to players, but experience alone is not enough to make a game memorable, which is usually one of the main goals of the game creators. What makes game memorable is an emotional connection between a player and a game itself. This is called a sense of engagement [1].

Emotional experience is very unique to any person. What can be a memorable experience for one person will not necessarily be an experience for someone else. Therefore, the job of a game designer is to create a game that will bring unique experiences to each individual player.

Tracy Fullerton in her book "Game Design Workshop: A Playcentric Approach to Creating Innovative Games" [1] picks out a list of basic elements that work on player's engagement: Challenge, Play, Puzzle, Premise, Character, and Story. In this study, the focus is set to the challenge aspect of the game, which can be achieved by enhancing behavior of non-player characters.

1.1 Background

Conflict challenges a player, makes him feel tense, while the player tries to solve a problem. Since the challenge brings experience to a player it is also very personalized. Basically, it is "a task that is satisfying to complete, that require just the right amount of work to create a sense of accomplishment and enjoyment" [1], which is described in the theory of experience flow by Mihaly Csikszentmihalyi (see Figure 1.1). Level of challenge and player's skill should balance between frustration and boredom to keep the player interested in the game [1, 2].

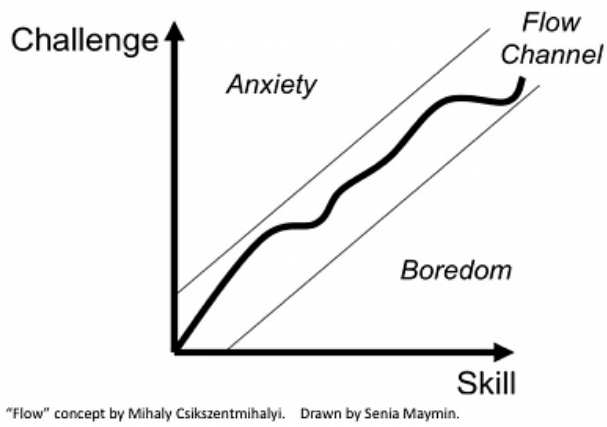

Figure 1.1: Flow theory by Mihaly Csikszentmihalyi. Figure originally from http://thisemotionallife.org/blogs/flow.

Tasks have a lot of variations depending on the context, design, mechanics and

other elements of the game. They can include time challenge (finish the task in a given amount of time), "clear the level" challenge (get rid of enemies or specified objects on the game level), solving a puzzle or a riddle, kill a certain amount of enemies, defeat the main antagonist and others.

In the most of single-player games, especially stealth, shooters, action and horror/survival games, the main challenge is associated with the game antagonists. They include soldiers, guards, bandits, monsters and creatures, whose job is to threaten, scare, hunt, and/or kill a player.

Keeping balance between frustration and boredom is a difficult task when designing in-game antagonist. Usually, difficulty setting of the opponents affects only strength and health and very rarely it influences tactics [3]. But mostly, the thing that makes antagonist hard to defeat is its behavior. According to research in game design and game balance, if game antagonist is too strong and hard to defeat, players will likely quit the game as it turns out to be impossible to finish. In the opposite situation, when opponent is too weak, players in most cases lose interest in the game [4]. So antagonist behavior and its adaptation to changing circumstances is a task that requires due attention.

1.2 Motivations

Number of game developers claim that NPC (non-player character including friendly characters and antagonist) AI problem is almost solved for most production tasks, e.g. searching the path, looking for places to hide, an immediate reaction to player's actions, difficulty adjustment to player's skill level etc [5].

Most common problems i.e. pathfinding (especially important for stealth games) and steering as parts of NPC behavior are usually solved by tried and tested algorithms and AI technologies like A* algorithm (used for pathfinding) [6].

More complex antagonist behavior – state change – is usually solved by less effective and flexible algorithms. One of the most basic and often used AI technologies for this task are Finite-State Machines and Decision Trees. Finite-State Machines are usually implemented by scripts and simple if-then statements, so they suggest only basic behavior control. FSMs, as they are defined formally, are computationally limited and badly scaled, so they are not able to solve large problems and synchronize multiple modular behavior together, what makes them unable to provide complex challenge experience to player [7].

Another innovation – belief-desire-intention model (abbreviated BDI) [8] – was first used in *Black & White*[1]. But it did not bring desirable experience to players as it was not used properly. The idea itself was novel and quite promising as this kind of innovation had not been used in video games before, but it had poor design and integration, so players experienced inconvenience and problems teaching their monsters as treat/punishment system did not work as expected.

Concerning accordance of NPCs actions to the environment, it is often established with cheats and tricks rather than real artificial intelligence. For example, Half-Life game designers created an illusion of NPCs collaborative work, so they seemed to be intelligent, while, in reality, they were not.

As it can be seen, in practice, game AI even in most complex games is not bringing desirable results or implemented with tricks to cover lack of sophistication, so sometimes it is called *artificial stupidity*, rather than intelligence [9, 10].

[1] Lionhead Studios, 2001. https://www.mobygames.com/game/black-white

Though game AI received quite a lot of development since the beginning of video game age, still it makes only small steps towards adaptivity to player's actions, e.g. learning from player's actions, behavior and tactics in order to fit player's level, skills and preferences. There are adapting AI techniques that rarely used by big companies in AAA-games and yet very promising. Many researchers take an interest in adaptive game AI.

Research is being done on so-called opponent modelling and case-based adaptive games [9, 11]. For example, in the game *GHOSTS*[2], AI was able to learn opponent's (human player) playing style and adapt to it (i.e. attack the opponent's piece etc.) inferring unknown information about the game state [11]. Besides, opponent modelling was successfully implemented in real-time strategy games (RTS) [12]. In addition, there are AI techniques that can predict sequences of player actions, e.g. predicting of player position in first-person shooters [13].

Current gameplay adaptation, e.g. adapting to the game circumstances while the game is in progress, has been successfully implemented in some simple video games [14], but yet all of these innovative techniques are rarely used in single-player AAA-games. There are only a few commercially successful games with adaptive AI. Among them, there are such promising games like *ECHO*[3] and *Hello Neighbor*[4].

Creators of ECHO developed a game NPC adaptive controllers, that can alter tactics of the enemies, so they behave in a way a player behaves, copying his or her playing style [15]. In Hello Neighbor, the main antagonist - the in-game neighbour of the player - can remember player's actions and ways he or she used in previous rounds, and set traps on visited places, forcing the player to look for other ways to deal with the antagonist [16].

The general problem of single-player games is that when player plays the game, at some point he will meet in-game antagonist (in horror/survival games, there are the most explicit single antagonist or just a few of them; other considered genres can have numerous antagonists, i.e. soldiers, guards, monsters).

Generally, there are three possible outcomes:

- player defeats the antagonists or, at least, fights them back;
- player loses (dies in most cases);
- player runs away avoiding the direct battle (common in stealth and survival horror games).

After meeting the antagonist, the player becomes familiar with the NPC's behavior. Once s/he finds out the weak point of this NPC opponent, the game progression becomes much easier, as nothing can stop the player from exploiting this weakness [9, 17]. Therefore, it is possible for the player to lose interest, if the antagonist does not modify its behavior and change it through the game (but still in the way to make the game progression and victory possible). It has to be well-balanced to remain in between frustration and boredom (see Figure 1.1 in Section 1.1). [1, 2]

[2]GHOSTS is a board game designed by Alex Randolph for two players, released in 1982 by Milton Bradley.

[3]ULTRA ULTRA, 2017. http://www.echo-game.com

[4]Dynamic Pixels, 2017. https://www.helloneighborgame.com

People from academia and game industry predicted increasing of the importance of AI in game development years ago [18, 19] as a way to increase the game playing challenge and, as a result, popularity and financial earnings [18, 20]. A lot of academic research has been made in the field of adaptive game AI. But still, due to state-of-art observation of adaptive game AI, adaptive behavior is quite rare case in video games development as (1) AI learning process requires numeral trials to adapt its behavior to the circumstances [17, 21], and (2) applying adaptive techniques may result in unpredictable and uncontrollable behavior [17].

This brief research reaffirmed us that there are still game AI problems that need to be resolved to increase player's interest in single-player games, e.g. more advanced adapting to the player and player's actions (players gain more memorable experience from the game, if the game and in-game antagonist are consistent with their play style [22]), adapting to environment (game context), increasing NPC behavior believability [23, 5], and improving AI integration.

Improving AI integration and adapting also means personalizing player's experience to increase emotional connection between player and game. Knowledge about the player's preferences, that can be gained from player's in-game behavior, can help in providing a stronger emotional impact and more meaningful experience [23].

However, as we could see, the field of game artificial intelligence in academic research is still rather new and unexplored. There are numerous researches in techniques and experimental methodologies that are used or can be used in video games, however, adaptive AI in general is a rare target of these researches.

Yildrim and Stene in their work [24] tried to define if there is a need of AI technologies in games of different genres and if the in-game NPCs are intelligent. The features intrinsic to intelligent game agents defined by the authors were further used as a basis for basic AI classification in this master thesis. The result of the classification corresponds to expected behavior of the NPC within specified genres (Role Playing Games, First Person Shooters/Shooters, Real Time Strategies) described by the authors.

Rabin in "AI Programming Wisdom" [25] and Millington in "Artificial Intelligence for Games, Second Edition" [26] addressed learning AI in games in general, describing approaches and theory of adaptive AI that are used or can be possibly used in video games. Their classification of learning approaches was used in this work for classification of adaptive AI in games.

Numerous researches address adaptability towards human player including player modeling [27, 22, 28, 29] and adaptive components [27], however, they do not apply their research to the trends in modern video games and mostly reference experimental games and game modes developed by researchers.

As we could see from the brief literature review, the topic chosen for this work is unique in the scope of master thesis, but individual parts of the given work are related and referred to the research done by scientists in the field of game development and artificial intelligence in video games.

1.3 Problem Statement

Due to state-of-art observation, only a few video games suggest player a unique experience through adaptive AI, most of them are indie games like ECHO or Hello Neighbor mentioned in Section 1.2.

So here a question arises if adaptive game AI can make the game more popular and successful and if it is reasonable for game companies to apply complex AI in AAA-games. We expect to find a relation between challenging adaptability of AI in games and success of such games among players and critics.

Based on examination of the recent and current state-of-art application of AI technologies in computer games, we propose to investigate ways to classify and compare games in terms of adaptability of the (hostile) NPC AI towards the human player. We assume that classification and comparison will be done according to a value along the spectrum or set of features representing a level of adaptation. Such a classification could then make it possible to investigate positive or negative correlations of *adaptability* to popularity or commercial success. The classification also could point out the different aspects of game AI adaptation, possible levels of adaptation and remarkable approaches and implementations in popular video games.

The two research questions and two hypotheses defined for this thesis work are formulated below.

RQ1 How can AI technology be used in computer games in the context of the adaptability of the NPC behavior towards the player?

RQ2 What features can be used to classify and compare games depending on the amount of adaptability of the NPC behavior towards the player?

H1 Games with higher adaptability of the NPC behavior towards the players are more well liked in terms of popular opinion, compared to games with lower adaptability.

H2 Games with higher adaptability of the NPC behavior towards the player's are more commercially successful, compared to games with lower adaptability.

1.4 This Thesis Report

In order to answer the research questions stated in the previous section, we carried out a thorough research in the academic fields of game design and game AI, and game development industry.

Deep literature review in the field of computer game AI was performed, with a focus on adaptability of NPC behavior towards the player, to answer . Based on the results of this review, a vast classification of game AI was developed addressing the complexity and adaptability of game NPC control systems ().

On the next step, a list of games was collected for analysis purpose. We chose the most prominent representatives in all the genres, claimed by critics and reviewers, or the ones that appeared to have interesting implementations due to available data, our findings. The game set also includes popular games in terms of sales and scores. These games were further classified using the classes we have defined in the previous stage.

Obtained classification also was used to analyze the correlation between scores and sales for different levels of complexity and adaptability in video games. During this stage, addressing and we defined if there is correspondence between complexity and popularity of video games.

As game development companies usually do not share the details of their implementation, availability of information comes as a limitation of this work. While

analyzing and classifying games, we can mostly rely only on third-party data, e.g., player's reviews, comments, blog posts, videos and, also, our knowledge and understanding of video games.

1.5 Contribution

The contribution of this work is developed set of features, that will allow to compare and classify games in terms of the adaptability of the (hostile) NPC AI towards the human player. Using a number of games classified using those features, the correlation between adaptability and popularity of video games will be examined.

There were several attempts to classify games regarding their complexity or ability to act as an intelligent agent (see subsection 1.2). Different classifications appeared in several research works, but most of them were theoretical, and only a few were applied to actual games (for example, [24]). In this master thesis we tried to incorporate different parts of researches in the field of game development under a comprehensive classification that touches different aspects of the game AI, and then apply this classification to existing trends in the game development industry.

1.6 Target Groups

The results obtained during the target research of this paper might be useful in the game development field and can be used by game developers and game designers.

The job of game designer is overall look and feel of the game, he defines the core elements of the game and how the game should be played. His job is to design a game environment that can provide the sense of engagement to the players and satisfying challenges. So he is the one responsible for providing personalized experience and to decide how it would be delivered through the game.

Game developers, as the actual builders of the system, are responsible for designing and implementing the system, that can maintain mechanics developed by the game designer.

1.7 Report Structure

This master thesis report consists of four chapters. Introduction chapter is followed by a broad background (Chapter 2). It describes the basic game development terms, techniques widely used in video game industry, and also contains vast literature review of adaptability in video games and adaptable game AI, adaptable components of the game, and examples of advanced AI techniques that can be used in video game industry.

Chapter 3 is dedicated to methods used for this master thesis project. It describes the general scientific approach and detailed steps performed in this work. It also contains results obtained from the literature review in a form of classification of video games based on their AI complexity and adaptability.

In Chapter 4 the obtained classification was used to classify a set of selected games. This classification was further used for analysis of popularity of video games, which can be found in the same chapter.

Finally, Chapter 6 contains highlights of our results obtained during the game analysis stage, and also conclusions, followed by suggestions for future work.

2 Background

This chapter will describe general usage of Artificial Intelligence (abbreviated AI) techniques in video games and their evolution through the history of game development. The chapter will also cover basic information about game terms and aspects specific to the industry.

2.1 AI in Computer Games

How is AI used in games? AI has found a use in different aspects of video game creation. AI techniques can be applied in a variety of ways in both the development process and game design. Since the early video games AI era the term *game AI* mainly refers to the behavior of *NPC*, varying from trivial path-finding to decision-making [23], but AI techniques have also been used in:

- **Narrative part** of the game design: The *Ice-Bound Concordance*[5] game used AI controlled combinatorial narrative system to build up a story from prewritten text fragments through the player and AI interactions. Narrative-aimed AI has also been used in the popular interactive conversation game *Façade*[6] and a platform for interactive stories *Versu*[7];

- **Game testing** process: AI was used as a tool for playtesting and game balance improvement of the tower defense (and offense) game *City Conquest*[8]. The AI represented a virtual team which could identify dominant strategies and minor elements that needed tuning during the game process. Also, AI system was used for walkability testing in *The Witness*[9] to prevent players from getting caught on edges or stuck in the walls.

- **Procedural content generation** (abbreviated PCG): AI has been used for procedural generation of maps or items. The most successful examples of using AI for PCG are *Minecraft*[10] and *Love*[11]. In addition, the *experience-driven procedural content generation* (EDPCG) framework was developed as a result of the research in PCG and was used for generating personalized *Super Mario Bros* [12] levels [23, 30].

- **Creating a whole game**: Michael Cook has created AI called ANGELINA ("A Novel Game-Evolving Labrat I've Named ANGELINA"), that can intelligently perform the whole game design process and create variety of games from arcades to platformers; and it continues to go further into other game genres.[31]

However, with the exceptions described above, AI techniques are mostly used for controlling NPC behavior.

[5] Down to the Wire, 2014. http://www.ice-bound.com
[6] Procedural Arts, 2005. http://www.interactivestory.net
[7] Versu, 2012. https://versu.com
[8] Intelligence Engine Design Systems, 2011. http://www.intelligenceenginestudios.com/cityconquest.htm
[9] Thekla, Inc., 2016. http://the-witness.net
[10] Mojang, 2011. https://minecraft.net
[11] Eskil Steenberg, 2010. http://www.quelsolaar.com/love
[12] Nintendo Creative Department, 1985.

2.2 Non-Player Characters and their behavior

NPC in games is a character that is not controlled by a human player. Instead, it is usually controlled by a computer via predetermined or responsive behavior. NPCs can be conditionally divided into three groups with respect to their behavior towards players: (1) hostile, (2) friendly, (3) neutral.

Usually, the term NPC refers only to the characters that are not hostile towards the human player, i.e. friendly or neutral characters, which can help and lead the player during the game or do not have any impact on the player's character and are created to fill the game environment.

This master thesis is mainly focused on hostile NPCs such as different kinds of enemies (soldiers, guards, bandits, monsters and creatures, whose job is to threaten, scare, hunt, and/or kill human player) and "mobs" (in most modern games this term refers primarily to NPCs that are meant to be killed by the human player [32]), but friendly and neutral NPCs will be referred to as well.

NPC behavior in computer games is, in most cases, strictly scripted and automatic (the terms deterministic, hard-coded, hand-coded, and prescribed are also used to describe such a behavior [33]), and it can be triggered by certain actions or dialogue with a non-player character. This indicates that almost all the ways and responses of NPC are prescribed on one level or another and cannot be changed during the game or out of the game process without rewriting the actual code.

However, since the late 1980s artificial intelligence for controlling NPC is being integrated into a game design to make behaviors more flexible and variable.

2.2.1 AI-driven NPC behavior

Artificial intelligence is used to control NPC behavior on different levels, from simple motion control tasks like pathfinding to decision making. Worth noticing, that term "game AI" is very different from academic definition of artificial intelligence and often applied to NPC control system in general.

Generally, AI control application can be divided into three levels of controlling NPC behavior [26]:

- **Movement control**: the very low level of NPC control, defines the algorithms that turn NPC decisions made by NPC AI into motion. This may include simple tasks like triggering an appropriate animation based on a decision, or some more complex algorithms like pathfinding, and navigation through obstacles.

- **Decision making**: AI is applied to perform complex decision making, choosing an appropriate reaction to player's actions, typically from a database of possible actions. The AI of this level decides what action should be performed next.

- **Strategy**: a higher level of decision making applied to a set of NPCs working in a group. Every individual character within the group might have its own decisions on a lower level, but the decision-making process is influenced by a group strategy.

Movement control itself has mostly a technical level focus, e.g. triggering an animation set or specific prescribed action (e.g. if an enemy in *Super Mario Sun-*

shine[13] appears to be close to a player, he will attack). But movement control is tightly coupled with the decision-making process as its task is to carry out behavioral decisions of the upper system.

The most simple and common usage of AI in video games is pathfinding at the edge of movement control and decision-making levels. Fixed routes are simple to implement, but they are really easy to be disrupted (e.g. by placing an object on the way of the NPC). Such a technique does not provide any adaption to an environment, and hence, sets a lot of restriction to game design and game process.

Therefore, pathfinding (including finding a path for cover) is one of the most important components in the game. A game system must be able to find the most efficient way for NPC from an origin to a destination point, avoiding obstacles and providing realistic movement.

The problem of pathfinding is usually solved by tried and tested algorithms and AI technologies like **A* algorithm** [6]. This algorithm has been applied in a wide range of games. However, some AI programmers have found that using A* algorithm can result in inadequate and unrealistic movement [34]. For example, in *Age of Empires*[14] units can get stuck in the environment elements like trees, because of non-effective and not proper usage of A* algorithm.

The next level of NPC control is decision making. There many ways to deal with decision making in computer games. The character has some set of information from the outer world of a game and it uses this information to pick up a solution and further actions. Most games use simple AI techniques to carry out NPC decisions. Typically these techniques are Finite State Machines and Decision Trees.

Decision Trees have an advantage of being modular and easy implementation [26]. They can be used in variety of ways on every level of NPC control from animation to strategy and tactics. Decision Trees generate a corresponding action from a set of possible actions based on the initial decision. Even though it is considered to be quite simple, the Decision Tree basic algorithm can be extended in order to carry out complex behavior. But this AI technique is rather old and is rarely used in modern computer games.

Finite State Machines (FSM) [35] are designed specifically for changing a state of NPC, when it is influenced by outer environment or when some event is happening, and are used in a variety of video games for decision-making systems.

Such kind of systems contains states of NPC as nodes with associated actions and behavior and transitions with a set of conditions that can lead an NPC from one state to another (see Figure 2.2). Finite-State Machines are usually implemented by scripts and simple if-then statements, so they suggest only basic behavior control. FSMs are computationally limited and badly scaled, so they are not able to solve large problems and run multiple behaviors at the same time [7].

A* algorithm, Decision Trees and Finite State Machines are the top AI techniques mostly used in video game development for decision making, but, as was stated before, they are quite old and begin to lose their popularity because of the bad scaling, limited abilities and inability to carry out complex behaviors.

Other techniques, like Planning and Behavior Trees, for managing behavior complexity gained popularity since such popular games like *F.E.A.R.*[15] and *Halo*

[13]Nintendo Entertainment Analysis and Development, 2002

[14]Ensemble Studios, 1997. https://www.ageofempires.com

[15]Monolith Productions, 2005. https://en.wikipedia.org/wiki/F.E.A.R.

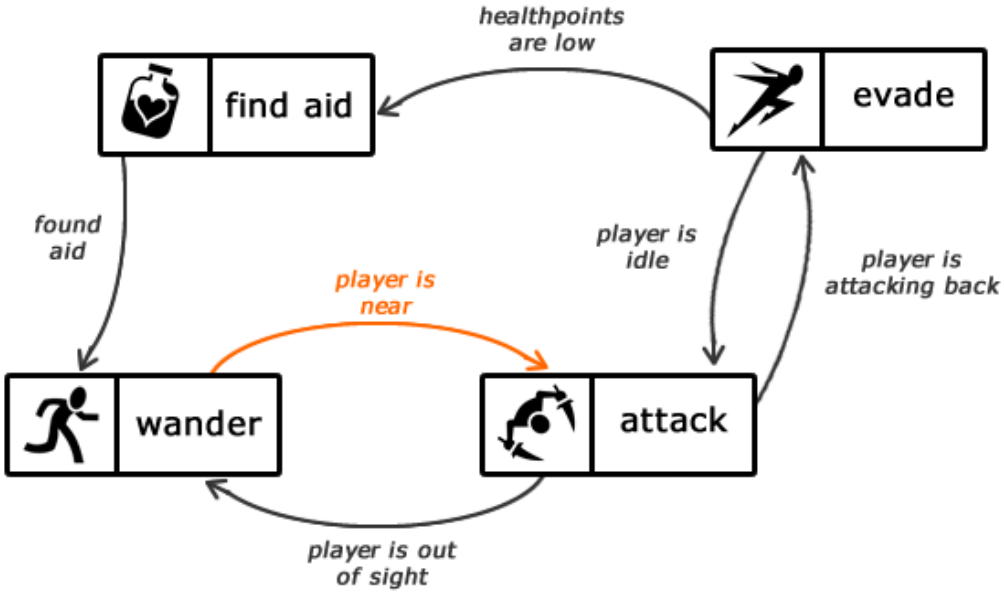

Figure 2.2: FSM algorithm usage in video games. Figure originally from [35].

