Budapest University of Technology and Economics
Faculty of Electrical Engineering and Informatics
Department of Telecommunications and Media Informatics

Dominik Márk Noszlopi

VIDEO GAME ITEM CLASSIFICATION BASED ON PREDICTED PRICE CHANGES

SUPERVISOR

Dr. Péter Babarczi

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Összefoglaló

Kevesebb mint két évtizeddel ezelőtt egy új üzleti modell kezdett elterjedni a videójátékokon belül, amely az egyik legjövedelmezőbb gyakorlatnak bizonyult: a mikrotranzakciók. A modell meghódította a játékipart, és számos formában jelent meg, például a játékon belüli megvásárolható kreditek, az exkluzív tartalmakhoz szóló belépők és a szerencsejátékhoz hasonló, véletlenszerű loot boxok formájában. A profitmaximalizálásra irányuló kísérletezésnek nincs vége: a kiadók nemrég elkezdtek non-fungible tokeneket (NFT-k) árulni játékon belüli tárgyakként, a játékosközösség kritikái és a kormányzati szabályozások ellenére.

2013-ban a Counter Strike: Global Offensive (CS:GO) bevezetett egy piacteret, amely lehetővé tette a játékosok számára, hogy egymás között játékon belüli mikrotranzakciós tárgyakat adjanak el vagy cseréljenek, amelyek játékon kívüli értékkel is bírnak. Ez a lehetőség új résztvevőket csábított a platformra: olyanokat, akiket nem is maga a játék érdekel, hanem a skinek kereskedelméből szeretnének profitálni. Bár a hagyományos piacterek esetében a modern technológiák, mint például a mélytanulás, előnyt jelentenek az árváltozások előrejelzésében, ezen módszerek alkalmazását meg kell vizsgálni ebben az új típusú piaci környezetben, ahol csak tisztán digitális eszközökkel lehet kereskedni.

Munkám során feltárom a videojátékok mikrotranzakcióinak történetét, megvizsgálom a kiadók bevett gyakorlatait, megismerem a skin piac különbségeit más piacterekhez képest, és belemerülök a játékon belüli skin kereskedelem sajátosságaiba. Először kereskedelmi adatokat gyűjtök a Counter Strike: Global Offensive játékhoz a Steam online piactérről, feldolgozom és elemzem azokat bevált adattudományi eszközökkel, majd kategorizálom a tárgyakat az árváltozási történetük alapján, hogy megkapjam a jövőbeli befektetési potenciáljukat. Ezután feltárom és felhasználom a mélytanulás eszköztárát, hogy egy - az összegyűjtött adatokon betanított – mesterséges neurális hálózatot készítsek a tárgyak árváltozási kategóriájának előrejelzésére. Végül alapos értékelést végzek a különböző tárgy jellemzőkről, és e megfigyelések alapján tovább javítom a javasolt neurális hálózat paramétereit.

Abstract

Less than two decades ago a new business model started to rise within video games, that turned out to be one of the most profitable practices: microtransactions. The model has conquered the games industry, appearing in many forms, such as purchasable in-game credits, passes for exclusive content, and randomized loot boxes comparable to gambling. The experimentation to maximize profit is never-ending: publishers recently started to sell non-fungible tokens (NFTs) as in-game items, despite the critiques of the gaming community and the regulations of governments.

In 2013 Counter Strike: Global Offensive (CS:GO) introduced a marketplace allowing players to sell or trade in-game microtransaction items amongst each other, which can be converted to different benefits outside the game. This opportunity lured new participants to the platform: people who are not even interested in the game itself but want to profit from trading skins. Although for traditional marketplaces modern technologies such as deep learning provides an advantage in predicting price changes, the application of such methods should be investigated in this new type of market environment where purely digital assets can be traded.

In my work I explore the history of microtransactions in video games, look at common practices by publishers, discuss the differences to other marketplaces and dive into the specifics of in-game skin trading. First, I gather item trading data for Counter Strike: Global Offensive from the Steam on-line marketplace, process and analyze it with well-established data science tools. Second, I categorize the items based on the price change history to get their future investment potential. Next, I explore and use the best practices in deep learning to propose a neural network model - trained on the gathered data - to predict the price change category of the items. Finally, I conduct thorough evaluation of different item attributes and further improve the proposed neural network parameters based on these observations.

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1 Introduction

The video game industry is fairly young, the emergence of the industry can be dated back to 1971 with the introduction of the first coin operated video game titled *Galaxy Game* [1]. Since then, it solidified itself within the entertainment industry, with rising popularity from generation to generation. As the industry and technology developed along the years, video game publishers came up with more and more ideas to monetize their games, such as expansion packs, merchandise, booster packs and many other practices. In this process a new business model was created under the name of *microtransactions*: the players can buy small parts of the games for a usually low amount of money. The practice has conquered the industry, nowadays found in most of the games. With the rise of these systems, a new demand has appeared to trade the items that the players do not want to possess.

In our work, we will explore the world of microtransaction systems and get to know the marketplace of the game *Counter-Strike: Global Offensive*, to find out more about the player-to-player item trading scene. As this market differs in multiple ways from traditional ones, speculating and investing in it raises new challenges. In this work we will experiment with machine learning models and neural networks, that are commonly used today for market analysis and prediction and assess its effectiveness in this extraordinary scene.

In Section 2, we will be introducing the types, history, evolution, and current state of microtransactions, discussing how the newest technologies like non-fungible tokens are getting used as microtransaction items and the many problems publishers and developers have to face upon using this monetization model. Section 3 dives into the world of *Counter-Strike: Global Offensive (CS:GO)* item trading: we will explore the different attributes of items on the market, get to know multiple common trading practices and learn about and analyze events influencing the market. In Section 4 we will collect, process and analyze data about the items on the *CS:GO* market, and create prediction models based on our data to measure the profitability of these items. Finally, Section 5 discusses and concludes our work.

2 Microtransactions in video games

Today microtransactions are inevitable in most video games. These systems have been normalized in the industry, to the point, that some companies have mastered the business strategy such a high level that they make thousands, even millions of dollars from free-to-play games using microtransactions. A good example is *Fortnite*, a product of Epic Games, in which 77% of players spent money on microtransactions although them being purely cosmetic as shown in Figure 1 [2][3].

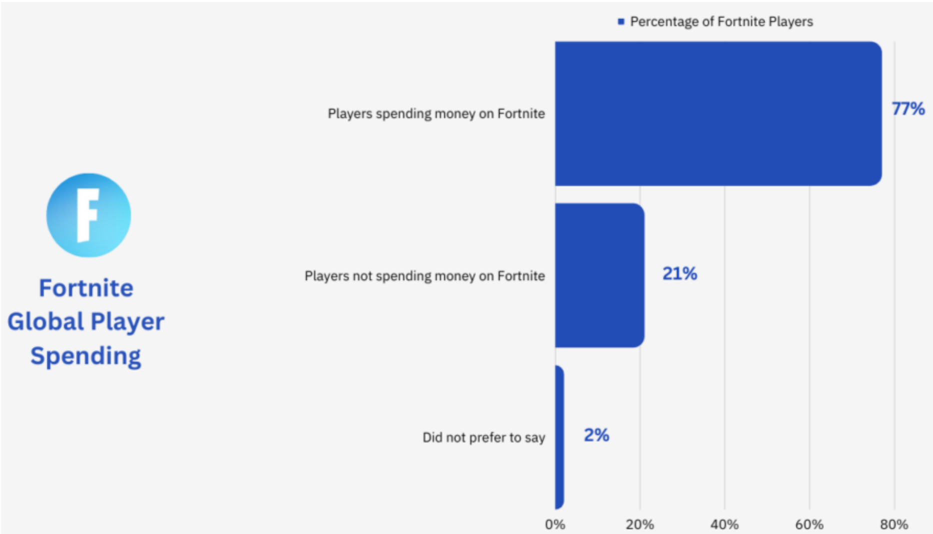

Figure 1: Distribution of Fortnite players by in-game spending [3].

We believe that learning the basics of microtransactions and players' relation with them is important to understand the environment and mentality of the skin trading market. In this section we will briefly go through the history of microtransactions, basic terms and different concepts of implementation.

2.1 What are the microtransactions?

2.1.1 Types of videogames

Before we investigate microtransactions, it is important to mention that there are two main types of video games in terms of pricing:

- **Free-to-play games**: Users can download and play the game with no cost.
- **Pay-to-play games**: Users must pay a given price to acquire and play the game.

2.1.2 Definition of microtransactions

Video game publishers – like other companies – are always trying to maximize profit. Capcom's president recently stated, that video games should be more expensive, as development costs rise; and he's not alone [4]. Publishers recently started charging $70 for games, increasing the previous standard price tag of $60, and are looking for other ways to generate revenue whether it be merchandise, downloadable extra content, or ***microtransactions***. The microtransaction business model in modern video games builds on players purchasing in-game virtual items for smaller amounts of money *(i.e., making a microtransaction)* [5]. Microtransactions are a core component in free-to-play games to generate revenue besides sponsors, advertisements, and merchandise. However, microtransactions also commonly appear in pay-to-play video games as an extra source of income.

2.1.3 Types of microtransactions and items

Touro University Worldwide states that there are four different types of microtransactions [6]. The various types are the following:

1. **In-game currencies**: One of the most popular microtransactions. Players buy virtual in-game money that can be used to purchase items in the given video game.
2. **Random chance purchases**: The player can pay a given amount for a mystery bag of items. The items' associated value can be lower or much higher that the price of the mystery bag. The associated price is influenced by the artificial rarity of the given item and subjective factors like appearance.
3. **In-game items:** Users can buy items directly with real-life currency in an in-game store at a predetermined price.
4. **Expiration**: The game has components that wear out or can only be used at certain number of times. As the expiration occurs, the player is prompted to make a decision to pay in-game or real-life currency to continue using the given component or to not pay and lose access to this item, function, etc.

The items purchasable by microtransactions can also be categorized:

- **Purely cosmetic items (skins)**: These items – commonly referred to as skins – are only aesthetic. They give an already existing in-game item a different look. This could mean a different color, pattern, a slightly altered 3D model or a custom animation.
- **Progression non-affecting items**: Items in this category add some extra content in the game without excluding other players or giving advantage to the buyer. A good example is pet companions, that follow the player. While they are not in the game essentially, they do not provide any benefit for the buyer over other players.
- **Experience altering items**: Exclusive items that give extra content to the user which cannot be experienced without payment. Usually there are similar items in the base game but with different characteristics. Examples are extra maps that can only be played when purchased, or exclusive cars, weapons etc. that have different characteristics in practice than their already in-game counterparts.
- **Pay-to-win items**: This is a subcategory of experience altering items. The difference is that these items provide advantage to the buyer, by being notably better than the items obtainable without paying. Examples include weapons, cars etc. that are better than the normally acquirable items, or boosters that provide faster development for the player.

2.2 History and evolution of microtransactions

Back in the days video games used to operate like big-budget films [5]. The games were developed for years with extensive testing and debugging. Nobody wants to purchase a faulty product, so the fact of how polished the game was one of the most important deciding factors between failure or success. If the product was successful maybe some expansion packs were released for the game, containing additional hours of content. However, with the spread of online connectivity in the late 90's and early 2000's a new concept was born: downloadable content (DLC). DLCs provided flexibility for the developers: if a game had bugs, they could react and provide solution for the players via downloadable patches. But not only that, DLC-s provided a new revenue stream for publishers, in the form of microtransactions. In the following few sections, we will go through the most important milestones of modern microtransactions.

2.2.1 The rise of the Xbox Live Marketplace

In 2005 prior to the release of Microsoft’s console, the Xbox 360, they reworked the Xbox Live Marketplace [7]. While Xbox Live supported online play, friend networks and purchasing games before, in the 2005 update microtransaction capabilities appeared among other features [8] [9]. Microsoft released a winter-themed outfit for the game *Kameo: Elements of Power* for $2.50, new maps for *Perfect Dark Zero* and new cars for *Project Gotham Racing 3*, as a proof of concept to video game publishers. Microsoft referred to this practice as a boon for players because they did not need to spend tens of dollars for expansion packs that contain content they did not want alongside the wished components. Instead, they can spend 1 to 5 dollars to directly buy what they want and just that. The first third-party publisher to release a microtransaction item was Bethesda, offering a horse armor for $2.50 to be used in their game *The Elder Scrolls IV: Oblivion (Figure 2)*. This microtransaction became infamous among gamers as they raised their voice against the uselessness of a cosmetic item.