2^{16}.

Unlike Decision Trees and Finite State Machines, **Planning** does not tell NPC how exactly it should behave in this and that situation. Planning AI system sets goals and set of actions, that can be performed in order to achieve a particular goal. So technically, Planning is "a formalized process of searching for sequence of action to satisfy the goal"[36].

The advantage of such a system is its ability to decouple goals and actions, so that different NPCs can decide about their tactics and differ from each other. Another benefit is layering approach nature, which allows composing a complex behavior of simple low-level behaviors.

Variations of these techniques can be synthesized into the AI technique called **Behavior trees** [37], which was firstly used by the creators of *Halo 2* game. Behavior Trees are a combination of Hierarchical State Machines, Scheduling, Planning and Action execution. Unlike in Hierarchical State Machines, the main block of the Behavior Tree is not a state of the game, but *a task*. Tasks can vary from picking a number from current game state or executing particular animation (see Figure 2.3). The main advantage of Behavior Trees is their hierarchical structure, i.e. tasks are composed into sub-trees, which represent complex actions, and then these actions can be composed into high-level behavior, so there is no need to worry about details of sub-task implementation. [37, 38]

Techniques described above also can be applied for the strategical level of NPC behavior control as it was done, for example, in *Half Life*[17], where FSM was also used for controlling the overall approach for an NPC group. In the game, an NPC team is able to cooperate in order to surround the player.

In spite of the obsolescence of mentioned techniques, there are some stunning examples of their usage. The game *F.E.A.R.* became a benchmark for first-person shooters with its AI-driven combat NPCs. They used well-known techniques de-

[16]Bungie Software, 2004. https://www.halowaypoint.com
[17]Valve, 1998. https://en.wikipedia.org/wiki/Half-Life_(video_game)

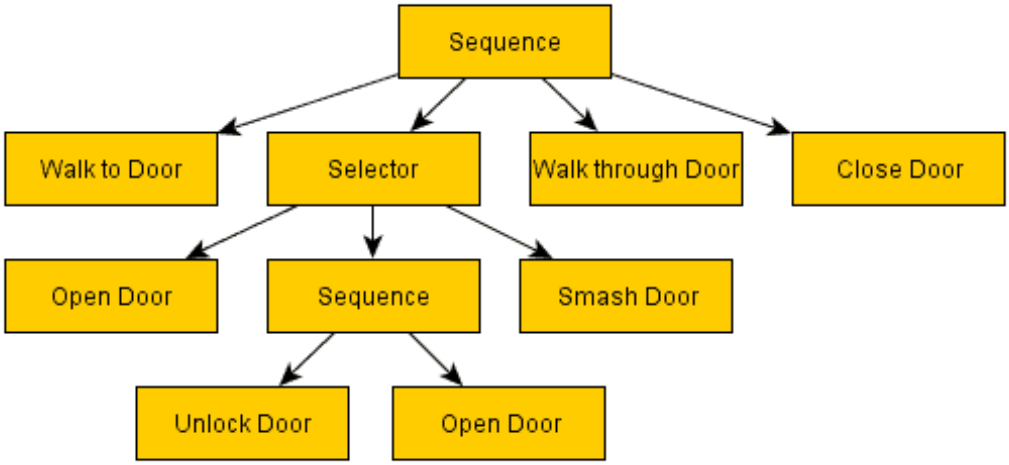

Figure 2.3: Behavior Trees usage in video games. Figure originally from [37]

scribed above such as Finite State Machines and Planning to control character behavior and A* algorithm both for pathfinding and planning of the actions sequence. Their behavior control system consists only of three states, but even though the AI can take cover, blind fire, jump through windows, communicate between each other and a lot of other actions [36, 39, 40].

F.E.A.R. and *Half Life* AI control systems are good representatives of how AI technologies like Finite State Machines and Decision Trees can be used if they are perfectly compatible at the game design level and able to solve the challenges faced by game designers.

One more remarkable thing about F.E.A.R. AI demonstrates an ability to respond to the environment and inner state of an NPC changes. For example, if the human player is about to take them over, the squad will try to find a safe way to retreat or apply blind fire to change the cover [36]. This is what is called **adaptive artificial intelligence** in game. But sometimes, although the behavior of the NPC might seem intelligent, no actual AI technique has been used.

2.2.2 Artificial Stupidity

Accordance of NPCs actions to an environment is often established with “cheats and tricks”, as it was done in Half-Life: the game designers provided the NPCs with dialogues and connected actions (for example, a character could scream “Grenade out” when throwing a grenade) that were not shared with the other team NPCs, creating an illusion of NPCs collaboration [41, 10].

This kind of practical and simple workarounds can be seen in many games. NPCs give players clues to their further actions by their behavior. For example, they can move before actually attacking, letting the player acknowledge the enemy presence and give him time to adapt, or they can intentionally miss the first shot, warn the player by some audible or visual messages. If the player is meant to be attacked by a group of strong enemies, only a few of them will initially make damage not to overwhelm the player.

All of these tricks are used to cover lack of AI sophistication in the game, so sometimes they are called artificial “stupidity”, rather than “intelligence”. More information about this can be read in [10].

2.3 Adaptability in Computer Games

This section describes ways of achieving adaptability in computer games and aspects of game control systems that can work on adaptation improvement, e.g., in-game sources of adaptability, levels of adaptation and adaptable components.

The majority of the game intelligent systems for decision making, strategical and tactical planning, seem to act like strictly scripted behavior [42, 40]. Decision Trees, Behavior Trees, Finite State Machines control decision-making process by choosing the appropriate reaction and sequence of actions from the base of possible actions, where each specific behavior is triggered by other certain action or dialogue variant.

The techniques described in Section 2.1 demonstrate satisfying results in specifying predetermined sequential behavior and basic sensitivity to contextual changes like changing in environment and player's actions (see F.E.A.R. example in Section 2.1). The input to the decision-making system of the F.E.A.R. is a goal to achieve and actions that can be performed; and the purpose of the system is to define appropriate sequences [40]. Nevertheless, the NPCs will perform the same actions in response to the same changes, making variances only in sequence with no accordance to what has happened previously in the game. So the gameplay appears to be similar and repetitive from one battle or encounter to the next.

However, more recent AI techniques allow developers to go beyond such prescripted interactions and create systems that can not only give basic response to player's actions and environmental changes but also learn about them and from them, use gained knowledge for adapting their own behavior; and therefore, provide reacher and more personalized experience to player. On this level, adaptive game AI can enhance challenging of the game by forcing the player to continuously search for different strategies and tactics in order to defeat the changing and adapting nature of the intelligent NPC [25].

Next subsections will describe terms and definitions specific to game AI, aspects that work on behavioral alterations and adaptation, and game parts that can be adapted.

2.3.1 Sources of Adaptation

Indirect adaptation of the game AI agent appears when the AI extracts statistical information from the world and a player's behavior and then uses it to modify own behavior. One example of the indirect way of adaptation is acknowledging the best way to kill a player. The AI can change an NPC's path, making it visit the locations that the human player tends to visit more often. Indirect adaptation can be seen explicitly in *Alien: Isolation*[18]. According to game reviewers and developer's reports, the *xenomorph*, the main game antagonist, can learn even from player's deaths and visit more often the places where the player was killed in previous game sessions. This approach, in general, works very well on the challenge and human player affection, as the main antagonist is always not far from the player (Alien: Isolation example [43]), visiting the places, where the player has been before, and thus, creating a feeling of tension and suspense.

Indirect adaptation has proved to be fast and effective as the statistical information can be easily extracted and applied rapidly through the game process, providing

[18]Creative Assembly, 2014. https://www.alienisolation.com

the almost immediate response. Also, the changes in behavior are well-defined and controlled, so they can be easily tested and the probability of inadequate and unbelievable behavior can be lowered [25].

However, ability to control NPC behavior appears to be a disadvantage of the method as both the data collected from the game and the behavioral changes must be specified by game designers at the production stage.

Direct adaptation, in practice, is done by parameterizing an AI agent's behavior. Learning algorithms for this kind of adaptation search for the parameters and behaviors that perform the best way in the game.

The main advantages of the techniques that can offer direct adaptation are that AI agents can learn directly from their experience in the game and discover new behaviors. Behaviors can almost endlessly evolve and hence provide a continuous challenge to the player.

The problem is very low control over AI agent adaptation, and therefore a high chance of unpredictable and inadequate behavior, that may occur as a result of wrong evaluation or impact of the random performance [25].

Popular god game *Black & White*[19] presented an innovative idea for controlling an NPC behavior by the means of Belief-Desire-Intention model as an architectural approach for the game AI incorporating decision trees and neural networks [44]. It has a complex learning system for the creatures, that are raised by players. The problem with this system is its vulnerability to unintentional impact from the player; and hence, AI adaptation may result in unpredictable and undesirable creature behavior causing inconveniences to the human player.

Besides, the evaluation requires many measurements to be done in order to define the best behavior. This can impact the game performance in general as it requires a great number of computational resources [25].

2.3.2 Intra- and Inter-behavior Learning

AI learning can be used on two levels of adaptation: intra-behavior and inter-behavior. These levels are described in [26].

Intra-behavior learning is the kind that will change a small area of NPC behavior. These areas can be, for example, defining the best path for patrolling area, learning about covers around the area etc. Intra-behavior learning is easier to implement and test, also, it can be mapped to indirect (statistic-based) adaptation.

But the algorithms of intra-behavior learning does not provide totally different behavior, the AI will not learn any new ways to achieve the goal.

The other way of learning is *inter-behavior* when the character changes his behavior to a new pattern in order to find new ways of defeating the player. For example, defining the best way of killing the player or choosing an appropriate reaction to the behavior that is typical for a particular player (if the player produces too much noise, the NPC will pay more attention to the sounds or find another way to find the player in opposite situation).

Absolute inter-behavior adaptation is a difficult case and unlikely to be used in the games, but the AI can learn to choose among some predefined behaviors and strategies (or combine basic behaviors in order to create new tactic or strategy).

These two kinds of learning can be combined: inter-behavior learning can be used for behavior pattern and intra-behavior learning might be used for tweaking

[19] Lionhead Studios, 2001. https://www.mobygames.com/game/black-white

some parameters of the behavior.

2.3.3 Opponent/player modeling

Personalized experience, what is considered to be one of the elements to achieve the feeling of immersion and engagement in the games, requires the game system to asses each individual player. *Opponent modeling* (in this case, by an opponent a human player is meant) is an approach used for establishing models of opponent players and using them in the actual gameplay [17].A *player model* is an abstracted description of the human player, that plays the game [27]. The player modeling is meant to be used for detection, prediction and expression of the human player characteristics that reveal themselves as cognitive and behavioral patterns. The goal of this approach is to adjust and improve the capabilities of the game AI to adapt to the game players and personalize the game experience.

The advantage of this approach is that the game is adapting towards each individual player, taking into account the player's preferences, needs, playing style and also emotions and physical response to the game events (heart rate, blood pressure etc.).

Player's preferences in this approach are defined during the game process itself or by the means of specific questionnaires and self-reports, in opposition to the preferences that are set to the human in-game avatar before the actual game (i.e. the character class, ammunition, skills etc.) [22].

Karpinskyj in [28] classified player modeling approaches according to input game data and the data collected during the actual gameplay. According to [28, 45], there are five basic categories that group the features, which differ players from each other:

Player preferences define the classification of the players by their tastes in video games apart from video game genres. It is applied to the player preferences for specific characteristics and concepts in video games, i.e. "cooperation", "strategic planning" etc. Karpinskyj's view of player preference should be distinguished from another view, which is called "play style" within a specific genre, such as "exploring" or "collecting" within RPG. However, in the Section 2.3.3.2 (Style recognition, which will be discussed later), player preferences are equated to the abstraction of "play style", that can be applied to the style independently of the game genre as it groups specific preferences with respect to personality.

Player personality category is very close to the previous one, but in this case, psychological personality models (Five-Factor model [46] and Myers-Briggs Type Indicator [47]) are used. For game adaptation based on player preferences, new specific personality models are proposed to describe different *players* types.

Player experience refers to the emotional and cognitive response of the player while s/he is playing. Categorization can be done by defining the relationship between in-game player's actions and physiological response or self-assessment reports.

Player performance is a measurement of how well the player makes progress through the game level. It focuses on the distinguishing players by the degree of difficulty by which they overcome obstacles, i.e. matching a difficulty level

to the player skill. Player performance can also refer to a rate of passing the mission.

Player's in-game behavior is similar to player preferences, but in this case, it refers only to the player's in-game behavioral style based on the actions taken and the predefined strategies used.

Yannakakis [29] suggested another subdivision of these traits. According to [29] the input data for the player modeling can be divided into three groups/types: (1) gameplay data (data on players behavior, preferences and in-game actions), (2) objective data (data collected from physical state of the player, i.e. speech and body movements, physiological measurements) and (3) game context data (which refers to player-game interaction and may include data retrieved from the created, viewed or played content).

Video game personalization using player modeling has been applied in a range of games for different elements of the game, categorized according to the input described above, but it was done mostly in research experimental games rather than commercial. Here are some examples, provided by Karpinskij, which demonstrate the type of input data and the game feature, for which the data has been applied:

- **Preferences**: role-play games maps and plot (set of player's preferences is an input level for game plot and maps transformation [48]), difficulty control (will be discussed later), platforming levels (multiple choice questions and player's performance are used to model player's preferences and create a level, that might be interesting for player [49]);
- **Experience**: camera position (using player's affective response to adjust camera position in order to create more affective experience [50]), plot and story (player affective state was used for managing the story to bring more dramatic effect [51]), platforming levels (in-game system is able to predict six affective states basing on players self-reports [52]);
- **Performance**: platforming levels (see [49]), enemy type and count (the test game created by Yu and Trawick [53] incorporates in-game behavior, brief preference survey and performance to adjust enemies), difficulty adjustment (will be discussed later);
- **In-game behavior**: quest structure (behavior was used by Bulitko in interactive storytelling [54]), difficulty adjustment (will be discussed later).

As it is specified from the description of the input types above, some of the data, that can be used for personalization, require specific equipment or extra data collected out of gameplay, what can break player's immersion into the game. Game preference data can be collected via questionnaires before the game begins, or as a part of the game via in-game dialogues with multiple choices, but the data can also be collected via the game process. Experience observation can be done in one of two ways or their combination: objectively by means of physiological signals (blood pressure, heart-rate, but mostly through facial recognition of emotions) or subjectively by self-reports [28].

Player performance and in-game behavior are the data types, that are collected during the actual game process. So the following study will mostly focus on these two data types as input, that can be collected directly from the gameplay process, and therefore more reliable.

2.3.3.1 Behavioral modelling

Behavioral cloning (or *modeling*) techniques have a potential for being used to increase strength and playing skills of in-game AI agents by copying human player's style. And thus, provide a challenging experience to the most skilled players, as well as to adapt to mediocre players and beginners and continuously adapt to increasing or decreasing player's skill.

This approach has been used by *Forza*[20] racing game for training their NPC drivers by copying player's gaming style. Their AI system, called Drivatar, is connected to the cloud storage, where the collected game data about players is pulled and then used to create non-human drivers. The characters mimic other players behavior including also their mistakes and weaknesses as well as strength, what makes NPCs more believable [55].

According to [27, 56], four approaches using player's in-game behavior can be applied to player modeling:

- **Modeling actions**: action models refer to the game actions observed in the game process and the ones deduced from the observation.
- **Modeling tactics**: tactical models are the models build from the observation of local short-term behaviors and are composed of actions.
- **Modeling strategies**: strategic models are made on the next level - long-term global game patterns. They are composed of the tactics used by a player.
- **Profiling a player**: all the above models are then can be composed to define the player profile, as they are motivated by the player's psychological type.

The reason for using *action models* is to predict player's actions, what is a goal for most game developers. By knowing possible actions, that the player might take in the nearest future, a game AI can generate an appropriate response. But in practice, these models are of limited use, unless they are used for other models.

Tactics and *strategy models* can be applied for providing a strong challenge for the players. They are capable of more generalization than action models; therefore, they can be used for adapting and personalizing game experience and challenge.

Generally, *player profile* includes all the knowledge of input and collected data described in Section 2.3.3 (opponent/player modeling). Yannakakis in [29] makes a distinction between player modeling and player profiling, stating that later is based on the static information, which does not change during the gameplay process. However, it may include information about behavioral, tactical and strategical patterns as they can also be motivated by the human player personality and psychological characteristics.

Player profiling has a great potential to provide a more significant influence on an experience that players can have with the game.

Once all of the aspects of the player behavior are recognized, the game AI can use collected data to improve personalization of the content, adjustment of the NPCs behavior or redesign the game environment in order to match individual player.

[20] Turn 10 Studios, Microsoft Studios, 2005. https://www.forzamotorsport.net/en-us

The main subtasks of the behavioral modeling are imitation, prediction, clustering and association mining [29]. The goal of *imitation* in the context of game adaptability is to develop believable NPC with human-like behavior to work on the immersion of the player. The *prediction* may help the NPC behavior AI system to define effectively the actions that should be taken in response to the predicted actions. *Clustering* is important for a personalized content generation as it allows to classify players and then emphasize on adapting of the specific game component. And *association mining* can be applied for defining the most frequent behavior patterns to determine how the player actually behaves in the game. This data can then be used for adapting different game components, which will be described later.

2.3.3.2 Player's style recognition and adaptation

Game adaptation to player's style is a promising direction of the research as it allows to provide an individual experience to players basing on their needs, preferences and motivation. Adjusting of games to playing styles and types can increase player's satisfaction with the challenge provided by the game.

Aleksieva-Petrova has defined four playing styles [57, 58] on a basis of Kolb's space of processing and perception continuums [59] and created the ADOPTA (ADaptive techn*O*logy-enhanced Platform for edu*TA*inment) family of playing styles, which includes the following playing styles (see also Figure 2.4):

- **Competitors**: skilled players, who enjoy taking great risks; experienced in fast decision-making; they prefer to start an active game as soon as possible; described by others as the most active players.

- **Dreamers**: players-observers, as they prefer to observe the game environment rather than control it; prefer guided gameplay on the same level until master the game till the end; very emotional and open-hearted; they like to play with clear scenarios instead of emergent gameplay; need to see different ways of solving the mission task and choose between them carefully.

- **Logicians**: prefer logical and analytic approaches for solving the problem; study all the complexities of the game rules and try to apply them to each move in a rational and perfect way; they try to establish and use structural time-based approaches for mission completion and assembly the game facts into a scheme that can be then used for defining tactics and strategies.

- **Strategists**: like solving complex game missions with a most effective strategy; find all the practical ways to solve the problem of the game in time; have long-term thinking when planning their strategies; they like creating theories, testing hypothesis about game strategies; appreciate the foreseen practical benefit of their actions and decisions; show good management skills.

To implement style-based adaptation of the game, player's style should be recognized efficiently for the purposes of adaptation [58]. There are two ways to perform the player style recognition: self-report and automatic recognition.

The style recognition can be done through the *self-report* in a form of a questionnaire. In this way, the style is calculated before the actual game begins. This approach requires additional game time and has a significant disadvantage as the

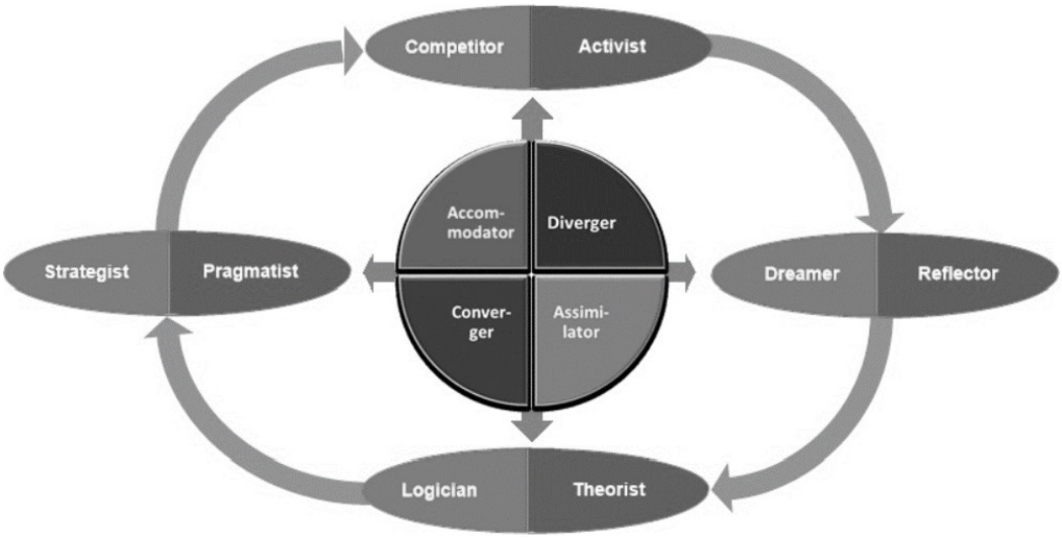

Figure 2.4: The ADOPTA playing styles together. Figure originally from [58].

player's self-assessment will possibly be subjective and thus not effective in the context of style-based adaptation.

But *automatic* playing style recognition is a much more promising approach because it defines the style of the human player by analyzing player's interactions with the game world and achieved results. In contrast to static self-report approach, the style-recognition is more effective as players are not aware of the process. This approach was implemented by automatic classification of game metrics and features relevant to specific behavior traits [58]. Playing styles can be categorized by means of a variety of approaches, which include self-organizing maps, fuzzy clusters analysis with hidden Markov models, and different classifiers. They perform online analysis of the game style and provide a basis for dynamic style-based adaptation of different game features.

2.3.4 Adaptive components

To deliver memorable experience to individual player, player models described in section 2.3.3 (Opponent/player modeling) can be then used to adapt different elements of the game environment, i.e. space (1), missions (2), characters (3), game mechanics (4), narration (5), sound (6), player matching (7) and difficulty (8). These elements were suggested by Bakkes in [27] as they are present almost in every game and thus can be applied to the vast majority of games.

Space adaptation Also can be referred to as **environmental adaptation**. The adaptation of the space, where the game is played, e.g. game environment. The data retrieved after prolong observation of the player's game process can then be used to gradually transform the game surrounding. Space adaptation also can be used for generating new game levels, that can force the player to perform actions, that s/he usually avoid, i.e. generate more dark space, if the player tends to avoid them (in horror/survival games).

Examples: Diablo (Blizzard North, 1996), Torchlight (Runic Games, 2009), MineCraft (Mojang AB, 2011).