Figure 2: The Elder Scrolls IV: Oblivion’s controversial horse armor [7].

Despite the controversy of the horse armor, fans purchased the upcoming DLCs such as the Wizard’s Tower or the Thieves Den although these were just different home bases for the player character. Additionally, players nowadays claim that they would prefer a system like the horse armor’s direct buy system much more than the today trending random chance purchases.

2.2.2 Free games with a twist

Publishers did not need a long time to realize the possibilities of using microtransactions. With this new business model, publishers can release a game for free and generate revenue over time by selling microtransaction items, perhaps even getting more money from a given player than with a one-time purchase. A successful early example for this model is *Farmville* by Zynga that released in the late 2000's on the rapidly growing social media platform, Facebook [10]. Players had the option to purchase time-savers for their crops, or items to increase their yield for real-world money. Not surprising that bigger companies moved to this direction after seeing the success of *Farmville,* leading to our day where the biggest titles like *League of Legends, Valorant* or *Fortnite* provide free access to the game while capitalizing on microtransactions [2] [11] [12].

2.2.3 Online passes – gatekeeping features

The games industry had a problem with the second-hand market from the start [7]. In the opinion of some publishers every game sold second-handedly is lost revenue, and a missed opportunity to sell a new copy. In 2010 Electronic Arts (EA) brought a solution to the problem: online passes. In the prior year they experimented with extra content for buying the game new: every copy had a code in them that could be activated to unlock outfits, characters, or items. If a code is redeemed it cannot be used again, so second-hand buyers miss out on that content.

Online passes took one step further: the one-time codes now unlocked previously standard features, the first example being *Tiger Woods PGA Tour 11*, requiring the single-use code to unlock online team play. In the same year other EA Sports games followed this practice with *NCAA Football 11*, *NHL 11*, *Madden NFL 11, NBA 11, FIFA 11,* and *EA Sports MMA* all incorporating this system. If a user bought these games on the second-hand market, they could not access online play, unless paying an extra $10 for Electronic Arts to get a new online pass code. The idea of the online pass came from Sony, who used unlock codes for multiplayer game modes in some of their PlayStation Portable (PSP) titles, to fight the widespread piracy affecting the console.

After Electronic Arts introduced online passes, other publishers like Ubisoft, Activision, Warner Bros, THQ, and more followed suit. Players criticized this practice heavily as they wanted to be able to sell, repurchase and rent games, while also fearing that in the future other parts of the games become also locked behind a code.

After 3 years, in 2013 Electronic Arts was the first to abandon this practice, stating that they were listening to players' feedback. It was one of the few times when the gaming community's dissatisfaction made the industry completely back away from a business practice.

2.2.4 Season passes – preordering DLCs

A new business practice appeared in 2011, when Rockstar Games announced the Rockstar Pass for their new game, *L.A. Noire* [7]. The deal was simple: you could buy the Rockstar Pass to access all future downloadable content for $12, or buy the DLCs after separately, which would cost $20. The trick is, that most players would not purchase all DLCs for the game if they were sold separately, bundling them with a pseudo-discount actually makes more money to the publisher. The industry realizing the potential in this practice quickly reacted and suddenly in most of the games season passes were present.

However, players were discontent once again. Buying a season pass for $20 or $30 could worth every cent in theory, but also could be a very bad deal, depending on the quality of the downloadable content. At the time of the purchase a user has absolutely no way to know which outcome should be expected. Even worse, some publishers released exclusive maps as a part of their season passes – like Activision's former *Call of Duty Elite* system, that required $50 for yearly membership – which in the end led to a split player base [13].

While season passes are present nowadays as well – sometimes in a form of *"Deluxe Editions"*, which in reality is the base game with a season pass included – their frequency in games dropped since their peak between 2012 and 2014 [10].

2.2.5 Loot boxes – the trending practice

Loot box system are based on random chance purchases, the practice can be traced back to 2004 [10]. The role-playing game *Maplestory* introduced Gachapon tickets to their Japanese servers, which after paying the 100-yen price gave the player a random in-game item [14]. The business model started to spread in Asia, as developers began to make free-to-play games with loot boxes, in order to generate revenue. For example, the

Asian mobile game *Puzzle & Dragons* was the first mobile game to earn over $1 billion from its microtransaction model, using loot boxes [15].

The western video game industry took interest in the practice later, first example being Valve's *Team Fortress 2* [16], which introduced loot boxes in the game in 2010, and became free-to-play in 2011 [7]. Their reasoning was, that while releasing the game for free would result in less revenue per player, the increased player base combined with a loot box system would make the transition profitable. Their experiment succeeded; the game's player count rose by over 12 times the original player base.

While Valve continued the practice by incorporating it in their following game, *Counter-Strike: Global Offensive* [17], other publishers also started using the business model. Loot boxes started rapidly appearing in other free-to-play games, like *HearthStone* [18], or *Lord of the Rings Online* [19]. They also became a part of pay-to-play games like *Overwatch* [20], or sports games like the yearly installations of *FIFA* [21] and *Madden NFL* [22].

Publishers frequently offer different tiers of loot boxes: if you buy a more expensive one, it is more likely to contain a rarer item.

2.2.6 Battle passes – a transparent reward system

Epic Games' hit, *Fortnite*, popularized a new form of microtransactions: battle passes [2] [10]. The concept is based on seasons, which are 10-week periods in the game. Players can buy a battle pass for a single season, which then rewards them with different cosmetic items and in-game currency for playing. Players generally prefer this method, because battle passes have transparent progression systems showing exactly what rewards can be earned and approximately how much play-time is needed to reach a milestone. Also, these systems encourage play instead of straight up giving the rewards to the user after payment.

2.2.7 Current practices

Publishers today create more and more complex microtransaction systems to generate revenue. Most games use multiple microtransaction business models at the same time. For example, *Fortnite* and *Apex Legends* both have a battle pass system, but you can also buy the games' virtual money to spend it in-game on cosmetic items, moreover *Apex Legends* even has loot boxes [2] [23].

Publishers also introduced limited time items and event items. Players can purchase these items within a given period, and after an end date the items are removed from the store. This method gives a sense of exclusivity to the items, which motivates players to buy them, led by the fear of missing out or by the opportunity to show off the items after they become unavailable to acquire. *Overwatch, Apex Legends,* and many others use this practice [20] [23].

Some games even let the players to trade the items between each other for other items or for money. This motivates players and even bring in non-playing users to the games as with smart trading they can generate profit for themselves. Valve's games, *Team Fortress 2* and *Counter-Strike 2 (the successor of Counter-Strike: Global Offensive)* both implement this system. This way players can buy preferred items and sell the ones that they got from loot boxes but do not want to possess.

Even publishers who formerly put out statements against microtransactions, have implemented this practice. CD Projekt Red stated that their game *The Witcher 3: Wild Hunt* would not include microtransactions, and while the studio provided multiple free DLCs to the players, they also released two pay-to-play expansion packs, and the game's soundtrack for sale [24] [25]. Later CD Projekt Red also released their own online collectible card game Gwent, which although being free-to-play offers a microtransaction system as a mean to collect new cards [26].

It is safe to say, that the microtransaction business model became an industry standard. Figure 3 shows us, that more and more players play with games that include microtransactions.

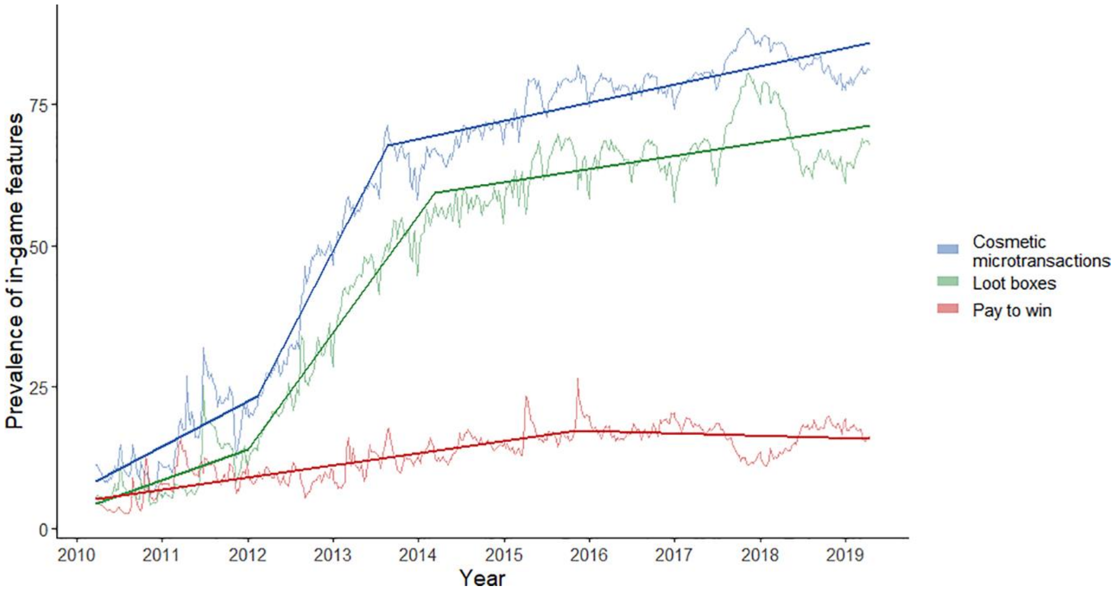

Figure 3: Percentage of players that played with games containing different types of microtransactions between 2010 and 2019 [27].

2.3 Scandals and regulations of microtransactions in video games

Microtransactions are often criticized by gamers, as can be seen from *The Elder Scrolls IV: Oblivion's* horse armor fiasco mentioned in Section 2.2.1 or the player base insisted abandonment of online passes mentioned in Section 2.2.3. However, there are some notable examples of publishers facing resistance from players and even regulations by governments related to microtransactions, that we will discuss in this section.

2.3.1 Player dissatisfaction

Players are usually not too keen about microtransactions but the rising frequency of video games that contain loot boxes is the most current subject matter. The dissatisfaction reached its peak in 2017 before the release of Electronic Arts' *Star Wars: Battlefront II* [28].

The game expanded the so-called Star Card system, that the predecessor introduced, making it a required part of player progression. When the open beta launched from October 6 to 11 players were concerned about the importance of these cards, and moreover the mean of getting them: loot boxes. The players' frustration was outstandingly expressed under a Reddit post, making a developer comment under the same post the most disliked comment in the platform's history.

Mainstream media began to cover the case, while Electronic Arts spent the next few days commenting and explaining the situation until November 16, when – one day prior of the game's launch – they pulled all microtransactions from the game. Although an in-game currency called Crystals returned in the April of 2018, they can only be used to purchase cosmetic items, instead of loot boxes containing character upgrades [29].

2.3.2 Concerning psychological tricks

Microtransaction systems got critiques over the years for their shady practices, and since loot box systems exist, due to their addictive nature [30]. Publishers intentionally or not, are using multiple psychological tricks to push sales, such as the ones mentioned below [31]:

- **In-game currencies**: As mentioned in Section 2.1.3, this is the earliest form of microtransactions. This extra layer of purchase makes it harder for the user to understand the real-life price of an item.
- **Loot boxes**: This system is based on a psychological principle by the name of "variable rate reinforcement". The human dopamine system responds more intensively to an uncertain reward, than getting the same reward in a predictable manner. Loot boxes are also carefully designed in the audio-visual aspect as well. Lots of colors and intense audio cues are used to increase player excitement before the big reveal.
- **Fun pain**: Similar to expiration, microtransactions mentioned in Section 2.1.3, this practice creates a stressful situation, then offers a way to solve it for a fee. A good example is the popular mobile game *Candy Crush*, where if the player runs out of moves the game is over. However, the app offers a solution by giving the opportunity to purchase extra moves, before terminating the session.
- **Offering fake discounts**: The game offers a discount – usually a higher discount for the higher amount spent – making the customer believe they can save more if they buy more.
- **Skill games vs money games**: A "skill game" is a game, where a user can progress without spending. The difficulty increases, which also makes the user feel more rewarded upon completing challenges. However, the

difficulty reaches a point, where the game becomes a "money game", meaning progression is extremely hard or impossible without spending money on some help.