Mission adaptation The game can evolve its tasks and missions in response to different player's behaviors. The approach for mission adaptation is to generate an open-ended task and then replace these open ends with the dynamically generated missions. This approach can be also coupled with space adaptation: the environment of the game might change in response to the missions changes. This type of adaptation may result in an implementation of fractal story [60], when the story unfolds more and more as player pays attention to certain parts of the story as it was done in *Her story* (Sam Barlow, 2015).

Character adaptation More specifically, **non-player characters adaptation**. This includes adaptation of NPC actions, tactics and strategies, which represent scopes of the NPC behavior, and is a primary research direction in the field of video games. Character's behavior adaptation is the main objective of this literature study, so it will be discussed throughout the work in more details. However, apart from NPC behavior, character adaptation may include altering the appearance or locomotion of characters.

Game mechanics adaptation The purpose of game mechanics adaptation is to vary them during actual gameplay. This type of adaptation is quite a rare case in industry, though the research in this field still continues, in particular, on the automated identification of gameplay schemes (which basically represent player's behavioral patterns and also can be considered as player's tactics and strategies) and schema-based adaptation by Lindley and Sennersten [61].

Narrative adaptation The forefront of this type of adaptation is interactive storytelling, which can be defined as "a gaming experience where the form and content of the game are customized in real time and tailored to the preferences and needs of the player to maximize enjoyment" [62]. Player modelling can improve the narrative adaptation of the games by applying psychologically-verified knowledge on player satisfaction and experience to them.

Narrative adaptation has been used in numerous games, especially for chaining together appropriate actor actions and directing scenes. This approach can be found in the games mentioned in Section 2.1 (Artificial Intelligence in games) - Façade and Versu. Elements of narrative adaption through giving a variety of choices for players and the tailoring the consequences have been applied in many industry games, that provide a set of different endings dependable on player's choices. These elements are most explicit in *Mass Effect* series (BioWare), *The Witcher 3* (CD Projekt RED), *Dishonored* series (Arkane Studios) and others.

Sound adaptation This type of adaptation has existed since the early game development era. The music can change depending on the location, where the player locates at the moment, the time of the day in the game environment etc. Also, sound can change in accordance with the events that are going to happen i.e. battle start or antagonist approach.

The sound and music adaptation is also can be used for manipulating player's emotions and, therefore, increase the level of immersion and engagement.

Player matching Adaptation element for multiplayer games. Research made in this direction has proved that if the opponent human player's skill is lower

then the particular player's one, the player loses interest in the game [63]. The same happens in opposite situations when the opponent is too strong. So it is important to apply reliable player matching techniques to find appropriate players. Besides, accurate skill rate of players is important for team games, so the skill rate of the whole team matches the overall skill of the opponent team.

Player matching has been applied to a lot of online games (for example, *DotA 2*[21], *Hearthstone*[22], *GWENT: The Witcher Card Game*[23] etc.), taking into account the characters chosen by the player or his/her in-game level. But player modeling techniques can also be applied for player matching in order to find an opponent, whose tactics and strategies can enhance the level of challenge to the player.

Difficulty adaptation The technique for automated adaptation of the game difficulty to the skill and experience of the human player (*experience*, in this context, is defined as practical contact with the games before playing the particular game).

Among all the described adaptive elements, *difficulty adaptation* is the most common adaptable element in variety of games. Since difficulty scaling can also be applied to strength and behavior of NPCs, this technique is of interest of this study, so it will be observed in details.

2.3.5 Dynamic game difficulty balancing

Difficulty balancing or *difficulty scaling* is an automatic adaptation of game difficulty level according to a human player's skill. In terms of AI, difficulty scaling is aimed to achieve an "even game" for the player, whether the player is strong or mediocre. [3, 9]

Game AI is considered to be more entertaining when it is hard to defeat, although this is not true for novice players, who will be overwhelmed by the strong AI system. For every type of players, game antagonist should be challenging, but beatable.

Difficulty scaling can be implemented as a predefined game difficulty setup (the one that the player chooses before game start), and in this way, is used quite often in the games.

The predefined game difficulty can be referred to as *difficulty setting*, i.e., it is represented as a discrete parameter, which defines how difficult the game is. Usually, this parameter tweaks only NPCs' physical parameters, e.g. amount of health, speed, amount of hostile NPCs in general, strength of an enemy (amount of damage that a character can make) and rarely influences tactics. Even on a "hard" level, behavior of NPC has only a slight difference from what can be experienced on lower levels. Also, with predefined difficulty, sometimes it is hard for a player to find an appropriate hardness immediately. It might be too strong on the "hard" level and strong not enough on the "medium". Besides, once the player figures out that the difficulty level is too high or too low, s/he sometimes cannot change the difficulty without restarting the whole game campaign. However, most of the games provide a possibility of changing the difficulty in-process.

[21] Valve, 2013. http://www.dota2.com
[22] Blizzard, 2014. https://playhearthstone.com
[23] CD Projekt RED, 2018. https://www.playgwent.com

Concerning dynamic difficulty scaling or adjustment (DDA), if it is implemented in the game, it usually adapts a few of the parameters mentioned above, but, as it is specified in the name, in real-time, learning from the skills of the player during the game process. This can be performed both online (directly during the encounter) and offline (between the levels or stages of the game). This approach was successfully implemented in a variety of games. For example, in the Crash Bandicoot game series the obstacles can slow down and more continue points appear if the number of player's deaths increases. In Fallout 3, as the player reaches new levels in the game, old enemies are replaced with tougher NPCs, that have higher physical parameters and better equipment to keep the "even game".

But still, as it was mentioned before, the *behavior adaptation* to player's skills via DDA approaches is quite a rare case. In Resident Evil 4[24] "Difficulty scale" system was applied to adjust both enemies strength and behavior by evaluating player's performance with values from 1 to 10. These grades are also mapped to the difficulty setup, e.g. "Normal" level starts with 4 and can be developed to 7 or decreased to 2.

However, the DDA systems in the context of behavior have got an interest in academic game AI research. The co-evolutionary algorithm was used to teach game characters to behave by Demasi and Cruz [64]. Another way to apply DDA was developed by Spronck: the developed game AI uses weights assigned to possible strategies to determine if predictably strong strategies should be applied [9, 3].

2.3.5.1 Dynamic scripting

Dynamic difficulty adjustment received attention from people in academia. One of the examples is the technology called *dynamic scripting* developed by Spronck [21], that uses data collected from the player's in-game behavior to adjust the behavior of NPC.

Dynamic scripting is an online adaptation technique, a form of reinforcement learning adapted to be efficient enough to produce scripts on-the-fly [21, 65]. This technique generates different scripts for intelligent agents in the game according to player's behavior.

For each NPC agent class in the game, there is a separate ruleset database, which includes weighted rules for the character behavior. The databases are set up by game developers in accordance with the game domain. With every encounter, a new script controlling the agent is generated from rulebase associated with it. For the first time, the basic script is created with every rule having the same chance of being called. After an encounter with the human player, Dynamic scripting system adjusts the weights of the rules in the rulebase to adapt to player's behavior. The rules with a higher weight (which means they were more successful in the encounter) have a higher probability of being chosen again. The order of the actions is decided by the implementation approach.

Dynamic scripting is a very attractive technique as it is based on the scripts, the technique that is popular among game developers because they are predictable, understandable and easy to implement. However, they are hard-coded and cannot be changed during the process, what makes their weaknesses easy to exploit.

This also can be considered as a disadvantage of the dynamic scripting: the rulebase is hard-coded by the developers, what makes the AI constrained by the

[24]Capcom, 2005. https://en.wikipedia.org/wiki/Resident_Evil_4

strategies developers had in mind during the design process. As the game becomes larger, the rulebase always extends making it more error-prone and hard to maintain.

The second disadvantage is related to the random nature of the approach [42]. It means that there is always a chance of poor tactics and strategy even after numerous encounters. It may appear that the AI system will not use potentially strong rules as they were not used during the first encounter. These rules might never get a higher weight to increase their probability of being chosen.

Yet, the dynamic scripting is proved to be an effective approach due to performed experiments [21]. Later it was tested in the commercial game *Neverwinter nights*[25], where it met the requirements set for the performance of the AI system.

2.3.5.2 Genetic Algorithms

As it was mentioned in Section 2.3.5 (Dynamic game difficulty balancing), Cruz and Demasi[14] suggested co-evolutionary genetic algorithm for adapting the game agents to the player's skills. The technique allows only those agents to survive, whose skills most closely fit the player's abilities.

The online co-evolution, used by Cruz and Demasi[14], speeds up the learning process by using pre-defined agents with good features as parents for genetic operations of creating new agents. These predefined agents can be constructed using an offline trainer or be defined manually by game creators.

However, this approach is quite limited. It is very difficult to design predefined characters, that can cover all the possible skillful players or players with uncommon strategies and behaviors, so the algorithm will work poorly for unpredicted cases. Besides, this technique allows NPC's power only to increase, what makes it impossible to provide equal abilities for players whose level decreases due to some events.

2.3.5.3 Non-NPC control DDA. Flow/pace control and content generation

Dynamic Difficulty Adjustment has found application in so called *flow* or *pace control*. In the Left 4 Dead game series, the system called AI Director was implemented to manage the pace of the game [66, 55]. The intensity and frequency of zombie attacks in the game can change during the game level in accordance with the players' skills. The goal of AI Director is to keep the human players on the edge: they receive as much time free of enemies attacks as it is enough to reload weapons or heal the wounds. The frequency of attacks will be then adjusted in the way to keep players proceeding through the level. AI Director was later used in Far Cry game series[26], Evolve[27] and Rocksmith 2014[28].

DDA may also refer to *content generation* based on the player's skill and player's progress through the game. This approach was used in *Mario Kart* game [29], where

[25] BioWare, 2002. https://en.wikipedia.org/wiki/Neverwinter_Nights

[26] Crytek Corp., Ubisoft. https://www.ubisoft.com/ru-ru/franchise/far-cry

[27] Turtle Rock Studios, 2015. https://evolvegame.com/

[28] Ubisoft San Francisco, 2014. https://www.ubisoft.com/en-us/game/rocksmith-2014-remastered-edition

[29] Nintendo, 1992. https://en.wikipedia.org/wiki/Mario_Kart

special items are generated through the race, that help an individual player to overtake the opponents. In this case, the backward player has a higher chance of getting speed up, whereas the players on the first or second position are unlikely to get such supplies (and they will also be weaker).

2.3.6 Personalized Procedural Content Generation

Procedural Content Generation (abbreviated PCG) is a development of the algorithms for the automatic content generation. In this context, *Game content* mostly refers to the game environment within the game world and may include maps, landscapes, levels, missions, collectibles (object within the environment, that are created for supplying the player), even story and music etc. (however, excluding NPC-behavior).

Research in personalized PCG has resulted into *experience-driven procedural content generation* (abbreviated EDPCG) framework [67]. In this framework, content is represented in the form of building blocks, that can be adjusted to improve the experience of the player.

This framework was used in the development of adaptive content generation framework by Shaker [30] for Super Mario Levels generation based on the *fun reports* about mini-game levels.

In addition, strategy maps, game rule sets, weapons and other supplies can be generated based on models of playing experience.

2.3.6.1 Storytelling and game design

Storytelling is "a gaming experience where the form and content of the game are customized in real time and tailored to the preferences and needs of the player to maximize enjoyment" [62] and also give a sense of overall control over a game course.

Baston and Marsh in their work [62] propose five levels of the customization: story structures (the way the plot unfolds), virtual world (including physical appearance, geography, history etc.), virtual agents (as well the the human player in-game avatar), rewards (experience points, items, collectibles etc.) and difficulty. They claim that it is important to provide customization on all of the levels to provide the most fulfilled experience to the player.

And even here, AI can find application for defining the overall principled manner of how to make the human player's experience more valuable, enjoyable and memorable.

In [22], authors propose a few general roles in which AI can act: opponent, companion and neutral NPC; dungeon masters; plot writers; and finally game designers. And the more we go down the list, the more responsibility is taken by the AI system for the quality of the experience provided. The AI system can not only oppose or assist players in terms of NPC but also define how the story unfolds and how the game should be played. An intelligent system within the game has great potential to act as a game designer, make decisions about the occurring events and their sequence to work for positive player's experience.

2.4 Summary

The majority of the game AI systems for NPC control seem to act like strictly scripted behavior [42, 40]. Techniques like Decision Trees, Behavior Trees, Finite State Machines control decision-making process by choosing the appropriate reaction and sequence of actions from the list of possible actions, where each specific behavior is triggered by other certain action (set of actions) or dialogue variant.

The techniques described in Section 2.1 demonstrate satisfying results in specifying predetermined behavior patterns and basic sensitivity to contextual changes. Even in most advanced techniques popular within game development industry, the NPCs will perform the same actions in response to the same changes, making variances only in sequence with no accordance to what has happened previously in the game.

More recent AI techniques allow developers to go beyond such pre-scripted interactions and create adaptable game AI systems. However, they are not widely used in modern computer games industry. Adaptability in video games has been studied by scientists in the game development field and game designers, but most of the studies are theoretical and have not found application in modern games or are left without proper attention.

Rabin in [25] described the application of learning in computer games AI systems. He defined two types of adaptation based on different sources: indirect adaptation that uses static information from the game environment (including the player) and direct adaptation implemented in a form of parameters that can be adjusted during the gameplay. Examples of such adaptation can be found in several popular games famous for their gameplay, e.g., *Alien: Isolation* and *Black & White*.

Two types of learning were suggested by Millington and Funge in [26]. In general, they can be described as levels - intra-behavior learning and inter-behavior learning. Intra-behavior learning changes only a small part of NPC behavior, while inter-behavior learning can significantly change the way NPC behaves. The strict definitions given by authors are hardly applicable to modern computer games, even authors speak of them as of "pure fantasy" [26]. However, alternative definitions of intra- and inter-behavior learning can be interpreted in a way that can be found in various computer games. For example, AI can learn to choose among some predefined behaviors and strategies in order to demonstrate inter-behavior adaptation.

Opponent (or player) modeling is a major part of the study in the game development field since it can also be applied in serious games. Karpinskyj in [28] classified player modeling approaches according to input game data and the data collected during the actual gameplay. His classification features five basic categories: Player preferences, Player personality, Player experience, Player performance, and Player's in-game behavior. Alternative subdivision was suggested by Yannakakis, highlighting three groups/types: gameplay data (player's behavior, preferences and in-game actions), objective data (data collected from physical state of the player, i.e. speech and body movements, physiological measurements) and game context data (which refers to player-game interaction and may include data retrieved from the created, viewed or played content). Player modeling is a rare-case in entertainment video games and mostly applied to experimental games withing academic research. Only a few application can be found in modern games.

Experimental adaptable game AI techniques were developed within scientific research. Among them there are technique called *Dynamic scripting* developed by Spronck [21]) and *Genetic Algorithm* used by Cruz and Demasi [14] for Dynamic

game difficulty balancing. The technique *AI Director* was developed by Valve for a special case of Dynamic game difficulty balancing - Flow control [66, 55].

AI techniques can also be used for adaptable (or personalized) content generation and storytelling, which has been applied in several games and services (e.g., *Façade* and *Versu*).

3 Methodology

This section is dedicated to the scientific approach and description of the methods used in this master thesis.

3.1 Scientific Approach

Methods used in this project:

- literature review (LR) in the field of computer game AI, with focus on adaptability of NPC behavior towards the player, to answer RQ1;
- based on the LR, developing a set of features for classification and comparison of aspects of such adaptability, to answer RQ2;
- define a sample of recent games that feature interactions between NPCs and the player
  - ◇ classify these games according to the developed features
  - ◇ collect data regarding the popularity (review scores from critics and users) for the games
    - ○ examine correlation between adaptability and popularity, to address H1
  - ◇ collect data regarding the commercial success (e.g. number of units sold) of the games
    - ○ examine correlation between adaptability and success, to address H2

3.2 Literature review

By using the methods stated previously, the data on game artificial intelligence and user experience was manually collected and analyzed in order to answer research questions and use them in the comparison of existing cases of game AI adaptation to player's actions.

Based on knowledge gained from literature, features for comparing and classification of game AI are developed in order to define best examples of game AI implementation and usage. These features were then used for classification of game AI adaptability.

These features were used for proving the hypothesis, that games with higher adaptability are more commercially successful and popular among players and critics. By doing so we expect to make predictions on the success of the game based on the adaptation, that the game can provide to personalize user experience.

Based on the brief preparative research, we defined the next terms for the search of related literature: artificial intelligence in games, learning, game adaptability & adaptation, believable NPCs, NPC adaptation, player modeling, dynamic difficulty adjustment.

The articles chosen for this study were selected by these criteria:

- topic of the article is related to artificial intelligence in video games
- topic is related to study of NPC behavior

- topic is related to techniques used in video games for controlling NPC behavior
- topic is related to adaptability in video games
- topic is related to adaptable AI techniques in video games
- case studies of existing game systems
- development of new experimental AI system for NPC control done by academia

Numerous articles were excluded from the literature review. Since artificial intelligence term describes any NPC control systems used in video games, some of the revealed articles describe a new experimental technique developed for games, however, without using any AI technique. These articles were discarded. Also, numerous articles refer to storytelling adaptation and adaptable procedural content generation, which are out of our interest in this study. Studies that include descriptions of approaches for measuring experience, were also excluded. A number of articles were dedicated to the believability of NPC, but most of them described personality and appearance. Since types of NPC vary from game to game and often appear in non-human form or a group of humans, advanced tactics and strategies are more preferable in terms of challenge than personality and appearance. These articles were not studied deeply in this work.

Different sources were used for literature review in order to get relevant information in the field of artificial intelligence in games. They include *ResearchGate*[30], *The ACM Digital Library*[31], *IEEE Xplore Digital Library*[32] and *Elsevier*[33] as sources for scientific studies and articles. Websites like *AiGameDev*[34], *Gamasutra*[35], *AI and Games*[36], *Kotaku*[37] and others are generous sources of information related to game industry in general as well as information about AI techniques used in video games.

In total, over 50 articles and books were studied for this work to get relevant information about scientific directions in video games AI, numerous websites, articles and blogposts were chosen as a source for specific information related to current trends in video games.

For the analysis stage, third-party data from articles, case studies of games, players and critics' reviews were collected and analyzed. The popularity of the video games was analyzed based on the information gained from *Metacritic*[38] and *VGChartz*[39].

[30] https://www.researchgate.net/
[31] https://dl.acm.org/
[32] https://ieeexplore.ieee.org/Xplore/home.jsp
[33] https://www.elsevier.com/
[34] https://aigamedev.com/
[35] https://www.gamasutra.com/
[36] https://aiandgames.com/
[37] https://kotaku.com/
[38] http://www.metacritic.com/about-metacritic
[39] http://www.vgchartz.com/about.php

3.3 Development of Game Classification Based on AI Complexity and Adaptability

In Section 2.2.2 (Artificial stupidity) masking techniques for controlling non-player characters were discussed, showing how simple tricks and cheats can make non-intelligent NPC seem intelligent.

Also, AI techniques commonly used by game developers were discussed in Section 2.2.1. Decision and Behavior trees, Finite State Machines and Planning are still widely applied for controlling NPC characters in video games, as long as they fulfill the requirements and are compatible with game design decisions. And even though the lack of intelligence or "stupid" behavior is often discussed in the players' communities, most of the games are still commercially successful enough to be accepted by the game development studios and publishers. For example, *Tom Clancy's Ghost Recon: Wildlands*[40] AI has got a lot of dissatisfaction among players[41]. It was stated by the game communities that the hostile NPCs, as well as computer control teammates, are "dumb" since they often get stuck in the environment or do not perform the actions they are supposed to perform (e.g. not helping the human player during the fight). Also, the believability of the AI controlled NPCs in this game was addressed. According to players' reviews, the accuracy of enemies shootings is very high and the overall strength makes them hardly beatable. However, the game was one of the Ubisoft's bestsellers according to Ubisoft Sales Report [68].

Addressing both players and developers communities, Yildrim and Stene in [24] tried to define what kind of *intelligent* behavior is expected from NPCs and what makes NPC *an intelligent agent*. Based on the different definitions of the term *intelligent agent*, Franklin and Graesser in [69] defined a set of properties intrinsic to intelligent agent in terms of academic artificial intelligence, but which can also be applied to game NPCs since they are controlled by AI system and can be counted as agents as well. Some of the properties, that can be applied to NPC agents, are stated below:

- **autonomous** - able to control its own actions.
- **character** - believable "personality".
- **reactive** - responds timely to environmental changes.
- **goal-oriented** - or *pro-active*, has a goal to be fulfilled within the game process.
- **learning** - adapts the behavior basing on the previous experience.
- **flexible** - actions and their sequence are not strictly predefined.

Most of the characters in modern games are *reactive* since they have to respond to player's in-game actions with appropriate reactions, e.g. to shoot in response, if the player starts attacking the NPC. In most games, NPC should also change their

[40] Ubisoft Paris, 2017. https://ghost-recon.ubisoft.com/wildlands/en-US/home/index.aspx

[41] https://gamefaqs.gamespot.com/boards/168640-tom-clancys-ghost-recon-wildlands/75096470; https://steamcommunity.com/app/460930/discussions/0/1471967615859849570/; https://www.reddit.com/r/Wildlands/comments/5y6txe/dear_ubisoft_ghost_ai_is_terribleseriouslyplz/

behavior in accordance with game environment changes. One of the examples is pathfinding, which is present in most games on different levels of complexity.

Goal orientation is mostly dependent on game design and AI techniques used for NPC system. Goal-oriented NPCs consider both the consequence of their actions, their impact on the environment, and how much their actions satisfy the given goal. In the modern computer games *Planning* approach can be used for goal-oriented NPC (see Section 2.2.1 (AI-driven NPC behavior)). And basically, ability to define the sequence of actions and choose among sets of actions makes goal-oriented agents *flexible*.

Personality of the non-player character has multiple sides and depends on the goals of game creators. Personality can be expressed through character dialogues, emotions and behavior. All of these features can be scripted if they are aimed to tell a story written by creators as well as be adaptable if this is a developers' decision in the context of game design. The latest was implemented in the game *Forza* (see Section 2.3.3.1).

Agent autonomy is a hard question in the video games development process as well as in academic research since it has a variety of definitions. But basically its an ability to control own actions. According to [70], features of autonomous agent include self-sufficiency, situatedness, learning and evolution, so basically it consists of all properties inherent to intelligent agents listed above.

Yildrim and Stene also suggested other properties, that can increase autonomy of NPC [24]. These features include supervision by higher level agents (hierarchy of agents of different complexity), visible inter-agent communication (when one NPC agent can inform other about the environment), complexity of decision making (or quality of decisions in terms of the NPC goals) and variety of action repertoire (important for autonomy since NPC has more choice among actions).