- **Reward removal**: This technique grants a user a significant reward for a limited time *(e.g. boosters or advanced equipment),* then threatens to take it away if the user would not purchase it.

2.3.3 Government regulations

As loot boxes became mainstream and psychological and moral concerns arose some governments also interfered with the practice. The actions were induced by the gambling-like world of loot boxes and the straight up gambling that could be experienced in some games, like *Counter-Strike: Global Offensive (now Counter-Strike 2)*, where users could bet on *CS:GO* pro-tournaments with in-game skins. *(Although this might change in the future, as Valve recently updated their Steam platform's online conduct policy, stating that Steam users should not engage in commercial activities* [32].*)*

Japan took action in 2012, declaring *complete gacha* illegal [33]. *Complete gacha* is a loot box variant, with a prominently problematic technique: to progress in the game, a set of rewards must be obtained via purchasable loot boxes. This means users must engage in the system, until luck favors them.

The next country to act was China: in 2016 they passed a law, that makes mandatory for publishers, to reveal not just the names of the items available in the loot boxes, but the probability of receiving said item as well. Since then, China has intensified older restrictions and added further ones, such as limits on the number of loot boxes purchasable within a single day.

The Netherlands Gaming Authority conducted a study of 10 unnamed games in April of 2018. In conclusion 4 of the 10 games were in violation of Netherlands laws of gambling, as the loot boxes or their contents could be marketed, making them illegal in the country.

After the Netherlands, Belgium declared loot boxes as a form of illegal gambling. The statement was based on an inspection of various games containing loot boxes, such as *FIFA 18* and *Overwatch*, with the conclusion that the randomized risk-reward system is equivalent to gambling. This resulted in some publishers, like Valve altering their games in the country, while others like Nintendo removed their mobile games from the Belgian app stores. As of 2023 the legislation seems flawed as 82 games out of the top 100 in the Belgian Apple App Store contain loot boxes [34].

2.4 New technologies in microtransactions

New technologies are infiltrating the world of microtransactions as well. One of the most promising ones are non-fungible tokens (NFTs), which are blockchain-based digital assets.

2.4.1 What are NFTs?

Non-fungible tokens have gotten popular since 2020 but the first implementation was created 5 years before that [35]. Non-fungible tokens build on the technology of blockchains. They are cryptographical tokens for digital assets that usually have an artistic value, for example digital graphical art, music, videos etc.

The main difference between NFTs and traditional blockchain content such as cryptocurrencies, is that NFTs are unique. That is what their naming represents as non-fungible means "non-replaceable". For example, if two participants swap Bitcoins then nothing will really change [36]. Both will have the same asset: a specific amount of Bitcoins with no functional differences. Thus Bitcoin *(as well as other cryptocurrencies)* are fungible. However, if someone buys the NFT representing the artwork of Beeple, called "Everydays—The First 5,000 Days", they will have a proof that they "own" the artwork [37] via a digital signature. Even if there is another token with the artwork of "Everydays—The First 5,000 Days", they have different identifiers, so they are not the same. Inspecting the blockchain containing the tokens anyone can determine which NFT was created first, which one is the "original one". Anyone on the Internet is still capable to look at the artwork but the user owning the token is the only one that can prove they own it. *(The owner's digital signature in the token proves that they have access to the digital asset.)*

It is also important to mention that the token itself does not contain an image or any other asset, only a (web)link to it. For example, Jack Dorsey, the co-founder, and former CEO of Twitter sold an NFT with the link of the first-ever tweet. If that tweet gets deleted, then the token will have a non-functioning link [38].

2.4.2 Why NFTs could work for microtransactions?

Non-fungible tokens have multiple characteristics that make them favorable in the eyes of the publishers as microtransaction items:

- Non-fungible tokens are unique, which can be seen as an evolution of the artificial rarity of microtransaction items. Players are more likely to buy unique, exclusive items.
- NFTs could be used only as cosmetic items, not modifying gameplay, or making the game pay-to-win. Such microtransactions are more favorable in the eyes of players.
- Non-fungible tokens can be traded between users like microtransaction items – specifically skins – can be traded in some games, like the previously mentioned *Team Fortress 2*, or *Counter-Strike: Global Offensive (now Counter-Strike 2)* [16] [17].

2.4.3 NFTs already present in some video games

While NFTs are not yet the standard in videogames, some smaller companies have already incorporated them in their games. One of the biggest NFT games of today is *The Sandbox*, which is entirely based on NFTs and blockchain technologies [39]. Users can create voxel *(the 3D equivalent of a pixel)* art, avatars or items, then tokenize and sell them to other players. Players also have the opportunity to buy in-game land to create mini-games, buildings or interactive experiences on them.

Other games are also experimenting with the technology, like *Gods Unchained* [40], a trading card game using NFT cards, *Defi Kingdoms* [41], a fantasy role playing game with NFT heroes and *Axie Infinity* [42], a Pokémon-like battler with NFT pets [43]. Even games that previously did not have NFTs are trying them out, like *Krunker* [44], a free browser-based first-person shooter [45].

2.4.4 Problems with NFTs in video games

Introducing non-fungible tokens in video games are – like introducing any new microtransaction model – can be problematic.

2.4.4.1 Backlash from players

We previously mentioned the *Star Wars: Battlefront II* fiasco in Section 2.3.1 but NFT content is also fairly controversial between gamers. Some examples are the following:

Ubisoft Digits

Ubisoft announced in the beginning of 2022 that they are releasing their NFT line called Digits which would be sold on their own platform Quartz [46]. Digits offer unique in-game cosmetics with serial numbers. Players soon began criticizing the idea, even some Ubisoft employees raised their voice against the concept calling it an exercise in *"private property, speculation, artificial scarcity, and egoism"* [47].