Most of these features are present in modern video games AI controlled NPCs on one level or another, making non-player characters intelligent on a basic level (in accordance to the academic definitions) even if they are implemented with some tricks.

Next level of intelligence in behavior is adaptability to player's in-game behavior and player's preferences which is defined by all the properties stated above and can have an impact on them on different levels.

Adaptable AI-controlled NPC is *reactive* since player and his actions are part of the game environment and NPC is supposed to react to any changes in the game world in some way or another [24].

Adaptable AI-controlled NPC is *flexible*, as its actions and their sequence are not strictly predefined and can be changed in response to game state [24].

Adaptability itself requires observation of the player's in-game behavior and statistics, analyzing it and *learning* from it. Data gained from the player's behavior and preferences can then be used for adapting NPC agents goals and the sequence of the actions, i.e. impact *goal orientation*.

Deeper into the autonomy of NPC agents, supervision on different levels of agent complexity can provide tactical and strategical adaptation, adding control over general NPC behavior decisions and goals as well. Complexity and quality of decisions and goals can also increase in terms of the quality towards concrete player's behavior, explicitly showing the learning process.

Variety of action repertoire and visible inter-agent communication can be viewed as tools to increase adaptability, improve quality of the decision-making process and

make NPC characters more realistic and believable.

Based on the material gained from the literature and case studies, we have selected a set of features to represent different aspects of artificial intelligence in games and, in particular, their ability to adapt to a human player. This subsection is dedicated to selected features and the proposed classification description based on our interpretation of studied information.

3.3.1 Autonomy

First, we define the autonomy level of NPC in a game based on the features defined by Yildrim and Stene in [24] and described before in the Section 3.3. These features are: (1) reactivity, (2) goal-orientation, (3) flexibility, and (4) learning.

Reactivity is a determining feature for the further selection of games to analyze since it should be a basic feature for the intelligent NPC *in a game*. Interaction of a human player with world environment including NPCs is a foundation of any game. It is not necessary for neutral characters, e.g. fillers - people and creatures created to fill the background scene and bring more life into it. However, it is crucial for hostile NPCs. All the games chosen for analysis have reactive NPC, so this feature was not present in the analysis record.

Goal-orientation is a common characteristic of NPC in a variety of games as the analyses of the game set revealed. Most of the game developers blogs reported Planning techniques used in their games or features that demonstrate visible goal-oriented NPC.

Flexibility is another feature present in most of the games. Goal-oriented agents in games tend to be flexible: techniques used in games to provide goal-oriented NPC encompass an ability to choose a series of actions among a predefined set of elementary actions or short subsequences. Nevertheless, the level of flexibility varies, and some goal-oriented NPC does not have visible flexibility.

Learning feature is an ability of NPC to change the behavior based on previous experience, and it is quite a rare case in video games since it requires advanced artificial intelligence techniques, numerous observations and resources-consuming analysis. Only a few games were reported to have learning AI implemented in the product. Variety of games suppose to have learning NPCs according to players reviews, however, developers do not confirm that.

3.3.2 Sources of Adaptation

We defined two classes of adaptation sources: direct and indirect adaptation. They were described in details in subsection 2.3.1.

Direct adaptation is done by parameterizing NPC behavior. The goal of the AI control system is to look for the parameters values and behaviors that perform in the best way in the game and against the human player.

This type of adaptation is difficult and resource-consuming to implement and use in the game, but simplified implementations are present and taken into account when analyzing the set of games.

Direct adaptation class, in turn, is divided into three subclasses defining the different usage of parameterizing approach: (1) sensory system, (2) flow control, and (3) others.

The *sensory system* is usually implemented in form of NPC alertness triggered when a human player crosses the "hearing", "scent" or "sight" area of NPC. The system is not usually adaptable by itself (its parameters are determined; however, these values might be defined on production stage using learning techniques), but it can cause changes in some defined parts of NPC behavior to adapt to player's behavior.

Flow control is another major usage of direct adaptation in video games. It is one of the forms of dynamic difficulty adjustment (see subsections 2.3.5 for Dynamic Difficulty Adjustment and 2.3.5.3 for Flow/pace control). AI Director is a widely used system for pace adjustment. AI-Director-like systems do not control NPC on a single unit level, but it acts like a supervisor for groups and overall AI (not NPC) strategy adjusting number of enemies and frequency of attacks and regulating "exhaustion" of players. The system acts upon player's performance in the game.

Others group includes cases that do not fit any of the classes described above and extraordinary ones. Among them, there are games like *Black & White* and Sprocnk's mod for *Neverwinter Nights*. First one is a good example of Direct adaptation since all the behaviors of NPC monsters here are parametrized and changeable in response to treatment or punishment from a human player. In the latter, every action of NPC has a weight which is adjusted through the game process to find actions that perform the best (for more details see section 2.3.5.1).

Indirect adaptation is performed using static information extracted from the game environment and player's behavior. The needed information and its usage are defined by game design and game mechanics. Unlike Direct adaptation, the Indirect class is not subdivided into subclasses since there is no specific pattern found among studied games and no specific information provided by developers regarding the implementation of game adjustment systems. However, most of the games use information gained from the player's in-game actions.

Combination of Direct and Indirect Adaptation is a rare case, but it often appears in the games of Stealth and Survival Horror genres. We distinguish two types of source combinations:

- *common goal* for both of the sources;
- *separate goals* for the sources;

In the case of common goal, both sources work for adaptation of single behavior part or common set of behaviors. The case study revealed that this type of combination is mostly used for pure Stealth games, where hiding is the primary goal (in games like *Alien: Isolation* and *Monstrum*): the sensory system, as well as static information about previous encounters, are used to adjust monster behaviors. Revealed usage is primary pathfinding.

Systems, oriented on separate goals, often use different sources for different aspects of the game. Thus one source can be used for NPC behavior and the other is for the story and/or environment adaptation (as it is done in *Dishonored* series, which will be described later in the analysis section).

3.3.3 Intra-behavior Adaptation

In general, *Intra-behavior adaptation* changes a small area of NPC behavior or a single aspect of the game (see subsection 2.3.2). Set of available behaviors varies from game to game depending on the game goals and game design. In numerous games, a few parts of behavior alter through the encounter or the game process. However, we decided to analyze games based on the most discernible behavior changes. Thus, we segregate three major parts of intra-behavior into three classes and fourth class for the games with no significant alterations in behavior.

These classes are:

- **Combat adaptation** class;
- **Pathfinding adaptation** class;
- **Others adaptation types** class;
- **None** class;

Combat adaptation is mostly used in games with an emphasis on battle. It includes action and weapon selection, and cover finding (including finding a path to a cover place).

Pathfinding adaptation is inherent to games where hostile NPCs should be close to the player most of the time, and therefore, adapt their patrolling paths over time based on the information about possible player locations.

Others adaptation types includes games that do not fit Combat or Pathfinding classes due to genre specifics or outstanding game design, but intra-behavior adaptation is present due to developers reports or player's reviews.

None class contains games that do not provide any significant or visible intra-behavior adaptation.

3.3.4 Inter-behavior Adaptation

Inter behavior is an overall behavioral pattern of the NPC. *Inter-behavior adaptation* is a type that changes this pattern to find new ways of defeating the player. This type of adaptation was described in Section 2.3.2 (Intra- and Inter-behavior adaptation).

For this type of adaptation, we decided to use a scale with three levels representing the complexity of inter-behavior adaptation:

- **None** label is assigned to games where no visible inter-behavioral adaptation present;
- **Low** label is assigned to games with advanced decision-making and planning systems that can provide visibly different behaviors. In other words, it is **high reactivity** in response to the player's action. These patterns, however, cannot be considered as an adaptation to a player's style;
- **High** label is assigned to the games where behavior pattern changes in response to player's actions and gaming style to bring more challenge and force the player to find new ways of task accomplishment.

Suggested division is based on our state-of-art observation of the games and may not include personalized adaptation towards human player, since, as it was observed, it is a rare case. However, we decided not to exclude major AI system type claimed by critics and players as one of the best representatives of AI in games.

3.3.5 Player Profiling

Advanced player profiling is rarely used in video games, and, even if it is, the function is often informative or very narrowed. Only a few games use information, gained from the player, to adjust the game environment.

Based on the game analysis, we have defined two classes out of five possible categories (see Section 2.3.3) of player profiling applied in modern games: (1) **Progress class** (or *Performance* category), that collects information about player progress through the gameplay; and (2) **Player's Style** (refers to *Player's behavior* category), which is more advanced player's in-game behavior analysis.

Highly reactive NPCs, that belong to the Low class of Inter-behavior adaptation and are able to provide various behavior patterns, are not taken into account since they do not adapt behavior pattern to player's style.

The complete classification with meta-classes, classes and subclasses, developed for this master thesis, can be found below (see Table 3.1).

3.4 Reliability and Validity

As it was stated previously, data collected for the analysis stage is third-party data gained from articles, case studies of games, players and critics' reviews. However, only a small number of these sources are official reports from company-developer or publisher, and therefore reliable. Conclusions made on the data from reviews and case studies are biased, so they cannot be considered as absolutely objective.

The data collected for total sales analysis is also approximated since only a few companies report their sales. The source used for this type of data collects and approximates an information from numerous sources, so there are no real numbers available. However, the purpose of the analysis is a ratio between total sales, so numbers gained from the specified source can be used for this work, but the precision of the results might be affected.

Metacritic score used for assessing the popularity among critics/reviewers is an average score of a given game based on the scores from different popular sources like *Edge*, *Game Informer* etc. This score is given to a game in general, taking into account all the aspects of the product and reviewer's opinion, and can not be considered as fully objective. However, according to the research [71], there is a positive correlation between Metacritic Score and player's experience in terms of challenge, so we can rely on the result based on Metacritic score.

In addition, Metacritic score is used by major game development companies as an indicator of success [72, 73], therefore it is a reliable source of information on game popularity.

Meta-class	Class	Subclasses	General criteria
Autonomy	Goal-oriented		NPC has a goal to be fulfilled
	Flexible		actions and their sequence are not visibly predefined
	Learning		reported or NPC visibly adapts the behavior basing on the previous experience
Source of adaptation	Direct	Sensory system	*alertness* feature triggered by senses, i.e. “hearing”, “scent” or “sight”
		Flow control	frequency or intensity of attacks is changed based on player’s performance
		Others	reported or gradual adaptation of enemy amount or strength spotted
	Indirect		statistics of the player used in game
	Combination	Common goal	a few of the previous are aimed on one feature adaptation
		Separate goals	a few of the previous are aimed on several features adaptation
Intra-behavior	Combat		reported or visibly different combat patterns spotted
	Pathfinding		reported or visibly different patrolling routes spotted
	Others		reported or alterations in behavior that do not fit previous
	None		no visible alterations
Inter-behavior	High		reported or behavior pattern changes in response to player’s actions
	Low		reported or behavior pattern is slightly changed between encounters
	None		no visible inter-behavioral adaptation
Player profiling	Player’s Style		reported within the game
	Progress		dynamic difficulty adjustment feature

Table 3.1: Complete game classification and general criteria.

4 Analysis and Classification of the Games' AI

This section is dedicated to the analysis of the games and their classification based on our observations and classification described in the section 3.3. It includes a description of the set of the selected games, the legend for the classification (analysis) table, analysis of the games, detailed explanation of the results for certain game examples from different classes, and popularity analysis of the games based on the complexity of their AI system.

4.1 Game List Description and Selection Criteria

The sample of games chosen for analysis covers almost all the genres popular within the video game community. They are:

- **action games**:

  adventure

  role-playing game (abbreviated RPG)
- **shooters**

  first-person shooters (abbreviated FPS)

  third-person shooters (abbreviated TPS)
- **stealth & survival horror**
- **real-time strategy**

Action games are games with an emphasis on the physical challenge, fast tactical decisions and reaction. Except for pure action genre, the games included in the sample represent specific subgenres which are mixes of action genre with the other genres, e.g. *adventure*, aimed at interactive story and exploration, or *RPG*, with the focus on controlling of the character actions in some well-defined world, character development, complexity and immersion into story and in-game world.

Shooters is a subgenre of action games, however, the main emphasis is made on testing player's speed and reaction, tactical skills in a fight, usually with firearms, so we separate shooter games from the action adventure and action RPG basing on the aim of game mechanics. The most popular subsets of the shooters are *FPS* and *TPS*. The difference between them is the character's point of view. FPS simulates the real sight of the person where one can see as much as eyes can and TPS gives player an extended view of the playable character and environment.

Stealth is a type of game where player is supposed to hide, sneak or disguise in order to overcome the enemy or pass the level undetected. It is often overlapped with *survival horror* genre with the focus on survival in frightening circumstances often followed by scary creatures. However, later on, the survival horror subgenre incorporated more of action games features, so some action and shooter games might include it as an additional subgenre. In our game sample, survival horror mostly comes with stealth game mechanics.

Real-time strategy is a subgenre of strategy games in a real-time where players control their units at the same time (giving them orders to build, protect buildings, secure area, destroy opponent's units and assets), unlike turn-based strategy where players should wait for their turn to give orders. Nevertheless, these genres are

merged sometimes and features of one genre can emerge in the game of another type.

The games chosen for analysis are prominent representatives in all the genres, claimed by critics and reviewers, or the ones that appeared to have interesting implementations due to available data, our findings, and analysis. Game set also includes popular games in terms of sales and scores.

For ordering and analysis purposes we have created two tables: general table, which includes general information about games mentioned in this work and games chosen for analysis; and analysis table depicting information about game AI implementation in selected games.

The *general table* is shown in Appendix A and includes next relevant information about each selected game:

- published name
- company-developer,
- year of *first* official release,
- link to the official web-page (or Wikipedia page if the publisher or developer do not provide any official web-page),
- genre,
- *Metacritic*[42] score[43] of the first release (average score for platforms if the game was released on several platforms within one year),
- link to a game page and review list on *Metacritic*,
- Total sales (in millions of US dollars) gained from *VGChartz*[44]

A table with details of all the games mentioned and discussed in this thesis can be found in Appendix A.

The *analysis table* consists of game set selected for further analysis of the AI system and information about features described in Section 3.3. An example of an analysis table record can be seen in Figure 4.5.

		Basic information			Adaptation information				Popularity	
Game name	Genre	Goal-oriented	Flexible	Learning	Adaptation source	Intra-behaviour	Inter-behaviour	Player profiling	Metacritic score	Total Sales
Alien: Isolation	Survival Horror	Yes	Yes	Yes	Combination SS	Pathfinding	None	None	80	2,46

Figure 4.5: Example of a game record in the analysis table.

Record line in the Analysis table includes next information:

- general information section:

  published name as **Name** column,
  genre as **Genre** column,

- AI information section:

  goal-orientation feature as **Goal-oriented** column,
  flexibility feature as **Flexible** column,
  learning feature as **Learning** column,

[42] http://www.metacritic.com/about-metacritic
[43] http://www.metacritic.com/about-metascores
[44] http://www.vgchartz.com/about.php

source of adaptation as **Adaptation source** column,
ability to change behavior pattern as **Inter-behavior** column,
ability to change small behavior areas as **Intra-behavior** column,
player profiling features as **Player profiling** column,

- popularity information section:

  Metacritic score as **Metacritic score** column,
  total sales (in millions of copies sold) as **Total Sales** column.

Each column in the AI section has a predefined set of values to be chosen for every game case. In most cases, a cell has two values: text value and cell color value. Color values also can be found in text form in the detailed tables throughout the next sections. The next subsection will describe a legend for the AI section of the analysis table (included in Appendix B).

AI information section of Analysis table consists of two subsections: basic information (Goal-oriented, Flexible and Learning columns) and Adaptation information (Direct/indirect adaptation, Inter-behavior, Intra-behavior and Player profiling columns).

Basic information subsection Columns cells can take one of *two* textual values: Yes (if the feature is present in the game) or No (if the feature is not present). Color cell values indicate authenticity and source of information: green (in **bold**) is for official developers or company reports, interviews or posts, and our conclusions on reported techniques; yellow (normal text) is for players experience, reviews and posts, and our conclusions based on available information.

Adaptation information subsection For this table subsection, values vary depending on the column. The common color scheme for columns indicates the source (as for Basic information subsection): green (in **bold**) for official sources; yellow (normal text) for players sources. Some columns might have additional color scheme representing subclasses and are described below.

Adaptation source column cells can take one of *four* textual values: Direct, Indirect, Combination, and None. For details see Section 3.3.2. A cell can have two color values: source indicator, and Subclass color for Direct subclasses.

Subclass colors are:

- bright blue (with *DDA* mark) is for **Flow/pace control** subclass,
- light blue (with *SS* mark) is for **Sensory system** subclass.

Intra-behavior column cell has one of the following values representing game belonging to a specific class of intra-behavior adaptation: Combat, Pathfinding, Other or None. Details can be found in the Section 3.3.3 (Intra-behavior adaptation)).

Inter-behavior column cells take one of the following values representing levels of the intra-behavior adaptation: None, Low, or High (the detailed description can be found in the Section 3.3.4 (Inter-behavior adaptation)). Cell colour values have only source indicator.

Player profiling column cell can have one of the following values describing an aspect of player behavior analyzed by the game system: Progress, Player Style or None (see details in Section 3.3.5 (Player Profiling)).

The color scheme is also present for *Metacritic score* column in Popularity section indicating rating gradient:

- green is for High game scores (75-100),
- orange is for Average game scores (50-74),
- red is for Low game scores (0-49).

High scores indicate critically acclaimed games, welcomed both by game critics and reviewers. They are proved to be well-designed, have unique and high-detailed visual style, balanced and interesting gameplay, and engaging story. From the technical side, the game is optimized, stable and have comfortable game controls system.

Games with Average scores usually have problems with any of stated game parts, often touching technical aspect of the game, e.g. lower level of optimization, low graphics optimization or badly balanced control system.

Low game scores are given to the games with bad optimization, non-balanced gameplay, frequent game crashes, simplified combat system etc.

4.2 Analysis and classification of games

This subsection is dedicated to our analysis of game AI systems of popular video games and their classification according to our findings.

For the readability of tables present in this section some names of the selected games were shortened. Here is the list of abbreviations:

- **Amnesia I** - Amnesia: The Dark Descent
- **Arkham Asylum** - Batman: Arkham Asylum
- **Arkham City** - Batman: Arkham City
- **Deus Ex III** - Deus Ex: Human Revolution
- **MGSV** - Metal Gear Solid V: The Phantom Pain
- **Shadow of Mordor** - Middle Earth: Shadow of Mordor
- **NWN (Spronck)** - Neverwinter nights (Spronck mode)
- **R6 Siege** Rainbow Six: Siege
- **Shadow of Chernobyl** - S.T.A.L.K.E.R: Shadow of Chernobyl
- **GR Wildlands** - Tom Clancy's Ghost Recon Wildlands
- **Blacklist** - Tom Clancy's Splinter Cell: Blacklist
- **Pandora Tomorrow** - Tom Clancy's Splinter Cell: Pandora Tomorrow
- **Fall of Cybertron** - Transformers: Fall of Cybertron
- **WoW** - World of Warcraft
- **XCOM: EU** - XCOM: Enemy Unknown

4.2.1 Similar features within genres

The first stage of the game sample analysis is referring to the basic features of game AI including goal-orientation, flexibility and learning. Reactivity of the game non-player characters was excluded from the further analysis since reactivity was a precondition for the game sample selection: NPCs in most of the modern games are reactive and responsive to the player's actions and/or environment changes on different levels of game AI complexity.

Initial grouping by common features, mentioned above, showed that games within one genre tend to have similar basic AI.

4.2.1.1 Action genre

Action RPG NPCs appear to be goal-oriented in most studied cases, but at the same time, only a few of NPCs have noticeable flexibility (see Table 4.2). In most studied cases, learning NPC control AI is not used. Also, a brief overview of the Action RPG group showed that games within this genre do not provide any inter-behavioral adaptation, but there are slight variations in intra-behavior of the NPCs. A few games appear to have combat adaptation, that can be explained by a domination of Action aspect of the game, while only some elements of RPG appear in the game.

	Basic information			Adaptation information		
Game name	Goal-oriented	Flexible	Learning	Adaptation source	Intra-behavior	Inter-behavior
Mass Effect	No	No	No	None	Combat	None
The Witcher 3	No	No	No	None	None	None
Dark Souls	Yes	No	No	None	None	None
Dark Souls 2	Yes	No	No	None	Combat	None
Diablo III	Yes	Yes	No	None	None	None
Fallout 3	Yes	Yes	No	None	None	None

Table 4.2: Action RPG genre features.

Action and Action Adventure NPCs in most cases are goal-oriented and flexible. Games also tend to use learning AI that is used to provide adaptation both intra- and inter-behavioral by means of both direct or indirect adaptation.

However, there are outliers in the genre group that demonstrate different AI features. They can be seen in the Table 4.3[45]. These games belong to Rocksteady Studios' Batman Series and include *Batman: Arkham Asylum* and *Batman: Arkham City*. Basing on the features gained by game analysis, Batman series AI matches Action RPG series. A closer look at the games with features similar to Batman's revealed that they feature an open world, where emphasis is made on world exploration rather than advanced combat experience (see Table 4.4).

The overall look at adaptation features of games of Action genre and subgenres has revealed that combat adaptation is common to the genre since experience emphasis in these games is often made on combat, a popular feature within game world.

[45]Here and further: *Comb.* is short for *Combination. Path* is short for *Pathfinding*

	Basic information			Adaptation information		
Game name	Goal-oriented	Flexible	Learning	Adaptation source	Intra-behavior	Inter-behavior
Far Cry 4	Yes	Yes	Yes	Indirect	Combat	Low
Shadow of Mordor	Yes	Yes	Yes	Comb.	None	High
Arkham Asylum	No	No	No	None	None	None
Arkham City	No	No	No	Direct	None	None
ECHO	Yes	Yes	Yes	Indirect	Combat	High
Tomb Raider	Yes	Yes	No	None	Combat	None
The Last of Us	Yes	No	No	None	Combat	None

Table 4.3: Action and Action Adventure genre features.

	Basic information			Adaptation information		
Game name	Goal-oriented	Flexible	Learning	Adaptation source	Intra-behavior	Inter-behavior
Arkham Asylum	No	No	No	None	None	None
Arkham City	No	No	No	Direct	None	None
Mass Effect	No	No	No	None	Combat	None
The Witcher 3	No	No	No	None	None	None
Dark Souls	Yes	No	No	None	None	None
Dark Souls 2	Yes	No	No	None	Combat	None

Table 4.4: Action with open world genre features.

4.2.1.2 Stealth genre

Analysis of the games of Stealth/Survival horror genre revealed high goal-orientation and flexibility of NPCs. And even in the light of the fact that only around 30% of the games have learning NPC control system, around 80% of the analyzed games provide adaptation on different levels and different aspects (see Table 4.5).