Digits and Quartz officially launched since, included in the game *Ghost Recon Breakpoint*, but the numbers are rather underwhelming and looks like the concept did not work as expected [48] [49]. Since then, Ubisoft announced that they stop developing Ghost Recon Breakpoint without any comments on the future usability of Breakpoint Digits [50].

Worms' NFT art collectibles

The creators of the *Worms* strategy series Team17 tried to launch a range of NFT art collectibles called MetaWorms, but the reaction from fans was so vile that they cancelled the project [51] [52]. This scandal led to employees speaking out about poor wages, sexual harassment, and other problems within the company [53].

S.T.A.L.K.E.R. 2 NFT characters

The creators of *S.T.A.L.K.E.R. 2* tried to implement NFTs in their game in an interesting manner [54]. The concept was that the owners of the tokens released by the company can have their own non-playable characters in-game, modeled after them, and appear in the world for other players too. The fans did not support this practice, so the studio announced on Twitter that they will not implement NFTs in the game [55].

2.4.4.2 Security concerns

There are concerns about the security measures of video games generally, but if real-life money is at stake with non-fungible tokens, these concerns are more highlighted.

The previously mentioned *Axie Infinity* gained its fame not solely for the gameplay: it suffered a $625 million exploit from hackers in March 2022, which may be the largest exploit in decentralized finance history ever [56]. After the incident the studio asked for help from the Federal Bureau of Investigation (FBI) and tried to compensate the users affected. The FBI connected the attack to a North Korean hacking entity called Lazarus Group, who are tied to multiple crypto thefts in the past years [57]. The FBI recovered $30 million worth of cryptocurrency in September 2022, but most of the money got laundered through a privacy mixer called Tornado Cash [58]. The U.S. Treasury Department later raised sanctions against Tornado Cash for facilitating money laundering. However, these actions are so slow that some of the users who relied on these NFTs as investments are begging for the hackers to give back their tokens [59].

2.4.4.3 Ecological concerns

A lot of NFTs use blockchain networks with *Proof of Work* consensus models. *Proof of Work* systems are based on computationally heavy puzzles, thus using a lot of electricity, and generating heat. Minting – the step of tokenizing and releasing the NFT – an item on the Ethereum blockchain uses the same amount of power that an average U.S. household in about 9 days [60]. *(It is fair to mention, that Ethereum plans to switch to a Proof of Stake consensus model, which will drop the power consumption by approximately 99.95%. After that a token's minting will consume as much energy as 20 minutes of television watching.)*

Companies can reduce this negative aspect in multiple ways, such as:

- They can choose a more energy efficient consensus models. For example Ubisoft announced that they will use the Tezos blockchain for their Digits in the future [61].
- Companies can switch to a permissioned *(authorized)* blockchain system in which consensus models are way more energy efficient. *(Microtransaction systems already have an authority – the game company – and users are also identified.)*
- They can use renewable energy to mint and transfer NFTs or invest in such technologies to reduce their overall ecological footprint.

- They can recover the heat from criptocurrency mining in order to heat homes or even towns with the otherwise lost energy, like the Canadian company MintGreen [62].
- Some NFT vendors are choosing to pay for carbon offsets, but this practice is problematic in multiple ways [63].

2.4.5 Reaction from the industry

The industry is divided on the topic of non-fungible tokens. Some companies try to capitalize on NFTs in games such as Ubisoft – mentioned already in Section 2.4.4.1 – or Epic Games Inc. *(owner of Epic Games Store)* stating that they will try to implement the technology [64].

Others released NFTs but not as in-game items, like Konami – the company behind the *Castlevania* series – publishing an NFT art collection for the 35th anniversary of the series [65]. Despite fans not supporting the project all the 14 tokens were sold for an average of $12000 per token [66]. Another example is Atari releasing an NFT line called GFTs, a hybrid of a loot boxes and NFTs. The buyers purchased a mystery image without knowing what it was until the big reveal on February 28, 2022 [50]. The collection sold out, but plenty of tokens got resold by their original buyers [67].

Lastly, there are publishers opposing non-fungible tokens: *MineCraft's* studio Mojang stated that they do not permit blockchain technologies in their game because in their opinion it can damage the safe and inclusive experience of players [68]. Valve – who owns the digital video game marketplace Steam – is on the same page as they announced that they'll ban NFT related Steam games and items [69].

3 The market of Counter-Strike: Global Offensive skins

In the following section we will learn more about the *CS:GO* skin market, to better understand the subject of the predictions. At this point it is also important to note, that since September 27, 2023 *CS:GO* became unplayable, as Valve replaced it with the sequel *Counter-Strike 2 (CS2)*. However, all the virtual items of players' got transferred to *CS2*, and the item trading mechanisms stayed the same, so the game's investigated aspect is only partially affected.

The *CS:GO* skins in many aspects bear similarities to collectible card games, such as *Magic the Gathering (MtG)* [70]. Players can obtain items from randomized packs, like the booster packs is *MtG*, and resell them on a secondary market where price is determined by the supply and demand, the current happenings, the in-game meta, and unique features differentiating the items from the others. The market can also be heavily influenced by the owner company with the introduction of new rules or the release of new items.

Then again, being a digital marketplace *CS:GO* has many differentiating factors from materialistic markets. The supply is theoretically infinite, only the money and time of players influence it. There is artificial rarity, that we will explore in this section, but if someone opens enough cases, they will eventually get what they want. Another key difference is that the developers have full control over the market: in *MtG*, the company can make rules and introduce new cards, but they cannot retrieve already sold instances. Valve can and have done it in the past because one of the skins – the M4A1 Howl – had copyright issues, making the company remove the item from cases. These characteristics not only differentiate the *CS:GO* skin trading from materialistic markets, but also from non-fungible tokens as for NFTs, scarcity and distributed authorization is key.

In the following section we will find out more about this trading scene, the characteristics of items populating it, the possible trading methods and the events shaping the market.

3.1 Introduction of the market

The *CS:GO* skin trading scene is a favorable subject-matter for multiple reasons: the game has a 10 year old trading history, with new items releasing frequently and a public Application Programming Interface *(API)* as a mean to collect data.