Indirect adaptation, provided by collecting, analyzing, and using in-game statistics, is usually applied for such kind of intra-behavioral adaption as patrolling paths of the main antagonist. In games like *Alien: Isolation* and *Monstrum* pathfinding adaptation is used for creating a sense of tension and fear for a human player, making him feel like the monster is always nearby and can catch the player at any moment. In games like *Thief* and *Dishonored*, smart NPC, when alerted, start looking for a player, making tasks harder to accomplish and, therefore, forcing the player to find new ways of solving the problem or to get into the fight.

The most common kind of direct adaptation is parameterizing of NPC senses, e.g. hearing, scent, sight. The result of touching one of those sensors is expressed than in a form of alertness of the NPC. The alertness measure can be then subdivided into several levels starting with noticing/suspicion and rising to a fully alerted state. This kind of adaptation was firstly used in *Thief*'s advanced sensory model, which allowed the player to take advantage of shadows, lights, and covers, and then successfully inherited by following *Thief* sequels and inspired *Dishonored* series and Survival Horror games.

Combat intra-behavioral adaptation appeared to be quite a rare case in Stealth games and is typical for those which combine Stealth and Action genres. Tasks in such games typically include the elimination of numerous enemies which often

forces players to go into combat. Examples of such games are *Metal Gear*, *Deus Ex*, and *Tom Clancy's Splinter Cell* series.

	Basic information			Adaptation information		
Game name	Goal-oriented	Flexible	Learning	Adaptation source	Intra-behavior	Inter-behavior
Dishonored	Yes	Yes	No	Comb.	Path	None
Dishonored 2	Yes	Yes	No	Comb.	Path	Low
Hitman:Absolution	Yes	Yes	No	Direct ·	Combat	None
MGSV	Yes	Yes	Yes	Indirect	Other	Low
Thief 1	No	No	No	Direct	None	None
Thief 4	Yes	No	No	Direct	Path	None
Pandora Tomorrow	Yes	Yes	Yes	Indirect	Combat	None
Blacklist	Yes	Yes	No	Direct	Combat	Low
Deus Ex III	Yes	Yes	No	None	Combat	None
Alien: Isolation	Yes	Yes	Yes	Comb.	Path	None
Amnesia I	Yes	Yes	No	Comb.	None	None
Dying Light	No	No	No	None	None	None
Hello neighbor	Yes	No	Yes	Indirect	Other	None
Monstrum	Yes	Yes	No	Direct	Path	None

Table 4.5: Stealth/Survival Horror genre features.

4.2.1.3 Shooters

The below description touches two types of shooters: first-person shooters and third-person shooters.

First-person shooter is the most popular video game genre. It gives a human player the highest sense of engagement since s/he sees environment through the eyes of the main protagonist. It was the first genre to challenge resource-consuming 3D graphics since players had to see the believable world around them in order not to break immersion.

To increase this sense of immersion into the game environment, the believability of hostile NPC is of the great importance and challenge. FPS usually is the first genre to adopt new AI techniques in order to enhance tactical and strategical strength and skills to bring NPC control systems on the new level.

The most popular technique used in FPS is *Goal-Oriented Action Planning* first adopted by the game *F.E.A.R.* (described in Section 2.2.1 (AI-driven NPC behavior)) and its successors like *Hierarchical task network (HTN) planning* [74].

Overview of the selected FPS games allows us to divide state-of-art shooters in two big group:

- *GOAP family* with games that use AI techniques mentioned above or that appear to have similar AI features, however, was not reported to use any of the given techniques,
- *Flow control family* includes first-person shooters where the emphasis is made on gameplay intensity and complexity flow.

Games that use Planning in their NPC control systems are goal-oriented by definition and flexible since action sequence is not predefined and depends only on current goal. Games of these family usually do not have any learning ability and do not progress through the game process. However, ability to define action sequence depending on player's actions and current goal provide these games with a low level of inter-behavior adaptation since behavior is not strictly predefined. The type of inter-behavioral adaptation is mostly Combat adaptation dictated by specific features of FPS genre. The above description can be seen in Table 4.6.

Among outliers there is *S.T.A.L.K.E.R: Shadow of Chernobyl*. They started building their AI control system from simple determined FSM and went through hierarchical FSM to GOAP. However, usage of planning technique is restricted only to choosing the first action and it does not touch other parts of plan [75]. The system of S.T.A.L.K.E.R appears to be very adaptive to environmental changes, rebuilding the whole plan if some of the world parameters have changed. This system was primarily applied to stalkers (characters that hunt treasures in abandoned zones like Chernobyl Exclusion Zone filled with anomalies due to the nuclear explosion) and not to monsters that walk around The Zone.

Another outlier is *Rainbow Six: Siege*, which has a set of feature typical for GOAP family. However, due to player's reviews, at some point in the game, the NPCs can totally change a type of their behavior. Nonetheless, the Inter-behavior feature of the game is set to Low since there is no visible adaptation towards the human player, so the game can be considered as highly reactive.

	Basic information			Adaptation information		
Game name	Goal-oriented	Flexible	Learning	Adaptation source	Intra-behavior	Inter-behavior
F.E.A.R.	Yes	Yes	No	None	Combat	Low
Half Life	Yes	Yes	No	None	Combat	Low
Halo 2	Yes	Yes	No	None	Combat	Low
Killzone 3	Yes	Yes	No	None	Combat	Low
R6 Siege	Yes	Yes	No	Direct	Combat	Low
Shadow of Chernobyl	Yes	Yes	No	Indirect	Other	Low

Table 4.6: FPS GOAP family features.

The second group of games have many common features with the first group regarding NPC behavior (goal-orientation and flexibility, see Table 4.7). But except for that, games of this group apply learning techniques to adapt to players' progression through the game via *dynamic difficulty adjustment* (see section 2.3.5.3).

The intensity of these games is parametrized and adjusted through the game by analyzing players' game proceeding speed and decreasing/increasing not only power and frequency of attacks, but also the number of enemies attacking.

Despite having goal-orientation and flexibility features, Inter-behavioral features of these games are set to *None* unlike the same feature in GOAP family. This is done since players reviews report about the overall visible simplicity of NPC behavior itself. In the case of these games, Goal-orientation and Flexibility are mostly related to *process* changes.

	Basic information			Adaptation information		
Game name	Goal-oriented	Flexible	Learning	Adaptation source	Intra-behavior	Inter-behavior
Evolve	Yes	Yes	Yes	Direct	Combat	None
Far Cry	Yes	Yes	Yes	Direct	Combat	None
Left 4 Dead	Yes	Yes	Yes	Direct	Combat	None

Table 4.7: FPS flow control family features.

Regarding third-person shooters, the analysis did not show any specific pattern among selected TPS. In most cases, values are typical for GOAP family FPS, which makes these values common for Shooter as a genre (see Table 4.8).

However, it should be taken into account that there are very few pure shooters from the third-person perspective. This genre is the most influenced by other genres and almost never goes alone with TPS only in description. Grouping by features often sets mentioned games close to Action Adventures, since most of the Action Adventures games include fights and shootings from the third-person perspective.

Worth mentioning that genre of the game does not necessarily allow to judge about game antagonists and gameplay. *Resident Evil* series, for example, is defined as Survival Horror by the developer, but we can say of this genre as of game setting and atmosphere definitions in terms of story and environment. The gameplay of Resident Evil series is typical for shooters according to players and our analysis.

	Basic information			Adaptation information		
Game name	Goal-oriented	Flexible	Learning	Adaptation source	Intra-behavior	Inter-behavior
Gears of War	No	No	No	Direct	Combat	None
Max Payne 3	Yes	Yes	No	Direct	Combat	Low
GR Wildlands	Yes	Yes	Yes	Indirect	Combat	Low
Fall of Cybertron	Yes	Yes	No	None	Combat	None
Resident Evil 4	Yes	Yes	No	Direct	Combat	None

Table 4.8: TPS features.

Only one outlier for shooter genre appeared in the game list (see Table 4.9). *Titanfall* is a multiplayer online shooter, so NPCs there act as fillers, even though they can deal damage to the players. In this game, no complex AI was designed, but the NPCs are able to perform visible communication and inform the player about the situation on the battlefield and some prescribed actions.

	Basic information			Adaptation information		
Game name	Goal-oriented	Flexible	Learning	Adaptation source	Intra-behavior	Inter-behavior
Titanfall	No	No	No	Indirect	None	None

Table 4.9: Features of outlying shooter games.

4.2.1.4 Strategies

Strategy is one of fewer game genres where the goal of the AI is to win over human player rather than keep him on the edge but allow to win in the end. Good AI in RTS should be goal-oriented, flexible, smart and more important - learning.

Almost all of the modern strategies played against computer AI player (we do not take into account multiplayer games) adopt learning techniques as can be seen from the Table 4.10. Old games are an exception since, at the time of their development, smart learning game AI was rare and quite resource consuming feature.

However, learning feature will not necessarily appear in the final project and be delivered to actual players. Even though these games have learning AI, systems are trained before they reach the final user. But in most cases, nevertheless, they are trained by humans.

Looking at other features, due to specifics of the genre, Strategy genre uses indirect adaptation, gathering authorized relevant information from the game world and the current state of the game. This information is then can be used for making major decisions on tactical and strategical levels, thus, providing the game with high inter-behavior adaptation.

	Basic information			Adaptation information		
Game name	Goal-oriented	Flexible	Learning	Adaptation source	Intra-behavior	Inter-behavior
Attila:Total War	Yes	Yes	Yes	Indirect	None	High
Empire:Total War	Yes	Yes	Yes	Indirect	None	High
Supreme Commander	Yes	Yes	No	None	None	None
Total war	Yes	Yes	Yes	Indirect	None	High
WoW	Yes	Yes	No	None	None	None
XCOM: EU	Yes	No	No	None	None	None

Table 4.10: Strategy features.

At the same time, games of this genre do not provide any intra-behavior adaptation. Smaller units do not make their own decisions and do not select actions. All moves made are dictated by AI player according to its tactical and strategical decisions, so most of the developers refused from independent unit control.

However, this features mostly belong to *Total War* series as one of the most progressive games. The first game was released in 2000, and since then developers continuously review and improve the AI of the game series, adding progression to AI systems. These features were not spotted in other representatives of the genre.

Other popular strategy games, that appeared in the table, are rather old games, even *XCOM: Enemy Unknown* (being a new game, it is a remaster of the old game *UFO: Enemy Unknown*[46]). But even since the time of their first release, the AI systems have been keeping the same course of development without focusing on inter-behavioral adaptation.

[46]Mythos Games, MicroProse, 1994. https://en.wikipedia.org/wiki/UFO:_Enemy_Unknown

4.2.2 AI learning in popular video games

Since the ability to learn is a basic feature of artificial intelligence by academic definition, we decided to take a look at how often it is used in modern state-of-art video games and how it is used to bring adaptability to a human player.

Only 32% out of 50 selected games were reported to use learning techniques or they appeared to use them according to players and critics' reviews. In all the cases of learning ability of AI in those games, learning technique was used to adapt to human player actions. Selection of games with learning AI can be seen below in Table 4.11.

As can be seen from the table, a great percent of games with learning AI is using advanced AI techniques to provide high inter-behavior adaptation towards a player, which means that NPCs are able to follow players actions and change their behavior in a very reactive way in response to environmental changes. The behavior is mostly changed by means of analysis of static information that can be extracted from the game environment and is *allowed* for retrieval by the intelligent system (Indirect adaptation feature). This could be explained by the fact that this kind of learning and adaptation is easy to test and the least resource consuming, what is critical for computer games which require high performance rate.

	Basic information			Adaptation information		
Game name	Goal-oriented	Flexible	Learning	Adaptation source	Intra-behavior	Inter-behavior
ECHO	Yes	Yes	Yes	Indirect	Combat	High
Shadow of Mordor	Yes	Yes	Yes	Comb.	None	High
NWN (Spronck mode)	No	Yes	Yes	Direct	None	High
Attila:Total War	Yes	Yes	Yes	Indirect	None	High
Empire:Total War	Yes	Yes	Yes	Indirect	None	High
Total war	Yes	Yes	Yes	Indirect	None	High
Black & White	Yes	Yes	Yes	Direct	Other	High
GR Wildlands	Yes	Yes	Yes	Indirect	Combat	Low
Far Cry 4	Yes	Yes	Yes	Indirect	Combat	Low
MGSV	Yes	Yes	Yes	Indirect	Other	Low
Evolve	Yes	Yes	Yes	Direct	Combat	None
Far Cry	Yes	Yes	Yes	Direct	Combat	None
Left 4 Dead	Yes	Yes	Yes	Direct	Combat	None
Pandora Tomorrow	Yes	Yes	Yes	Indirect	Combat	None
Hello neighbor	Yes	No	Yes	Indirect	Other	None
Alien:Isolation	Yes	Yes	Yes	Comb.	Path	None

Table 4.11: Games with learning AI.

However, there are few examples of the games, that use Direct adaptation type. In the selected games they are *Black & White* god game and *experimental AI mod* for *Neverwinter Nights* by P. Spronck [21]. Behavior in these games is parametrized and changes immediately in response to player actions.

In Spronck's Neverwinter Nights mod every action or sequence has its weight which is adjusted through the game process, marking the most and the least effective actions. For the next encounter with a human player, the new action sequence is

chosen by selecting the most effective ones. But, despite for Direct adaptation type, changes are applied between stages of the game and not directly. The technique used in this mode was described in Section 2.3.5.1 (Dynamic scripting)

Black & White is rising a pet game. The monsters, main NPCs of the game, change their behavior by being punished or treated for certain actions. Evidently, they will choose to perform the actions they are treated for more often than actions that they are punished for. More about AI in Black & White can be read in [44].

A smaller amount of games uses learning techniques for low inter-behavior, adjusting behavior pattern to fit player's behavior and force to find cheats to overcome new actions. For example, *Metal Gear Solid V: The Phantom Pain* learns from player's preferable actions and adds new behaviors to the current set. If a player prefers sneaking at night and killing in stealth style, enemies will start patrolling area borders with flashlights, preventing the player from secret sneaking. Or they will start wearing helmets if the player tends to perform a lot of headshots.

Learning techniques can also be used for intra-behavior adaptation. Collecting and analyzing static information from game environment allows hostile NPC to choose most effective patrolling paths like it is done in *Alien: Isolation*. The alien, main protagonist, uses its senses and memory to visit places where he noticed or killed player last time or patrol the area close to loud noise sources.

Regarding games that seem not to use learning techniques, they still can provide some level of inter- and intra-behavior adaptation, which, however, can be considered as high reactivity rather than adaptability. The games shown below (see Table 4.12) are reported without learning features of NPC control system, however, advanced decision-making and action-selecting technique allows hostiles to perform visibly different behaviors.

	Basic information			Adaptation information		
Game name	Goal-oriented	Flexible	Learning	Adaptation source	Intra-behavior	Inter-behavior
R6 Siege	Yes	Yes	No	Direct	Combat	Low
Max Payne 3	Yes	Yes	No	Direct	Combat	Low
Blacklist	Yes	Yes	No	Direct	Combat	Low
F.E.A.R.	Yes	Yes	No	None	Combat	Low
Half Life	Yes	Yes	No	None	Combat	Low
Halo 2	Yes	Yes	No	None	Combat	Low
Killzone 3	Yes	Yes	No	None	Combat	Low
Shadow of Chernobyl	Yes	Yes	No	Indirect	Other	Low
Dishonored 2	Yes	Yes	No	Comb.	Path	Low

Table 4.12: Games with no learning AI and low inter-behavior adaptability.

Learning technique is not a necessary feature for providing intra-behavioral adaptation as well. As can be seen from the Table 4.13, some games use direct and indirect adaptation to change different areas of their behavior, which, however, can be considered as *distraction* from primary behavior.

	Basic information			Adaptation information		
Game name	Goal-oriented	Flexible	Learning	Adaptation source	Intra-behavior	Inter-behavior
Dishonored	Yes	Yes	No	Comb.	Pth	None
Resident Evil 4	Yes	Yes	No	Direct	Combat	None
Hitman:Absolution	Yes	Yes	No	Direct	Combat	None
Gears of War	No	No	No	Direct	Combat	None
Thief 4	Yes	No	No	Direct	Path	None
Monstrum	Yes	Yes	No	Direct	Path	None

Table 4.13: Games with no learning AI and intra-behavior adaptability.

4.3 Intra-behavior Adaptation Analysis

Intra-behavior adaptation appears to be a very frequent case in modern video games. Around 60 % of studied games are able to change parts of NPC behavior, including combat behavior and pathfinding as the most frequently used.

		Adaptation information		
Game name	Genre	Adaptation source	Intra-behavior	Inter-behavior
Far Cry 4	Action	Indirect	Combat	Low
Tomb Raider	Action Adventure	None	Combat	None
ECHO	Action Adventure	Indirect	Combat	High
Mass Effect	Action RPG	None	Combat	None
Dark Souls 2	Action, RPG	None	Combat	None
The Last of Us	Action, Stealth	None	Combat	None
Rainbow Six: Siege	FPS	Direct	Combat	Low
F.E.A.R.	FPS	None	Combat	Low
Half Life	FPS	None	Combat	Low
Halo 2	FPS	None	Combat	Low
Killzone 3	FPS	None	Combat	Low
Evolve	FPS	Direct	Combat	None
Far Cry	FPS	Direct	Combat	None
Left 4 Dead	FPS, Survival Horror	Direct	Combat	None
Hitman:Absolution	Stealth	Direct	Combat	None
Pandora Tomorrow	Stealth	Indirect	Combat	None
Blacklist	Stealth, Action	Direct	Combat	Low
Deus Ex III	Stealth, Action RPG	None	Combat	None
Max Payne 3	TPS	Direct	Combat	Low
Gears of War	TPS	Direct	Combat	None
Fall of Cybertron	TPS	None	Combat	None
GR Wildlands	TPS	Indirect	Combat	Low
Resident Evil 4	TPS, Survival Horror	Direct	Combat	None

Table 4.14: Games with combat intra-behavior adaptation.

More than 60 % of games that adapt intra-behavior use combat alterations (see Table 4.14) to prevent NPCs from repeating the same fight pattern. If a human

player spots a repeated sequence of actions in response to his behavior, nothing stops him from exploiting a revealed weakness of enemies further in the game. Combat adaptation became an essential part of AI control system in shooters and action games focused on a fight with enemies.

Most of the first-person shooters analyzed through the work use advanced combat adaptation in their systems. The initiator of this tendency is *F.E.A.R.* game mentioned a few times before. Their combat AI system remains one of the most challenging systems even thirteen years after the first release. Combat alterations appeared earlier (for example, in *Far Cry* released the same year with F.E.A.R., and in *Half Life*, 1998), however, on the lower level of complexity.

Another widely used part of behavior adaptation is advanced pathfinding. Despite pathfinding being a commonly referred problem and claimed to be solved, in most games, it is present on an elementary, not adaptive level. However, adaptive pathfinding is crucial for Stealth and Survival Horror games (see Table 4.15), where enemies are supposed to look for a hiding player orienting on their senses and, sometimes, memory.

		Adaptation information		
Game name	Genre	Adaptation source	Intra-behavior	Inter-behavior
Dishonored 2	Stealth	Combination	Path	Low
Dishonored	Stealth	Combination	Path	None
Thief 4	Stealth	Direct	Path	None
Monstrum	Survival Horror	Direct	Path	None
Alien:Isolation	Survival Horror	Combination	Path	None

Table 4.15: Games with pathfinding adaptation.

As can be seen from the table, adaptive pathfinding often uses direct adaptation source, a parametrized sensory system, responsible for the level of NPC alertness. Distracted by the noise, NPC will change its patrolling path to look for the source.

In games such as *Thief*, patrolling routes change for a limited amount of time, necessary to check out what is happening. However, if a player was not spotted, soldiers come back to their predefined routine.

In more recent games like *Alien: Isolation* or *Monstrum*, enemies' patrolling routes are the central source of challenge in the game since the goal of the game is to create a feeling of fear that monster is somewhere nearby. Once distracted, the enemy will change its route to be closer to the player, to look for him in places of past encounters.

A smaller group of games has got a kind of adaptation that does not fit into any mentioned group, so we separated them into *experimental* class grouping outliers (see Table 4.16).

Hostile monsters in *S.T.A.L.K.E.R: Shadow of Chernobyl* have stable behavior and fixed actions, but the game world is filled with so-called A-Life, e.g. *stalkers* that behave almost like players and have to adapt to the environment, set their goal and make decisions, which is a primary goal of NPC control system. *Black & White* NPCs have a complex, flexible behavior divisible into smaller adaptive parts, e.g. food choice. *Metal Gear Solid V: The Phantom Pain* appeared in experimental

class since the situation is similar to Black & White: complex behavior (called *Revenge System* or *Enemy Preparedness* in the game) is divided into smaller parts and decisions, e.g. wearing a helmet, patrolling borders with flashlights, etc. *Hello neighbor* AI can be considered as Revenge System as well: antagonist, a neighbor of the main hero, places traps on the spots of previous encounters. The remarkable thing about Hello neighbor is that setting traps is the only behavior type of the NPC. However, we considered this fact as not satisfying for setting High rank of *inter-behavior* adaptation.

		Adaptation information		
Game name	Genre	Adaptation source	Intra-behavior	Inter-behavior
Shadow of Chernobyl	FPS	Indirect	Other	Low
Black & White	God Game	Direct	Other	High
MGSV	Stealth	Indirect	Other	Low
Hello neighbor	Survival Horror	Indirect	Other	None

Table 4.16: Games with unique adaptation.

Overview of games that do not provide any type of inter-behavior adaptation revealed a few genres that typically relate to this class (see Table 4.17).

		Adaptation information		
Game name	Genre	Adaptation source	Intra-behavior	Inter-behavior
Shadow of Mordor	Action	Comb.	None	High
Arkham City	Action Adventure	Direct	None	None
Arkham Asylum	Action Adventure	None	None	None
The Witcher 3	Action RPG	None	None	None
Dark Souls	Action, RPG	None	None	None
Diablo III	Action, RPG	None	None	None
Fallout 3	Action, RPG	None	None	None
Titanfall	FPS	Indirect	None	None
NWN (Spronck)	RPG	Direct	None	High
Thief 1	Stealth	Direct	None	None
Supreme Commander	Strategy, RTS	None	None	None
WoW	Strategy, RTS	None	None	None
Attila:Total War	Strategy, RTS	Indirect	None	High
Empire:Total War	Strategy, RTS	Indirect	None	High
Total war	Strategy, RTS	Indirect	None	High
XCOM: EU	Strategy, TBT, RPG	None	None	None
Amnesia I	Survival Horror	Comb.	None	None
Dying Light	Survival Horror	None	None	None

Table 4.17: Games with no intra-behavior adaptation.

Most of the Action RPG games appeared in the class with no inter-behavior alterations. They feature open-world, focused on environment and enemies exploration rather then complexity if enemies behavior. However, *Dark Souls 2*, a sequel of *Dark Souls*, has made a step towards more challenging NPCs and implemented slight Combat pattern alterations to each enemy.

All of the selected RTS games do not have any inter-behavior adaptability as well. The reason for setting None-value is overall control of the player AI: the system decides about all the moves made and actions taken, but units do not have any control over their actions.

4.4 Inter-behavior Adaptation Analysis

Since the primary goal of adaptation to a human player is providing him with challenging gameplay that fits his skills and preferences and brings the sense of engagement, visible high inter-behavior adaptation is the best sign of success. However, only around 15% of games reviewed for this project, appear to adapt to the player's style and preferences completely or at a very high level (see Table 4.18).

The remarkable fact is a variety of genres with highly adaptable NPC control system, but high adaptation appears to be a rare case in shooters despite the popularity of the genre and a goal for developers to improve shooters game AI. Majority of games belong to the real-time strategy genre, where the primary goal of opponent player in RTS is a victory over the human player using the same rules. Should be taken into account, however, that these games belong to one series.

Other games with high changeable behavior are mostly experimental games like *ECHO*, *Black & White*, and *Middle Earth: Shadow of Mordor*. ECHO uses player action statistics and copies players style forcing the player to fight against himself and to find other ways of task accomplishment. Black & White game adaptation features were described in Section 4.2.2. Middle Earth: Shadow of Mordor uses specially designed Nemesis system to select most challenging enemies, based on in-game encounters, and evolve survived enemies in order to drop them to fight in later game stages.

		Adaptation information		
Game name	Genre	Adaptation source	Intra-behavior	Inter-behavior
ECHO	Action Adventure	Indirect	Combat	High
Shadow of Mordor	Action	Combination	None	High
NWN (Spronck)	RPG	Direct	None	High
Total war	Strategy, RTS	Indirect	None	High
Black & White	God Game	Direct	Other	High
Attila:Total War	Strategy, RTS	Indirect	None	High
Empire:Total War	Strategy, RTS	Indirect	None	High

Table 4.18: Games with high inter-behavior adaptation.

The amount of games with low inter-behavioral adaptation is higher, but still not a state-of-art in video games (see Table 4.19) despite the fact that some techniques are rather old, tested and tried (like the technique used in F.E.A.R., that still remains one of the most challenging [36]).

FPS appears more likely to have low inter-behavior adaptation. Based on specifics of shooter genre and our analysis, we can assume that the reason of providing low behavior adaptation rather than high is that the primary goal of shooters is a number of enemies killed, but not the quality of kills by themselves. In this case advanced decision making on-the-spot is more preferable then complete behavior changes which will be very resource consuming.

One more remarkable thing about low inter-behavior adaptation is that it does not necessarily need learning techniques to be adopted in the game system. As it was described in Section 4.2.2, low inter-behavior adaptation can be considered as high-level reactivity to human player actions. But these control systems do not learn from the player and do not remember his preferences and do not take advantage of his style.

		Adaptation information		
Game name	Genre	Adaptation source	Intra-behavior	Inter-behavior
Far Cry 4	Action	Indirect	Combat	Low
R6 Siege	FPS	Direct	Combat	Low
F.E.A.R.	FPS	None	Combat	Low
Half Life	FPS	None	Combat	Low
GR Wildlands	TPS	Indirect	Combat	Low
Halo 2	FPS	None	Combat	Low
Killzone 3	FPS	None	Combat	Low
Blacklist	Stealth, Action	Direct	Combat	Low
Max Payne 3	TPS	Direct	Combat	Low
Shadow of Chernobyl	FPS	Indirect	Other	Low
MGSV	Stealth	Indirect	Other	Low
Dishonored 2	Stealth	Comb.	Path	Low

Table 4.19: Games with low inter-behavior adaptation.

4.5 Adaptation Sources Analysis

Analysis of the ways how adaptation is implemented in the games revealed that despite the high complexity and resource requirements, numerous games (around 30%) use *Direct* adaptation (see Table 4.20).

Usage of Direct adaptation can be, in turn, divided into three subclasses highlighting primary features of Direct adaptation implementation.

The games marked with *Direct (DDA)* feature designate games with dynamic difficulty adjustment and flow/pace control described in Section 2.3.5.3. Multiplayer or co-op games with flow control orient on player's progress through the game, making sure that players still go further through the gameplay. *Left 4 Dead* and *Evolve* are significant representatives of these type with Left 4 Dead as developers of AI Director system used in a few games. Among DDA class of games, there is *Batman: Arkham City* which does not use AI Director-like system, however, amount of enemies is adjusted according to player's ability to pass the task. *Resident Evil 4* applies Dynamic Difficulty Adjustment as well.

The games with *Direct (SS)* feature use parametrized senses (sight, hearing etc.) for NPC decision-making system. As was discussed before, reaction to sensory

system irritations appears in Stealth and Survival Horror games where inappropriate player action can cause the enemy to spot him and reveal the current hiding place. For games like *Alien: Isolation* and *Monstrum* it is crucial since most of the face-to-face encounters lead to significant damage or death.

		Adaptation information		
Game name	Genre	Adaptation source	Intra-behavior	Inter-behavior
R6 Siege	FPS	Direct	Combat	Low
Max Payne 3	TPS	Direct	Combat	Low
Resident Evil 4	TPS, Survival Horror	Direct (DDA)	Combat	None
Arkham City	Action Adventure	Direct	None	None
NWN (Spronck)	RPG	Direct	None	High
Black & White	God Game	Direct	Other	High
Evolve	FPS	Direct (DDA)	Combat	None
Far Cry	FPS	Direct (DDA)	Combat	None
Left 4 Dead	FPS, Survival Horror	Direct (DDA)	Combat	None
Hitman:Absolution	Stealth	Direct (SS)	Combat	None
Blacklist	Stealth, Action	Direct (SS)	Combat	Low
Gears of War	TPS	Direct (SS)	Combat	None
Thief 1	Stealth	Direct (SS)	None	None
Thief 4	Stealth	Direct (SS)	Pathfinding	None
Monstrum	Survival Horror	Direct (SS)	Pathfinding	None

Table 4.20: Games with Direct adaptation.

The other records with Direct feature indicate outliers that do not fit these major classes. *Black & White* uses parametrized preferences and behaviors for the monsters, Spronck's *Neverwinter nights* mode assigns weights to enemies behavior and adjusts them through the fight. Some games are not reported to have any parameters, but, according to players reviews, *Rainbow Six: Siege* NPCs react on a significant amount of dead people among them and might decide to completely change their behavior. However, should be taken into account that this might be prescripted behavior since no learning AI was reported.

Indirect adaptation is another significant class of adaptation source in games (see Table 4.21). Around 20 % of games use static information from the game environment and player's action to adjust the behavior of NPC.

In *Total War* series, steps, taken by a human player, influence both tactics and global strategy of opponent AI player. *Hello neighbor* uses previous encounters as a basis for setting traps. Recent experimental game *ECHO* defines the whole behavior pattern based on player's actions. But in general, no visible pattern appears among games that use Indirect adaptation type.

A smaller amount of games use both Direct and Indirect adaptation for different or common purposes or in a couple.

Alien: Isolation implements both methods for optimization of pathfinding. Parametrized senses are used for spotting a player's hideout, while memory about previous encounters is a basis for choosing the best patrolling path. However, the latter was not reported by developers, so it is based on players' reviews. *Middle Earth: Shadow*

of Mordor's Nemesis system uses both types of information analysis to evolve survived enemies. Static information gained from the player after the encounter and about the player is remembered and then used to adjust parameters of the survived NPC, which can further be promoted to a higher rank and revenge [76, 77].

		Adaptation information		
Game name	Genre	Adaptation source	Intra-behavior	Inter-behavior
Far Cry 4	Action	Indirect	Combat	Low
ECHO	Action Adventure	Indirect	Combat	High
Pandora Tomorrow	Stealth	Indirect	Combat	None
GR Wildlands	TPS	Indirect	Combat	Low
Titanfall	FPS	Indirect	None	None
Total war	Strategy, RTS	Indirect	None	High
Attila:Total War	Strategy, RTS	Indirect	None	High
Empire:Total War	Strategy, RTS	Indirect	None	High
Shadow of Chernobyl	FPS	Indirect	Other	Low
MGSV	Stealth	Indirect	Other	Low
Hello neighbor	Survival Horror	Indirect	Other	None

Table 4.21: Games with Indirect adaptation.

		Adaptation information		
Game name	Genre	Adaptation source	Intra-behavior	Inter-behavior
Shadow of Mordor	Action	Comb.	None	High
Amnesia I	Survival Horror	Comb.	None	None
Dishonored 2	Stealth	Comb.	Path	Low
Dishonored	Stealth	Comb.	Path	None
Alien:Isolation	Survival Horror	Comb.	Path	None

Table 4.22: Games with combination of Direct and Indirect adaptations.

Dishonored series case has different purposes for both types of adaptation. The direct adaptation was implemented in the form of parametrized alertness to trigger behavior patterns. The static information from the world changes caused by the player influences some details of the story or even the whole final of the game. This is called *Level of Chaos*. For example, rats, the source of the plague that captures the city of Dunwall (setting of the game), appear in larger amounts if the player goes through the game with killing style. More rats cause more death among citizens which leads to high Level of Chaos and high rate of disorders in the city, making the final grimmer. In the sequel, *Dishonored 2*, stealing from black market shops causes rumours and, as a result, difficulties in visiting those shops again.

4.6 Player Profiling Analysis

Despite any adaptation to a human player being a player profiling (see Section 2.3.3.1) since it is based on player's actions, only a few aspects of the player's

style and in-game behavior are now analyzed and used by AI systems. Among the studied games, we separated two classes of player profiling: Player Style (see Table 4.23) and Progress or DDA which includes flow control (see Table 4.24). For more information about DDA and flow control see subsections 2.3.5 and 2.3.5.3.

		Adaptation information			
Game name	Genre	Adaptation source	Intra-behavior	Inter-behavior	Player Profiling
Dishonored 2	Stealth	Comb. (SS)	Pathfinding	Low	Player Style
Dishonored	Stealth	Comb. (SS)	Pathfinding	None	Player Style
Thief 4	Stealth	Direct (SS)	Pathfinding	None	Player Style

Table 4.23: Games defining Player Style.

Player Style is an important part of *Dishonored* series since it has an impact on the environment and story progression as it was described in subsection 4.5. *Thief 4* AI system is able to recognize player style as Ghost (absolute Stealth), Opportunist (taking advantage of available materials and tools, picking pockets etc.), and Predator (elimination of enemies on the way to the task accomplishment) citethief4playstyle. The playstyle is defined as the part of each of the given styles in percents with a further selection of prevailing. However, this information does not affect any part of the game except for Achievement section.

		Adaptation information			
Game name	Genre	Adaptation source	Intra-behavior	Inter-behavior	Player Profiling
Resident Evil 4	TPS	Direct (DDA)	Combat	None	Progress
Arkham City	Action	Direct (DDA)	None	None	Progress
Evolve	FPS	Direct (DDA)	Combat	None	Progress
Far Cry	FPS	Direct (DDA)	Combat	None	Progress
Left 4 Dead	FPS	Direct (DDA)	Combat	None	Progress

Table 4.24: Games adapting flow control.

Variety of games have the Dynamic Difficulty Adjustment system, but only a few cases were reported or studied by experts. As a rule, difficulty changes are smooth and hardly noticeable from the player's side. So we selected a set of games which have development reports announcing usage of DDA systems in their products. *Left 4 Dead* AI controls the flow of the game, making it more relaxing if players do not progress and increase tension (by increasing amount of monsters, a frequency of their appearance etc.) if progression is too fast. This system, called AI Director, was then used in several games, including *Far Cry* series and *Evolve*. *Batman: Arkham city* was not reported to use AI Director, however, the game can adjust the number of enemies based on the player progression.

Revealed DDA system in *Resident Evil 4* assigns a rank to the player based on in-game success. Every kill gives points to the player; the amount of given points depends on speed and efficiency of the kill. Complexity can change significantly through the game and even move from predefined level (the one selected in the game settings, typically includes Easy, Medium, and Hard) to lower or higher.

4.7 Summary of classification

In the analysis of usage of artificial intelligence in video games, a classification of game AI was developed to define specific AI agent features inherent to game genres; levels of complexity of AI in video games; adaptation type and sources in the game AI systems.

For game AI analysis, action (adventure/RPG), shooter (first-/third-person), stealth (including survival horror) and strategy genres were selected as the most popular genres. However, a few games of other genres appeared due to their outstanding implementation or other reasons.

Genre analysis revealed *three* overlapping subgroups in Action genre: Action RPG (1), Action Adventure (2), and Open-world (3). (1) features goal-oriented, but not flexible AI without any advanced implementations in most cases; (2) (including pure Action), in contrary, appeared flexible in addition to goal-orientation and provided combat adaptation. However, both groups had outliers which had an open-world as common feature defining other common features. These games form (3).

Stealth and Survival horror games had many features in common including goal-orientation and flexibility. Many games in the genre have learning AI, that uses the in-game information to adapt, mostly, certain parts of their behavior (usually, pathfinding).

Shooters have goal-orientation, flexibility and combat adaptation inherent to almost all of the selected games in the genre. The set of FPS games can also be subdivided into two subgroups: GOAP family (uses GOAP-like AI techniques) and flow control family (adapts intensity of game process). No specific pattern was revealed for TPS: the group demonstrated common shooter features and influence of neighbor genres since TPS is usually coupled to other genres (e.g. Action Adventure).

Strategy genre analysis revealed goal-orientation and flexibility as common features with learning as a frequent feature. Games of the genre usually have inter-behavior adaptation, but no intra-behavior alterations.

Analysis of learning AI usage in games revealed that 32% of selected games feature learning. In most cases, learning AI uses static information from games to adapt both behavioral patterns and certain parts of behavior (inter- and intra-adaptation). Two small group of games were separated from games without learning AI since they were still able to provide inter- and intra-behavioral adaptation: Highly reactive (1) and Distraction (2) groups. (1) uses advanced planning systems or other non-learning techniques to provide new patterns, and (2) has adopted advanced sensory systems or DDA.

Majority of high Inter-behavior adaptation cases was spotted in RTS genre and experimental games of different genres, so there is no visible genre pattern for highly adaptive games. Source of adaptation in this game group is usually static information gained from games environment and player's actions (indirect adaptation). A number of games with low inter-behavior adaptation do not use any source from player or environment, but advanced AI techniques like GOAP.

Intra-behavior adaptation was subdivided into *four* major classes touching different aspects of behavior: Combat (1), Pathfinding (2), Other/Unique (3), and None (4). (1) is primarily used in shooters and action games to interact with the environment and respond to player's actions. (2) is inherent to most stealth games since the hostile NPC's task is to look for player's location. (3) groups games with outstand-

ing adaptation types, not found in any other games or used in a very limited amount. Games with no intra-behavioral adaptation belong to (4). Most of the games in this group belong to Open-world Action games and RTS.

Games were also classified based on the source of adaptation they use for game adjustment: games with Direct (1), Indirect (2), Combined adaptation, and None class (4). (1) was also divided into three subclasses: DDA/flow control, sensory systems (not always provides adaptation, but able to analyze environment) and Outliers (do not fit previous subclasses, but uses Direct adaptation for other purposes). No significant pattern was noticed for (2), but this source is widely used for High Inter-behavior adaptation. (3) can use both sources, coupled, for one purpose, or for different parts of the game. (4) groups games that do not use any information from the player.

Player profiling abilities are another way of classifying games and the most related to adaptation to the human player. However, only a small amount of games that implement player profiling was found. They can be separated into two major classes: Player Style (1) and Progress (2). (1) analyzes player style based on preferable actions, and (2) uses player performance in the game to adjust the intensity and complexity of the game.

4.7.1 Popularity Analysis

Adaptable artificial intelligence is a promising technique to improve quality of games and bring in more challenge and sense of engagement to players. Popular modern video games are already making steps towards advanced AI systems in their games bringing more believability and challenge to game worlds. However, the need for advanced AI techniques in the game is still an open question [24]. The question is if games that can adapt to human player style are more welcomed both by critics and players and if it worths for game-development companies to adopt more advanced AI techniques in their products.

4.7.1.1 Advanced AI Popularity

Based on the analysis of selected games and their control AI systems, we have separated all the games into three groups depending on the complexity of the AI: games with (1) basic AI, (2) highly reactive AI and (3) advanced AI.

To the category (1) we decided to put games that have three or less positive features out of six (by positive we mean values *different from No/None*). In most cases, these games do not implement any adaptation features and rarely have goal-oriented and flexible AI agents. Some of them might have positive values for adaptation section features, but they are simplified or do not directly touch crucial part of NPC behavior.

Category (2) consists of games marked as *Highly reactive* during the analysis phase. The amount of games is less than 25% of the selection set, but they are praised representers of state-of-art game AI. The set includes highly-rated games like F.E.A.R., Half Life and Far Cry 4.

Games that have four and more positive values belong to category (3). Representatives of this category have goal-oriented and flexible AI with adaptation features present. Most of the games with learning AI belong to this category.

As can be seen from the Table 4.25, games from Basic AI (1) and Advanced AI (3) categories have a rather big difference between average scores with (1) as a leader. Score deviation of (3) is higher since *Hello Neighbor* and *Monstrum* has got extremely low score compared to the majority: only 40 out of 100 and 57 out of 100, respectively, when most of the games have scores between 80 and 91. After removing the outlier, the situation has got better: the average score became 4,6 points higher. At the same time, most of the games in (1) show higher rates with scores between 85 and 95.

The similar situation can be seen in Sales of (1) and (3): sales rate of (1) is twice higher than the sales rate of (3). The average sales amount of games in the category (3) is 1,98 millions of copies, while sales of games of (1) are about 4,3 million. Most of the games in (1) have sales amount in the range from 2 to 7, while the range of sales majority of (3) spreads in the range between 0,01 and 4. Removing outliers has not change situation. However, sales deviation is lower for (3).

Game category	Number of entries	Average score	Score deviation	Average sales, m	Sales deviation
Basic AI (1)	21	87,2	6,38	4,32	3,24
High-reactive AI (2)	12	85,3	7,18	4,05	2,53
Advanced AI (3)	16	80,8 (85,4)	14,04 (5,79)	1,98 (2,23)	2,06 (2,09)

Table 4.25: Average scores and sales of games with different AI groups.

Category (2) shows a higher average sales rate, but an average score is lower than (1)'s. However, the difference between scores is competitive and deviation of sales rates is also smaller. Besides, around 50% of games of (2) have sales rate around 4 million and higher, while (1) has only 47% and (3) has only 20%.

Regarding the relationship between Metacritic score and sales for games with different levels of AI complexity, only *Advanced AI* group shows a weak to moderate positive correlations as can be seen from the Figure 4.6 (here and further Pearson correlation coefficient is used). Two outliers have been excluded from the analysis due to their extremely low scores compared to the rest of the data.

4.7.1.2 Popularity of Adaptive AI

For the basic study of the popularity of games with adaptive AI, the set of analyzed games was divided into two groups: games that provide any kind of inter- or intra-behavior adaptation (positive values in Intra-behavior and Inter-behavior columns) and games with no such features. The results can be seen in the Table 4.26.

The average score of adaptive games is higher than non-adaptive games, however, the sales rates show a big gap: the average amount of sold copies of games with non-adaptive AI is 4,7 million, while adaptive games have 3,1 millions of copies. At the same time, games with adaptive AI have a much higher dispersion of scores, but, unexpectedly, sales dispersion is lower.

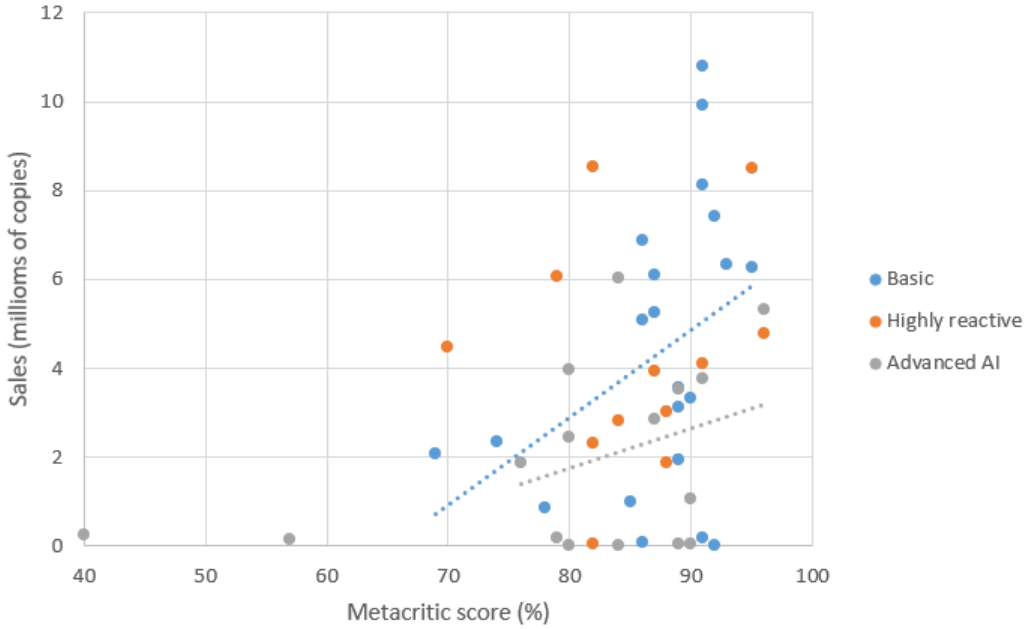

Figure 4.6: Scatter plot of total sales against Metacritic scores, for the different game AI groups. In the current study sample, there is a weak to moderate positive correlation for both the "Basic AI" and "Advanced AI" category (n=21, p=0,39 and n=16, p=0,25 respectively), but not for "Highly reactive AI" (n=12, p=0,147). The blue and gray lines show the linear models for the "Basic AI" and "Advanced AI" categories, respectively. See also Table 4.25.

Game category	Number of entries	Average score	Score deviation	Average sales, m	Sales deviation
Non-Adaptive AI	13	88,2	5,00	4,72	3,65
Adaptive AI	36	83,4	10,96	3,09	2,49

Table 4.26: Average scores and sales of adaptive and non-adaptive games.

To discover the relation between the complexity of AI and game popularity deeper, more specific grouping is needed to analyze the popularity of adaptive video games.

Most of the studied games implement adaptation on different levels of complexity. We have divided the game list into two groups containing cases that alter only certain parts of behavior (Intra-behavior adaptation) and game additionally implementing Inter-behavior adaptation.

As can be seen from the Table 4.27, the average score of Inter-behavior class is higher than average scores of games with Intra-behavior alterations. But in Intra-behavior group a few outliers appear having a big gap between the majority of values and outliers values.

However, the average amount of sales is comparable for both groups. Games with inter-behavior adaptation show slightly higher average sales, but the dispersion of the values is also bigger since some of the games are rather old and have not got high sales rates. Also, the unreliability of some sources influences the results of the analysis: only a small number of publishers report total sales of their products, so the data within the table is approximated values from different sources showing the

number of downloads.