In *CS:GO* the primary method to obtain items are cases. Cases can be earned for free by playing the game, but to open a case a player must have a key for the specific case type, see the example in Figure 4. Keys can be bought in-game and are single-use items. Cases are basically loot boxes *(previously mentioned in Section 2.2.5)*, each specific case type containing one item out of a collection of 10-20. Items are categorized by rarity and can appear in cases accordingly – items that are in a rarer category have a lower probability to be in a case *(read more about rarity in Section 3.2)*. The cases, keys and obtained items can all be sold on the secondary market.

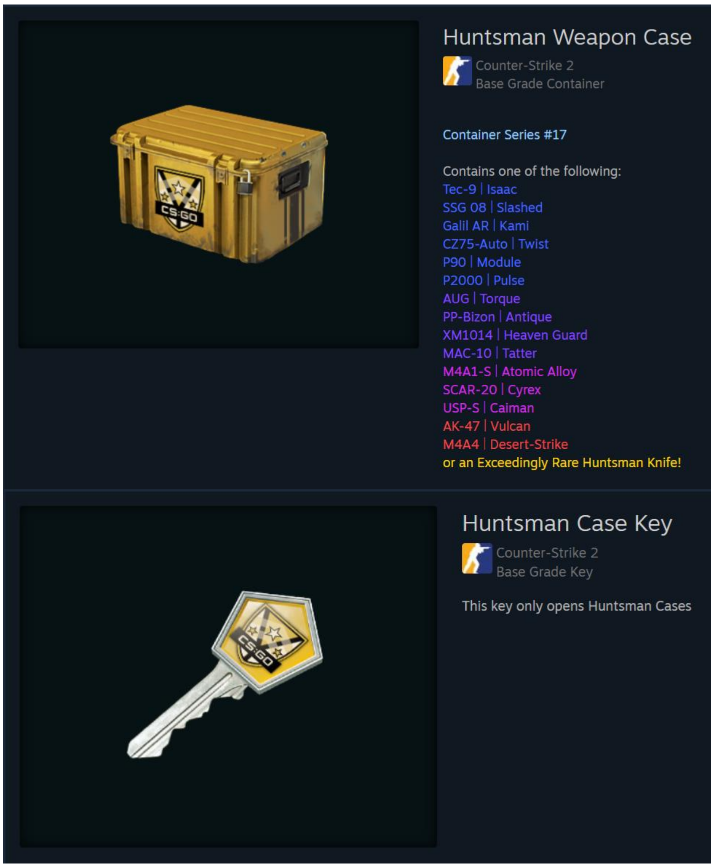

Figure 4: The Huntsman Weapon Case and the corresponding key to open it [71].

3.2 Attributes of items

CS:GO has a wide array of tradable items: weapon and agent skins, cases, keys, gloves, music kits, weapon stickers, agent patches, graffities and more. These items do not have public unique identifiers – this can be because the anti-NFT mindset of Valve, discussed in Section 2.4.5 – so they cannot be distinguished with full confidence; one could not track an exact skin's transactions. However, there are some attributes that can change the item's price that will be discussed in this section.

3.2.1 Rarity

Weapon skins have rarities indicated by colors. There are eight categories, each increasingly harder to get than the previous one. The least rare skins can be earned for free by playing, and usually cost a few euros at maximum, while some of the rarest skins can be sold for thousands of euros. Table 1 shows the rarity categories.

Table 1: Rarities of CS:GO weapon skins from least rare to the rarest and methods to obtain them [71].

Consumer Grade (White)	Can be obtained as post-match rewards or by trading.
Industrial Grade (Light blue)	
Mil-Spec (Blue)	Can only be obtained from cases or by trading. Each category's drop probability is less than the previous one's.
Restricted (Purple)	
Classified (Pink)	
Covert (Red)	
Extraordinary (Gold)	The rarest category obtainable from cases, all gloves are in this.
Contraband (Orange)	Discontinued item, only obtainable by trading. Only instance of this category as of writing is the *M4A1 Howl*.

3.2.2 Condition

The weapon's or gloves' condition is determined by a random float value assigned to the skin. Float values are 12 decimal place numbers ranging from 0 to 1. The condition categories with the associated float values are shown in Table 2.

Table 2: CS:GO weapon conditions and associated float values.

Factory New	0.00 - 0.07
Minimal Wear	0.07 - 0.15
Field-Tested	0.15 - 0.38
Well-Worn	0.38 - 0.45
Battle-Scarred	0.45 - 1.00

Condition affects the appearance of a skin: *Battle-Scarred* skins look used, while *Factory New* ones are pristine. This usually results in the skin's *Factory New* variant being more expensive than the *Battle-Scarred* ones as shown in Figure 5.

Figure 5: The AK-47 Asiimov skin in Battle-Scarred *(left)* and Factory New *(right)* condition. Their prices as of writing are 25 and 263.88 euros accordingly [71].

It is important to note, that different skins can have different float limits. For example, a skin could have a minimum float value of 0.1 and a maximum of 0.4, meaning it is only available in *Minimal Wear, Field-Tested* and *Well-Worn* conditions. Additionally, some hardcore traders look for specific float values that can bump up the price of a skin. *(E.g., some users hunting for the skin with the highest float value ever* [72].*)*

3.2.3 StatTrak counter

Some weapon skins and music kits have variants with a so-called StatTrak counter. StatTrak is a system, that tracks in-game statistics when equipped. For weapons it counts the number of kills the player has with the given weapon, while the music kits' StatTrak counters tracks the number when the user was the most valuable player (MVP) in a match. While StatTrak statistics are erased when an item is traded, users have the option to buy a StatTrak swap tool to transfer their statistics to another StatTrak music kit, or a StatTrak weapon skin for the same type of weapon.

3.2.4 Pattern seeds

A pattern seed is a number between 0 and 1000. It determines the position of the texture wrapping the model of the weapon. For simple colored skins this has no relevance, but for complex, patterned skins the seed could make the item look totally different as seen in Figure 6. Some patterns are more sought after than others, affecting the price.

Figure 6: The skin Bayonet Case Hardened with different pattern seeds [73].