Game category	Number of entries	Average score	Score deviation	Average sales, m	Sales deviation
Intra-behavior only	18	81,7	14,18	2,97	2,20
Inter-behavior	18	85,1	6,33	3,21	2,81

Table 4.27: Average scores and sales of games with intra-behavior adaptation only and with inter-behavior adaptation.

The scatter plot of total sales against Metacritic scores for groups with different types of adaptation (see Figure 4.27) demonstrates, that, despite the outliers, only intra-behavior group has a weak to moderate positive correlation between Metacritic scores and total sales.

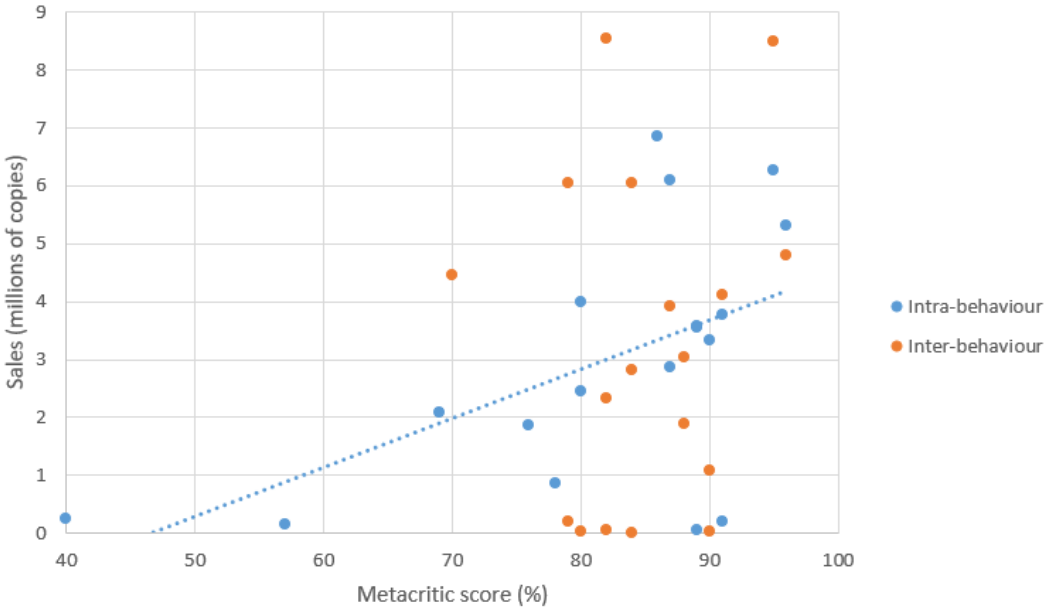

Figure 4.7: Scatter plot of total sales against Metacritic scores, for groups with different types of adaptation (intra-behavior and inter-behavior adaptation). In the current study sample, there is a weak to moderate positive correlation for games with intra-behavior adaptation (n=18, p=0,547) (the situation stays the same after removing outliers with scores less then 60), but not for games with inter-behavior adaptation (n=18, p=0,136). The blue line shows the linear models for the category of intra-behavior adaptation. See also Table 4.27.

Addressing **H1** and **H2** (see Section 1.3) about the popularity of adaptive AI in games, we examined correlations between different levels of adaptability towards a human player and popularity of the games.

For this stage of analysis we consider four levels of adaptability of video games:

- **None**: a game does not provide any NPC adaptation to the human player. Also, NPCs cannot be considered as highly reactive.

- **Low**: a game does not provide NPC inter-behavior adaptation, but it uses information gained from the game environment and player's actions to adjust some smaller parts of behavior (Intra-behavior adaptation). *Note*: games that provide the same type of adaptation but not using any information gained from the player are not included in this set.
- **Medium**: a game set includes games of Low Inter-behavior adaptation class (Highly reactive games are included).
- **High**: a game set includes games of High Inter-behavior adaptation class.

The results of the analysis of average scores and sales are shown in the Table 4.28.

Game category	Number of entries	Average score	Score deviation	Average sales, m	Sales deviation
None	13	88,2	5,00	4,72	3,65
Low	12	78,4	16,16	2,70	1,97
Medium	12	85,3	7,18	4,21	2,53
High	6	84,5	4,72	1,23	2,39

Table 4.28: Average scores and sales of games with different levels of adaptability.

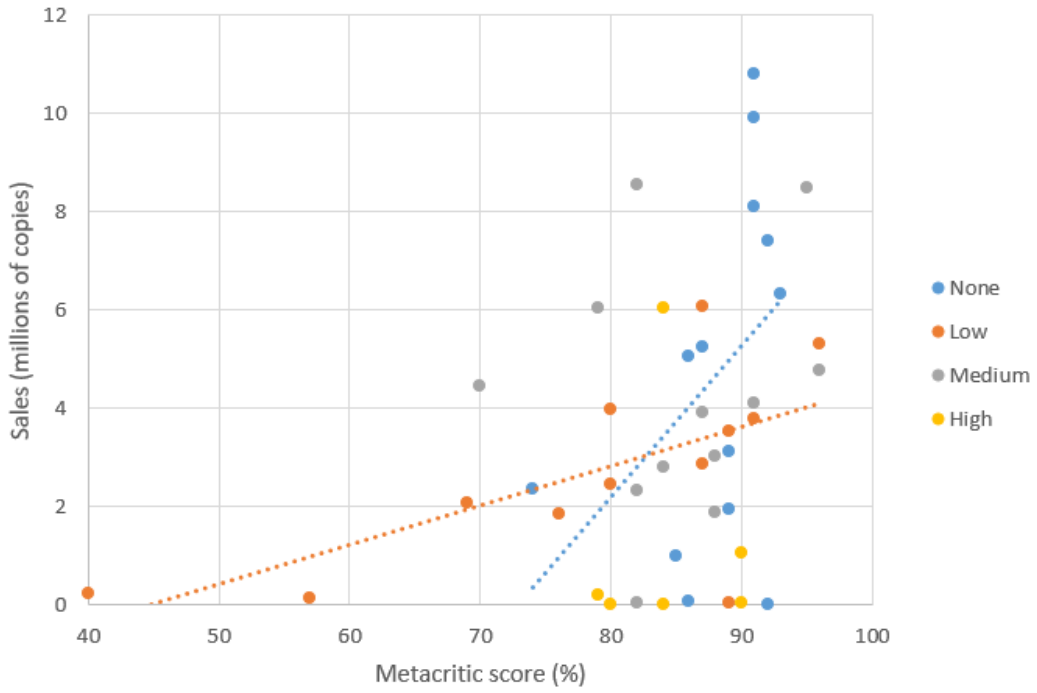

Figure 4.8: Scatter plot of total sales against Metacritic scores, for the different levels of adaptability in video games. In the current study sample, there is a moderate positive correlation for two level groups: "None" (n=13, p=0,421) and "Low" (n=12, p=0,656), but not for "Medium"(n=12, p=0,147) or "High" (n=76, p=0,0335). The blue and orange lines show the linear models for the "None" and "Low" categories, respectively. See also Table 4.28.

Set of games with Low adaptability has the lowest average score among all the sets, but it also has a higher dispersion of score values since set includes three outlier cases of relatively low scores. The highest average score with low deviation is observed for the None-class of adaptability. In spite of one case of a score lower than 80, all the games gained higher than 85. Worth noticing, that around 50 % of the games in this set are popular game series, which gives them an advantage. Nevertheless, games with Medium and High adaptability has got competitive scores with 85,3 for Medium and 84,5 for High, but a higher deviation of Medium set scores (outlier appeared in the set).

Similar situation is observed in the Sales analysis. Games with Low adaptability have low sales and sales deviation. Despite a few outliers, total sales of games included in the set are on the average level. Games from None set, regardless of high sales deviation, has also got the highest sales rates due to a few cases of the very high popularity of setting. Regarding Medium and High sets, the latter has got the lowest sales rates and low sales deviation showing much less popularity than Medium set.

As it can be seen from the Figure 4.8, only games without any adaptation ("None") or low level ("Low") of it have a moderate positive correlation. "Medium" level demonstrates very weak positive correlation, while "High" has the weakest negative relation, close to zero, between scores and sales rates.

4.7.2 Discussion

In the analysis of the popularity of video games with advanced artificial intelligence systems, we observed a moderate positive correlation between Metacritic score and sales rates for games that have basic and advanced AI systems. However, less advanced, but critically acclaimed AI systems have got the same average scores as Advanced AI group excluding outliers. Nevertheless, games with advanced AI average sales have the lowest values. The average score of games with basic AI is competitive with advanced AI, but sales are higher.

The analysis of the popularity of adaptive video games showed higher values of average scores and sales for games implementing adaptation of behavior pattern than the values for only partial behavior adaptation. However, in the deeper analysis of different levels of adaptation, we observed higher scores and sales values for the games with no adaptation. Highly adaptive games have got lower values, but the lowest was observed for the low adaptability. Also, a moderate positive correlation between Metacritic scores and total sales was observed only for games with the low level of adaptation and without any visible adaptation.

While observing and interpreting the results of the popularity analysis, it should be taken into account that some non-adaptive games belong to famous game series (e.g. Witcher, Fallout, Batman, Dark Souls), so they get high scores and high sales rates regardless complexity of the AI. Also, most of the games with advanced and outstanding AI implementations are experimental indie-games, so their sales are not influenced by advertisement campaign, but they have competitively high scores.

Given all the revealed relationship between adaptability and scores/sales, we concluded that advanced and adaptive AI systems are welcomed by critics and highly promising field for future development in video games. However, most of the complex AI systems are experimental, so the products are not always widely spread by famous publishers and do not get deserved attention from big companies.

5 Conclusions and Future Work

This section is dedicated to a summary of this master thesis, describing what has been done and what result were obtained during the work. Also, possibilities for future work in the part of the field of game development covered in this thesis are described in the following sections.

5.1 Conclusions

In this study, we observed existing research in artificial intelligence in video games and state-of-art of game AI systems in order to address RQ1. Based on these observations, we developed the classification of game artificial intelligence systems regarding their complexity and adaptability and examined the relationship between the popularity of video games and their gameplay complexity (addressing RQ2).

The features defined for AI agents in general and specific game AI agents allowed us to compare games in terms of complexity and adaptability and then divide them into classes and subclasses grouping games with similar features. The features were divided into two major groups: (1) basics of game AI and (2) Adaptive features. (1) were used to define the basic complexity of game AI systems and their ability to act intelligently. Sources and types of adaptation (2) in video games gained closer attention as the primary goal of the study. We defined two main sources and three superclasses of adaptation, which further were divided into subclasses.

Grouping of the games according to developed classification revealed that 67% of games were adaptable to human player's actions on different levels of adaptation complexity, and only around 33% could be considered neither adaptable nor highly reactive.

This classification can be further extended to cover more possibilities of video game adaptive AI systems.

This classification and game analysis were further used for examination of relations between popularity and game AI complexity/adaptivity in order to confirm or reject our two hypotheses. The dependency of popularity on AI complexity performed close to our expectations: advanced AI got average scores competitive with basic AI (excluding a few outliers), but games with simple AI showed higher sales rates. Nevertheless, the highest rates and average scores were found for basic AI, and less high but competitive scores were found for highly reactive AI, which is more complex than basic, but not enough advanced. Regardless of these results, only basic and advanced AI games had a positive correlation between sales rates and scores.

Specific examination of adaptive AI popularity revealed high scores for adaptive AI, but a few outliers with extremely low scores appeared in the set; the sales rates were significantly lower compared to non-adaptive AI games sales. Based on previous observations and conclusions, the popularity of levels of adaptability behaved close to adjusted expectation.

Games without adaptation got higher sales rates compared to games with different levels of adaptation. They also demonstrated higher scores, but games with medium and high levels of adaptability gained competitive values. Regarding levels of complexity themselves, games with medium and high adaptation were revealed to be more popular among both players and critics compared to games with Low adaptation (except for sales rates of the High group). However, only low-level

adaptation games and non-adaptive games showed a moderate positive correlation between Metacritic scores and Total sales.

Therefore, based on the data analysis conducted in this thesis, neither H1 or H2 can be confirmed. However further research (with additional and/or more accurate data sources) would be required before rejecting them. Discussing the results of the analysis, we took into account that gained games data was biased since the information was taken from third-party sources in most cases. Official reports from game development companies, authors of games selected for the analysis, would provide more objective data and therefore more precise analysis and judgment about game AI complexity and game popularity.

5.2 Future work

The goal of this study was to draw attention to the possibilities and perspectives of artificial intelligence in games. Game AI has got a vast and comprehensive development since it has started to be used in games, but, as we have discovered during literature and state-of-art observation, many possible aspects of artificial intelligence and adaptation towards human player have to be reviewed with further development and integration into game design. The contribution we hope this study to achieve is defining those aspects and their current usage in modern games, and also, the efficiency and profitability of advanced game AI usage.

The study revealed that profitability of highly adaptive games is relatively worse than less or non-adaptive AI, however, adaptive games have got high scores and excellent critic reviews regarding their AI systems. Given that most of such games are experimental and, in addition, developed and published by indie-developers, low sales rates are expected since these products do not get desirable spreading. Thereby, advanced AI meets expectations regarding engaging players by challenging mechanics and deserves further research.

This study was mostly focused on AI control systems of hostile non-player characters. However, with some modifications, the approach can be applied to other types of reactive NPCs such as player's in-game virtual companions, that can be seen in numerous games and also require advanced artificial intelligence systems.

Also, the techniques reviewed and discovered and also a classification with some modifications can be used in other artificial intelligence related fields. For example, adaptable game AI was studied for adaptive educational games that can personalize learning experience of the player [78].

Based on the current research, we expect recommendations for game designers and developers to be developed in the future. These recommendations would point to promising techniques and approaches developed by researchers for usage in games, AI techniques and game mechanics that can be adopted to develop AI system adaptive to a human player.

References

[1] T. Fullerton, *Game Design Workshop: A Playcentric Approach to Creating Innovative Games*, 2nd ed. Burlington, MA, USA: Elsevier Inc., 2008.

[2] M. Csikszentmihalyi, *Flow: The Psychology of Optimal Experience.* New York, NY: Harper and Row, 1990.

[3] P. Spronck, I. Sprinkhuizen-kuyper, and E. Postma, "Difficulty scaling of game AI," in *Proceedings of the 5th International Conference on Intelligent Games and Simulation (GAME-ON 2004)*, 2004, pp. 33–37.

[4] G. van Lankveld, P. Spronck, J. van den Herik, and M. Rautenberg, "Incongruity-based adaptive game balancing," in *Advances in computer games*. Berlin, Heidelberg: Springer Berlin Heidelberg, 2010, p. 208–220.

[5] A. Nareyek, "Game AI is dead. long live game AI!" *IEEE Intelligent Systems*, vol. 22, no. 1, pp. 9–11, Jan 2007. [Online]. Available: https://doi.org/10.1109/MIS.2007.10

[6] X. Cui and H. Shi, "A*-based pathfinding in modern computer games," *International Journal of Computer Science and Network Security*, vol. 11, no. 1, pp. 125–130, Jan. 2011.

[7] A. Champandard, *10 Reasons the Age of Finite State Machines is Over*, Dec. 28 2008, [Accessed: Nov. 28, 2017]. [Online]. Available: http://aigamedev.com/open/article/fsm-age-is-over/

[8] C. Go and W. Lee, *An Intelligent Belief-Desire-Intention Agent for Digital Game-Based Learning*. Berlin, Heidelberg: Springer Berlin Heidelberg, 2007, pp. 677–685. [Online]. Available: https://doi.org/10.1007/978-3-540-72432-2_68

[9] S. Bakkes, P. Spronck, and J. van den Herik, "Rapid and reliable adaptation of video game AI," *IEEE Transactions on Computational Intelligence and AI in Games*, vol. 1, no. 2, pp. 93–104, June 2009.

[10] L. Liden, *AI Game Programming Wisdom, Vol. 2*. Rockland, MA, USA: Charles River Media, Inc., 2003, ch. Artificial Stupidity: The Art of Intentional Mistakes.

[11] F. Aiolli and C. Palazzi, "Enhancing artificial intelligence on a real mobile game," *Int. J. Comput. Games Technol.*, vol. 2009, pp. 1:1–1:9, Jan. 2009. [Online]. Available: http://dx.doi.org/10.1155/2009/456169

[12] F. Schadd, E. Bakkes, and P. Spronck, "Opponent modeling in real-time strategy games," in *Proceedings of the GAME-ON 2007*, 2007, pp. 61–68.

[13] S. Hladky and V. Bulitko, "An evaluation of models for predicting opponent positions in first-person shooter video games," in *2008 IEEE Symposium On Computational Intelligence and Games*, Perth, WA, 2008, pp. 39–46.

[14] P. Demasi and A. de O. Cruz, "Online coevolution for action games." *Int. J. Intell. Games & Simulation*, vol. 2, no. 2, pp. 80–88, 2003. [Online]. Available: http://dblp.uni-trier.de/db/journals/ijigs/ijigs2.html#DemasiC03

[15] P. Parrish, *ECHO Interview Q&A with Ultra Ultra's Martin Emborg*, Sep. 7 2017, [Accessed: Jan. 30, 2018]. [Online]. Available: https://www.pcinvasion.com/echo-interview-qa-with-ultra-ultras-martin-emborg

[16] J. Lachenal, *Stealth Horror Game Hello Neighbor's Adaptive AI Will Make You Sick With Suspense*, Sep. 29 2016, [Accessed: Jan. 30, 2018]. [Online]. Available: https://www.themarysue.com/hello-scary-neighbor-please-dont-hurt-me/

[17] S. Bakkes, P. Spronck, and J. van den Herik, "Opponent modelling for case-based adaptive game AI," *Entertainment Computing*, vol. 1, no. 1, pp. 27–37, 2009.

[18] M. Ponsen, P. Spronck, H. Muñoz-Avila, and D. W. Aha, "Knowledge acquisition for adaptive game AI," *Science of Computer Programming*, vol. 67, no. 1, pp. 59–75, 2007, special Issue on Aspects of Game Programming. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S0167642307000548

[19] J. Laird and M. van Lent, "Human-level AI's killer application: Interactive computer games," in *Proceedings of the Seventeenth National Conference on Artificial Intelligence and Twelfth Conference on Innovative Applications of Artificial Intelligence*. AAAI Press, 2000, pp. 1171–1178. [Online]. Available: http://dl.acm.org/citation.cfm?id=647288.760205

[20] A. Nareyek, "AI in computer games," *Queue*, vol. 1, no. 10, pp. 58–65, Feb 2004. [Online]. Available: http://doi.acm.org/10.1145/971564.971593

[21] P. Spronck, M. Ponsen, I. Sprinkhuizen-Kuyper, and E. Postma, "Adaptive game AI with dynamic scripting," *Machine Learning*, vol. 63, no. 3, pp. 217–248, Jun. 2006. [Online]. Available: http://dx.doi.org/10.1007/s10994-006-6205-6

[22] M. Riedl, D. Thue, and V. Bulitko, *Game AI as Storytelling*. New York, NY: Springer New York, 2011, pp. 125–150. [Online]. Available: https://doi.org/10.1007/978-1-4419-8188-2_6

[23] G. Yannakakis, "Game AI revisited," in *Proceedings of the 9th Conference on Computing Frontiers*, ser. CF '12. New York, NY, USA: ACM, 2012, pp. 285–292. [Online]. Available: http://doi.acm.org/10.1145/2212908.2212954

[24] S. Yildirim and S. Stene, "A survey on the need and use of AI in game agents," in *Proceedings of the 2008 Spring Simulation Multiconference*, ser. SpringSim '08. San Diego, CA, USA: Society for Computer Simulation International, 2008, pp. 124–131. [Online]. Available: http://dl.acm.org/citation.cfm?id=1400549.1400565

[25] S. Rabin, *AI Game Programming Wisdom*. Rockland, MA, USA: Charles River Media, Inc., 2002.

[26] I. Millington and J. Funge, *Artificial Intelligence for Games, Second Edition*, 2nd ed. San Francisco, CA, USA: Morgan Kaufmann Publishers Inc., 2009.

[27] S. Bakkes, C. Tan, and Y. Pisan, "Personalised gaming: a motivation and overview of literature," in *IE*, 2012.

[28] S. Karpinskyj, F. Zambetta, and L. Cavedon, "Video game personalisation techniques: A comprehensive survey," *Entertainment Computing*, vol. 5, no. 4, pp. 211 – 218, 2014. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S1875952114000342

[29] G. Yannakakis and J. Togelius, *Artificial Intelligence and Games*. Springer, 2018, http://gameaibook.org.

[30] N. Shaker, G. Yannakakis, and J. Togelius, "Towards automatic personalized content generation for platform games," in *Proceedings of the Sixth AAAI Conference on Artificial Intelligence and Interactive Digital Entertainment*, ser. AIIDE'10. AAAI Press, 2010, pp. 63–68. [Online]. Available: http://dl.acm.org/citation.cfm?id=3014666.3014679

[31] *Games By Angelina*, [Accessed: Mar. 03, 2018]. [Online]. Available: http://www.gamesbyangelina.org

[32] E. Hecht, *The compleat WoW abbreviations*, Feb. 20 2007, [Accessed: Mar. 03, 2018]. [Online]. Available: https://www.engadget.com/2007/02/20/the-compleat-wow-abbreviations/

[33] G. Lecky-Thompson, *AI and Artificial Life in Video Games*, 1st ed. Rockland, MA, USA: Charles River Media, Inc., 2008.

[34] M. Pinter, *Toward More Realistic Pathfinding*, Mar. 14 2001, [Accessed: Mar. 03, 2018]. [Online]. Available: https://www.gamasutra.com/view/feature/131505/toward_more_realistic_pathfinding.php

[35] F. Bevilacqua, *Finite-State Machines: Theory and Implementation*, Oct. 24 2013, [Accessed: Mar. 05, 2018]. [Online]. Available: https://gamedevelopment.tutsplus.com/tutorials/finite-state-machines-theory-and-implementation--gamedev-11867

[36] S. Horti, *Why F.E.A.R.'s AI is still the best in first-person shooters*, Apr. 3 2017, [Accessed: Mar. 05, 2018]. [Online]. Available: https://www.gamasutra.com/view/feature/131505/toward_more_realistic_pathfinding.php

[37] C. Simpson, *Behavior trees for AI: How they work*, Jul. 17 2014, [Accessed: Mar. 05, 2018]. [Online]. Available: https://www.gamasutra.com/blogs/ChrisSimpson/20140717/221339/Behavior_trees_for_AI_How_they_work.php

[38] T. Thompson, *Outsmarting the Covenant*, May 11 2015, [Accessed: Mar. 06, 2018]. [Online]. Available: https://aiandgames.com/outsmarting-the-covenant/

[39] J. Orkin, "Three states and a plan: The A.I. of F.E.A.R." in *Proceedings of the game developer's conference (GDC)*, 2006, pp. 33–37. [Online]. Available: http://alumni.media.mit.edu/~jorkin/gdc2006_orkin_jeff_fear.pdf

[40] M. Lim, J. Dias, R. Aylett, and A. Paiva, "Creating adaptive affective autonomous npcs," *Autonomous Agents and Multi-Agent Systems*, vol. 24, no. 2, pp. 287–311, Mar 2012. [Online]. Available: http://dx.doi.org/10.1007/s10458-010-9161-2

[41] A. Schatz, *How Will Artificial Intelligence Change Video Games?*, Sep. 15 2017, [Accessed: Mar. 03, 2018]. [Online]. Available: https://www.forbes.com/sites/quora/2017/09/15/how-will-artificial-intelligence-change-video-games/#2afea4042bb5

[42] C. Hoekstra, "Adaptive artificially intelligent agents in video games: A survey," *UNIAI-06*, 2006.

[43] A. Dodd, *Could the Alien in Alien: Isolation Be Too Smart?*, July 23 2014, [Accessed: Mar. 15, 2018]. [Online]. Available: https://bloody-disgusting.com/news/3304238/possible-alien-alien-isolation-smart/

[44] J. Wexler, "Artificial intelligence in games: A look at the smarts behind lionhead studio's "black and white" and where it can and will go in the future," 2002. [Online]. Available: http://www.cs.rochester.edu/~brown/242/assts/termprojs/games.pdf

[45] C. Cruz and J. Uresti, "Player-centered game AI from a flow perspective: Towards a better understanding of past trends and future directions," *Entertainment Computing*, vol. 20, pp. 11 – 24, 2017. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S1875952117300095

[46] R. McCrae and O. John, "An introduction to the five-factor model and its applications," *Journal of Personality*, vol. 60, no. 2, pp. 175–215. [Online]. Available: https://onlinelibrary.wiley.com/doi/abs/10.1111/j.1467-6494.1992.tb00970.x

[47] I. B. Myers, *MBTI Manual: A Guide to the Development and Use of the Myers-Briggs Type Indicator*. Consulting Psychologists Press, 1998. [Online]. Available: https://books.google.se/books?id=XPbRQwAACAAJ

[48] K. Hartsook, A. Zook, S. Das, and M. O. Riedl, "Toward supporting stories with procedurally generated game worlds," in *2011 IEEE Conference on Computational Intelligence and Games (CIG'11)*, Aug 2011, pp. 297–304.

[49] N. Nygren, J. Denzinger, B. Stephenson, and J. Aycock, "User-preference-based automated level generation for platform games," in *2011 IEEE Conference on Computational Intelligence and Games (CIG'11)*, Aug 2011, pp. 55–62.

[50] G. Yannakakis, H. Martínez, and A. Jhala, "Towards affective camera control in game," *User Modeling and User-Adapted Interaction*, vol. 20, no. 4, pp. 313–340, Oct 2010. [Online]. Available: https://doi.org/10.1007/s11257-010-9078-0

[51] M. Sharma, S. Ontañón, M. Mehta, and A. Ram, "Drama management and player modeling for interactive fiction games," *Computational Intelligence*, vol. 26, no. 2, pp. 183–211, 2010. [Online]. Available: http://dx.doi.org/10.1111/j.1467-8640.2010.00355.x

[52] C. Pedersen, J. Togelius, and G. Yannakakis, "Modeling player experience for content creation," *IEEE Transactions on Computational Intelligence and AI in Games*, vol. 2, no. 1, pp. 54–67, Mar 2010.

[53] H. Yu and T. Trawick, "Personalized procedural content generation to minimize frustration and boredom based on ranking algorithm." in *Proceedings of the 7th AAAI Conference on Artificial Intelligence and Interactive Digital Entertainment, AIIDE 2011*, Jan 2011.

[54] D. Thue, V. Bulitko, M. Spetch, and E. Wasylishen, "Interactive storytelling: A player modelling approach." pp. 43–48, 01 2007.

[55] R. Moss, *7 examples of game AI that every developer should study*, Apr. 5 2016, [Accessed: Mar. 03, 2018]. [Online]. Available: https://www.gamasutra.com/view/news/269634/7_examples_of_game_AI_that_every_developer_should_study.php

[56] S. Bakkes, P. Spronck, and G. van Lankveld, "Player behavioural modelling for video games," *Entertainment Computing*, vol. 3, pp. 71–79, 2012.

[57] A. Aleksieva-Petrova and M. Petrov, "ADOPTA model of learner and educational game structure," in *Proceedings of the 12th International Conference on Computer Systems and Technologies, CompSysTech 2011, Vienna, Austria, June 16-17, 2011*, B. Rachev and A. Smrikarov, Eds. ACM, 2011, pp. 636–640. [Online]. Available: http://doi.acm.org/10.1145/2023607.2023713

[58] B. Bontchev and O. Georgieva, "Playing style recognition through an adaptive video game," *Computers in Human Behavior*, vol. 82, pp. 136 – 147, 2018. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S0747563217307264

[59] D. Kolb, *Experiential Learning: Experience as the Source of Learning and Development*. Englewood Cliffs, New Jersey: Prentice-Hall P T R, 1984.

[60] M.-L. Ryan, *Narrative As Virtual Reality: Immersion and Interactivity in Literature and Electronic Media*. Baltimore, MD, USA: Johns Hopkins University Press, 2001.

[61] C. Lindley and C. Sennersten, "Game play schemas: From player analysis to adaptive game mechanics," *Int. J. Comput. Games Technol.*, vol. 2008, pp. 8:1–8:7, Jan 2008. [Online]. Available: http://dx.doi.org/10.1155/2008/216784

[62] B. Bostan and T. Marsh, "The 'interactive' of interactive storytelling: Customizing the gaming experience," in *Proceedings of the Entertainment Computing-ICEC 2010*, 2010, pp. 472–475.

[63] S. Rabin, *AI Game Programming Wisdom*. Rockland, MA, USA: Charles River Media, Inc., 2002, ch. The Illusion of Intelligence.

[64] P. Demasi and A. Cruz, "Anticipating opponent behaviour using sequential prediction and real-time fuzzy rule learning." in *Proceedings of the 4th International conference on Intelligent Games and Simulation (GAMEON'2004)*, Jan 2003, pp. 101–106.

[65] D. Chang, "Dynamic difficulty adjustment in computer games," in *Proceedings of t11th Ann. Interact. Multimedia Systems Conf.*, 2013.

[66] T. Thompson, *In the Directors Chair: Left 4 Dead*, Dec. 1 2017, [Accessed: Mar. 05, 2018]. [Online]. Available: https://aiandgames.com/in-the-directors-chair-left-4-dead/

[67] G. Yannakakis and J. Togelius, "Experience-driven procedural content generation," *IEEE Transactions on Affective Computing*, vol. 2, no. 3, pp. 147–161, July 2011.

[68] S. Macy, *Ubisoft Games Top 2017's Sales So Far*, May 18 2017, [Accessed: Mar. 18, 2018]. [Online]. Available: http://www.ign.com/articles/2017/05/19/ubisoft-games-top-2017s-sales-so-far

[69] S. Franklin and A. Graesser, "Is it an agent, or just a program?: A taxonomy for autonomous agents," in *Intelligent Agents III Agent Theories, Architectures, and Languages*, J. Müller, M. Wooldridge, and N. Jennings, Eds. Berlin, Heidelberg: Springer Berlin Heidelberg, 1997, pp. 21–35.

[70] R. Pfeifer and C. Scheier, *Understanding Intelligence*. Cambridge, MA, USA: MIT Press, 1999.

[71] D. Johnson, C. Watling, J. Gardner, and L. Nacke, "The edge of glory: The relationship between metacritic scores and player experience," in *Proceedings of the First ACM SIGCHI Annual Symposium on Computer-human Interaction in Play*. New York, NY, USA: ACM, 2014, pp. 141–150. [Online]. Available: http://doi.acm.org/10.1145/2658537.2658694

[72] *Why Are Game Developer Bonuses Based On Review Scores?*, Mar. 12 2012, [Accessed: Oct. 5, 2018]. [Online]. Available: https://kotaku.com/metacritic-matters-how-review-scores-hurt-video-games-472462218

[73] *Now Metacritic can do developers out of bonus pay AND jobs. BioShock studio makes Metascore an application requirement*, July 26 2012, [Accessed: Oct. 5, 2018]. [Online]. Available: https://www.gamesradar.com/now-metacritic-can-do-developers-out-of-bonus-pay-and-jobs-as-bioshock-studio-demands-metascores-on-applications/

[74] T. Thompson, *HTN Planning in Transformers: Fall of Cybertron*, June 10 2016, [Accessed: July 15, 2018]. [Online]. Available: https://aiandgames.com/cybertron-intel/

[75] A. J. Champandard, *A-Life, Emergent AI and S.T.A.L.K.E.R.: An Interview with Dmitriy Iassenev*, Feb 25 2008, [Accessed: July 14, 2018]. [Online]. Available: http://aigamedev.com/open/interviews/stalker-alife

[76] J. Parkin, *Middle-earth: Shadow of War guide: The Nemesis System*, Oct. 9 2017, [Accessed: July 20, 2018]. [Online]. Available: https://www.polygon.com/middle-earth-shadow-of-war-guide/2017/10/9/16439610/the-nemesis-system-and-you

[77] *The Nemesis System*, Nov. 3 2015, [Accessed: July 20, 2018]. [Online]. Available: http://www.ign.com/wikis/middle-earth-shadow-of-mordor/The_Nemesis_System

[78] N. Peirce, O. Conlan, and V. Wade, "Adaptive educational games: Providing non-invasive personalised learning experiences," in *2008 Second IEEE International Conference on Digital Game and Intelligent Toy Enhanced Learning*, Nov 2008, pp. 28–35.

A General Table

Game name	Developer	Year	Genre	Metacritic score	Metacritic link
Age of Empires	Ensemble Studios, Relic Entertainmen	1997	RTS	83	Metacritic
Alien: Isolation	Creative Assembly	2014	Survival Horror	80	Metacritic
Amnesia: The Dark Descent	Frictional Games	2010	Survival Horror	85	Metacritic
Attila: Total War	Creative Assembly	2015	RTS	80	Metacritic
Batman: Arkham Asylum	Rocksteady Studios	2009	Action Adventure	91	Metacritic
Batman: Arkham City	Rocksteady Studios	2011	Action Adventure	91	Metacritic
Battlefield 3	EA Digital Illusions CE	2011	FPS	89	Metacritic
Black & White	Lionhead Studios	2001	God Game	90	Metacritic
City Conquest	Intelligence Engine Design Systems	2011	Tower Defense		
Crash Bandicoot	Naughty Dog	1996	Platformer		
Dark Souls	From Software	2011	Action, RPG	89	Metacritic
Dark Souls 2	From Software	2014	Action, RPG	91	Metacritic
Deus Ex: Human Revolution	Eidos Montreal	2011	Stealth, Action RPG	90	Metacritic
Diablo	Blizzard North	1996	Action, RPG	94	Metacritic
Diablo III	Blizzard Entertainment	2012	Action, RPG	87	Metacritic
Dishonored	Arkane Studios	2012	Stealth	91	Metacritic
Dishonored 2	Arkane Studios	2012	Stealth	88	Metacritic
Dying Light	Techland	2015	Survival Horror	74	Metacritic
ECHO	Ultra Ultra	2017	Action Adventure	79	Metacritic
Empire: Total War	Creative Assembly	2009	RTS	90	Metacritic
Evolve	Turtle Rock Studios	2015	FPS	76	Metacritic
F.E.A.R.	Monolith Productions	2005	FPS	88	Metacritic

Game name	Developer	Year	Genre	Metacritic score	Metacritic link
Façade	Procedural Arts	2005	Interactive story		
Fallout 3	Bethesda Game Studios	2008	Action, RPG	91	Metacritic
Far Cry	Crytek Corp.	2004	FPS	89	Metacritic
Far Cry 3	Ubisoft Montreal	2012	Action	88	Metacritic
Far Cry 4	Ubisoft Montreal	2014	Action	82	Metacritic
Forza	Turn 10 Studios, Microsoft Studios	2005	Racing		
Gears of War	Epic Games	2006	TPS	87	Metacritic
Half Life	Valve	1998	FPS	96	Metacritic
Halo 2	Bungie Studios	2004	FPS	95	Metacritic
Hello neighbor	Dynamic Pixels	2017	Survival Horror	40	Metacritic
Her story	Sam Barlow	2015	Interactive story		
Hitman: Absolution	IO Interactive	2012	Stealth	80	Metacritic
Killzone 3	Guerrilla Games	2011	FPS	84	Metacritic
Left 4 Dead	Turtle Rock Studios	2008	FPS, Survival Horror	89	Metacritic
Love	Eskil Steenberg	2010	Cooperative, Action		
Mass Effect	BioWare	2007	Action RPG	89	Metacritic
Max Payne 3	Rockstar Games	2012	TPS	87	Metacritic
Metal Gear Solid V: The Phantom Pain	Kojima Productions	2015	Stealth	91	Metacritic
Middle Earth: Shadow of Mordor	Monolith Productions	2014	Action	84	Metacritic
Minecraft	Mojang	2011	Sandbox		
Monstrum	Team Junkfish	2015	Survival Horror	57	Metacritic
Neverwinter nights (Spronck mode)	Spronck, BioWare	2002	RPG	91	Metacritic
Rainbow Six: Siege	Ubisoft	2015	FPS	79	Metacritic
Resident Evil 4	Capcom	2005	TPS, Survival Horror	96	Metacritic

Game name	Developer	Year	Genre	Metacritic score	Metacritic link
S.T.A.L.K.E.R: Shadow of Chernobyl	GSC Game World	2007	FPS	82	Metacritic
Super Mario Bros	Nintendo Creative Department	1985	Platformer, Action Adventure		
Super Mario Sunshine	Nintendo Entertainment	2002	Platformer, Action Adventure		
Supreme Commander	Wargaming Seattle, Hellbent Games	2007	RTS	86	Metacritic
The Forest	Endnight Games Ltd	2014	Survival Horror		
The Ice-bound concordance	Down to the Wire	2014	Interactive story		
The Last of Us	Naughty Dog	2013	Action, Stealth	95	Metacritic
The Witcher 3	CD Projekt RED	2015	Action RPG	92	Metacritic
The Witness	Thekla, Inc.	2016	Puzzle		
Thief 1	Looking Glass Studios	1998	Stealth	92	Metacritic
Thief 4	Eidos Montreal	2014	Stealth	69	Metacritic
Titanfall	Respawn Entertainment	2014	FPS	86	Metacritic
Tom Clancy's Ghost Recon Wildlands	Ubisoft Paris	2017	TPS	70	Metacritic
Tom Clancy's Splinter Cell: Blacklist	Ubisoft Torronto	2013	Stealth, Action	82	Metacritic
Tom Clancy's Splinter Cell: Pandora Tomorrow	Ubisoft	2004	Stealth	87	Metacritic
Tom Clancy's The Division	Ubisoft Massive	2016	RPG	79	Metacritic
Tomb Raider	Crystal Dynamics	2013	Action Adventure	86	Metacritic
Torchlight	Runic Games	2009	Action, RPG	83	Metacritic
Total war	The Creative Assembly	2000	RTS	84	Metacritic
Transformers: Fall of Cybertron	High Moon Studios	2012	TPS	78	Metacritic
Versu	Linden Lab	2013	Interactive story		
World of Warcraft	Blizzard Entertainment	2004	RTS	93	Metacritic
XCOM: Enemy Unknown	Firaxis Games	2012	TBT, RPG	89	Metacritic

B Analysis Table

		Basic information			Adaptation information				Popularity	
Game name	**Genre**	**Goal-oriented**	**Flexible**	**Learning**	**Adaptation source**	**Intra-behaviour**	**Inter-behaviour**	**Player profiling**	**Metacritic score**	**Total Sales**
Alien: Isolation	Survival Horror	**Yes**	**Yes**	**Yes**	**Combination SS**	**Pathfinding**	None	None	80	2,46
Amnesia: The Dark Descent	Survival Horror	Yes	Yes	No	Combination SS	None	None	None	85	1
Attila: Total War	Strategy, RTS	**Yes**	**Yes**	**Yes**	**Indirect**	**None**	High	None	80	0,02
Batman: Arkham Asylum	Action Adventure	**No**	**No**	**No**	**None**	None	None	None	91	8,12
Batman: Arkham City	Action Adventure	No	No	No	Direct DDA	None	None	Progress	91	10,81
Black & White	God Game	Yes	Yes	**Yes**	**Direct**	**Other**	**High**	None	90	0,04
Dark Souls	Action, RPG	Yes	No	No	None	None	None	None	89	3,11
Dark Souls 2	Action, RPG	Yes	No	No	None	Combat	None	None	91	0,19
Deus Ex: Human Revolution	Stealth, Action RPG	**Yes**	**Yes**	No	None	**Combat**	None	None	90	3,34
Diablo III	Action, RPG	Yes	Yes	No	None	None	None	None	87	5,24
Dishonored	Stealth	**Yes**	**Yes**	No	**Combination SS**	**Pathfinding**	None	**Player Style**	91	3,78
Dishonored 2	Stealth	**Yes**	**Yes**	No	**Combination SS**	**Pathfinding**	Low	**Player Style**	88	3,03
Dying Light	Survival Horror	No	No	**No**	None	None	None	None	74	2,35
ECHO	Action Adventure	**Yes**	**Yes**	**Yes**	Indirect	**Combat**	**High**	None	79	0,2
Empire: Total War	Strategy, RTS	**Yes**	**Yes**	**Yes**	**Indirect**	**None**	High	None	90	1,07
Evolve	FPS	Yes	Yes	Yes	**Direct DDA**	Combat	None	**Progress**	76	1,87
F.E.A.R.	FPS	**Yes**	**Yes**	**No**	None	**Combat**	**Low**	None	88	1,88
Fallout 3	Action, RPG	**Yes**	**Yes**	No	None	None	None	None	91	9,93

official source (**in bold**) — dynamic difficulty adjustment (DDA)
players and critic's reviews — sensory system (SS)
low score (0-49) — medium score (50-74) — high score (75-100)

D

		Basic information			Adaptation information				Popularity	
Game name	**Genre**	**Goal-oriented**	**Flexible**	**Learning**	**Adaptation source**	**Intra-behaviour**	**Inter-behaviour**	**Player profiling**	**Metacritic score**	**Total Sales**
Far Cry	FPS	Yes	Yes	Yes	**Direct DDA**	Combat	None	**Progress**	89	0,05
Far Cry 4	Action	**Yes**	**Yes**	**Yes**	Indirect	**Combat**	**Low**	None	82	8,54
Gears of War	TPS	No	No	**No**	**Direct SS**	Combat	None	None	87	6,09
Half Life	FPS	**Yes**	**Yes**	**No**	None	**Combat**	**Low**	None	96	4,79
Halo 2	FPS	**Yes**	**Yes**	No	None	**Combat**	Low	None	95	8,49
Hello neighbor	Survival Horror	Yes	No	Yes	**Indirect**	**Other**	**None**	None	40	0,24
Hitman: Absolution	Stealth	Yes	Yes	No	Direct SS	Combat	None	None	80	3,98
Killzone 3	FPS	**Yes**	**Yes**	No	None	**Combat**	Low	None	84	2,81
Left 4 Dead	FPS, Survival Horror	Yes	Yes	Yes	**Direct DDA**	Combat	None	**Progress**	89	3,54
Mass Effect	Action RPG	No	No	No	None	Combat	None	None	89	3,58
Max Payne 3	TPS	**Yes**	**Yes**	No	Direct	Combat	Low	None	87	3,92
Metal Gear Solid V: The Phantom P	Stealth	Yes	Yes	Yes	Indirect	Other	Low	None	91	4,12
Middle Earth: Shadow of Mordor	Action	**Yes**	**Yes**	**Yes**	Combination	None	**High**	None	84	6,04
Monstrum	Survival Horror	Yes	Yes	No	Direct SS	Pathfinding	None	None	57	0,15
Neverwinter nights (Spronck mode)	RPG	No	Yes	Yes	**Direct**	None	**High**	None	91	
Rainbow Six: Siege	FPS	Yes	Yes	**No**	Direct	Combat	**Low**	None	79	6,05
Resident Evil 4	TPS, Survival Horror	Yes	Yes	No	**Direct DDA**	Combat	None	**Progress**	96	5,32
S.T.A.L.K.E.R: Shadow of Chernoby	FPS	**Yes**	Yes	No	Indirect	Other	Low	None	82	0,06

official source (**in bold**)
players and critic's reviews
low score (0-49)
dynamic difficulty adjustment (DDA)
sensory system (SS)
medium score (50-74)
high score (75-100)

E

		Basic information			Adaptation information				Popularity	
Game name	**Genre**	**Goal-oriented**	**Flexible**	**Learning**	**Adaptation source**	**Intra-behaviour**	**Inter-behaviour**	**Player profiling**	**Metacritic score**	**Total Sales**
Supreme Commander	Strategy, RTS	**Yes**	**Yes**	**No**	None	None	None	None	86	0,09
The Last of Us	Action, Stealth	**Yes**	No	No	None	**Combat**	None	None	95	6,27
The Witcher 3	Action RPG	No	No	No	None	None	None	None	92	7,41
Thief 1	Stealth	No	No	No	**Direct SS**	None	None	None	92	0,01
Thief 4	Stealth	**Yes**	No	No	**Direct SS**	Pathfinding	None	**Player Style**	69	2,09
Titanfall	FPS	No	No	**No**	Indirect	None	**None**	None	86	5,07
Tom Clancy's Ghost Recon Wildlanc	TPS	**Yes**	**Yes**	Yes	**Indirect**	Combat	**Low**	None	70	4,46
Tom Clancy's Splinter Cell: Blacklist	Stealth, Action	**Yes**	Yes	No	**Direct SS**	**Combat**	Low	None	82	2,32
Tom Clancy's Splinter Cell: Pandora	Stealth	**Yes**	Yes	Yes	Indirect	Combat	None	None	87	2,87
Tomb Raider	Action Adventure	**Yes**	**Yes**	No	**None**	**Combat**	None	None	86	6,86
Total war	Strategy, RTS	**Yes**	**Yes**	**Yes**	Indirect	None	**High**	None	84	0,01
Transformers: Fall of Cybertron	TPS	**Yes**	**Yes**	No	None	**Combat**	None	None	78	0,85
World of Warcraft	Strategy, RTS	**Yes**	**Yes**	**No**	None	None	None	None	93	6,34
XCOM: Enemy Unknown	Strategy, TBT, RPG	**Yes**	No	No	None	None	None	None	89	1,94

official source (**in bold**)
players and critic's reviews
low score (0-49)
dynamic difficulty adjustment (DDA)
sensory system (SS)
medium score (50-74)
high score (75-100)