3.2.5 Souvenir skins

Souvenir skins can be opened from Souvenir Cases – a special type of cases, which are randomly rewarded to people watching the official livestreams of the biggest *CS:GO* tournaments, called Majors [74]. The Souvenir Skins are special variants of normal skins, that have four stickers on them: the two teams' logos, that are currently playing the match being livestreamed, and two signatures of a random member from each team. For esports fans the opportunity to have a unique skin with the signature of their favorite player, that was released during an important match could worth more.

3.3 The Steam Community Market and other means of trade

Users also have multiple options to trade their skins from simple bartering to auctioning and betting [75].

3.3.1 Barter

On launch *CS:GO* players only had the option to barter their items. One user could look at the inventory of another player, then select the items he would like to get, and offer items from their own inventory in exchange. The other person can decide if they accept the trade offer, or not and make a counteroffer. If during the negotiation a player accepts the other's terms, then the trade will automatically complete.

3.3.2 The Steam Community Market

9 months after *CS:GO's* launch, Valve introduced the Steam Community Market [71]. It is a trading platform where players can sell and purchase skins with Steam Wallet. Although being the official trading platform, there are some undesirable aspects: first off, Valve takes a 15% tax off every transaction. That means if a player buys a skin for 1 euro,

they must sell it for more than 1.1765 euros to be profitable. Secondly, as Valve is not a bank, users cannot withdraw money from their Steam Wallet, they can only spend it on Steam.

3.3.3 Trade Up Contracts

The Trade Up functionality in *CS:GO* lets the player trade 10 items of the same rarity to get 1 skin from the rarity one tier above *(see the rarity categories in Section 3.2.1)*. In Trade Up Contracts condition float values – *mentioned in Section 3.2.2* – have a role as well: the outcome skin's float is calculated from the average of the 10 traded skins, and the float limits of the outcome skin with the following equation [76]:

$$outcome\ skin\ float\ =\ ((max.float - min.float)\ \times\ avg.float)\ +\ min.float$$

Although being a game of chance, if a player uses Trade Up Contracts in a clever way, they could obtain skins with higher prices than the sum of the 10 skins they traded.

3.3.4 Third party platforms

As *CS:GO* skin trading became more popular third party sites popped up. These webpages exist for the sole purpose of trading *CS:GO* items, offering a way to exchange the skins for real money. This way players have an opportunity to turn their play hours and money spent on microtransactions into profit – the same mentality that NFT games promote *(Section 2.4)*. Although Valve encouraging people to not use these platforms as they are unofficial and possibly not safe, multiple types have appeared through the years:

- **Auctioning sites**, where users can ask for a specific amount in return for their skins, and other people can make offers. This procedure can take a lot of time.
- **Bot sites** are way faster. In these platforms robots scan through the players inventory and based on statistics they offer different amounts for the skins. The player can accept these prices and get real money for their skin. After that, the bot posts the acquired skin publicly, and anyone can buy it – with a margin of course.
- **Betting sites** are used to bet on professional *Counter-Strike* tournaments with skins as stakes. These sites are the most controversial as many people think that gamifying gambling in such way can influence younger

audiences in a bad way. Additionally, they go against the anti-gambling measures some governments trying to make for video games, discussed in Section 2.3.3.

3.4 Events influencing the market

3.4.1 Operation and case releases

Operations are limited time events, where players can get operation-related cases as an in-game drop for playing [77]. In 2020 Operation Shattered Web took place. The operation case contained four new knife models with custom animations – player reaction was positive. After the operation ended, unopened Shattered Web Cases gained value, until later that year, when the Fracture Case dropped. The case contained the same four knives causing the Shattered Web Case to lose value as seen in Figure 7.

Figure 7: The Shattered Web Case's price changes due to the end of the operation and the release of Fracture Cases [77].

3.4.2 Game updates

As *CS:GO* skins are tied to the game, any change that the developers make can have an effect on prices. A good example is when Valve released a patch that let players use StatTrak skins for Trade Up Contracts on March 31, 2015 [75]. Previously the items like the *StatTrak Sawed-Off Serenity* could be purchased for as low as 0.5 euros, as the Sawed-Off is not a favorable weapon in-game and could not be used in Trade Up Contracts. Meanwhile skins like the *StatTrak AK-47 Cartel* had high value, as the AK-47 is one of the staple guns in *Counter-Strike* and it could not be obtained from Trade Ups. After the update cheap StatTrak skins' prices skyrocketed, while previous expensive ones' plummeted as shown in Figure 8.

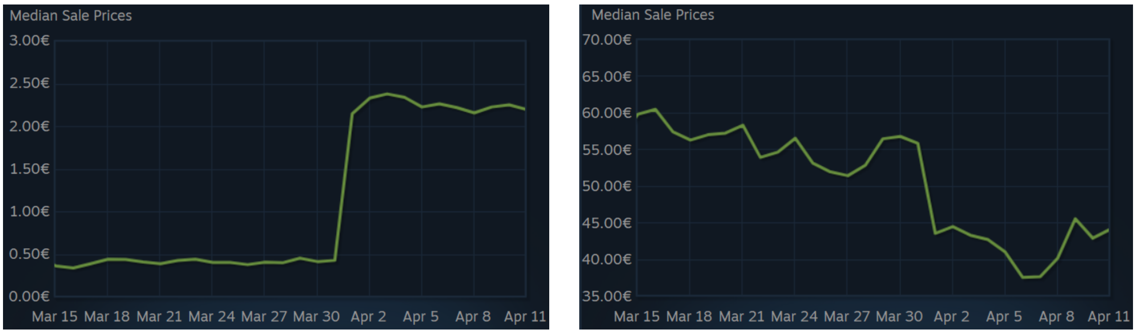

Figure 8: Price changes of the StatTrak Sawed-Off Serenity *(left)* and the StatTrak AK-47 Cartel *(right)* when the update dropped [71].

3.4.3 Esports events and rumors

One of the biggest transactions in *CS:GO* history happened right after the 2018 Boston Major [74]. The team Cloud9 won the majors, and the Most Valuable Player trophy was given the team's player Tyler Latham, known as Skadoodle. This was the first time that a North-American team won a Major so there was no lack of hype: the following day a *Souvenir AWP Dragonlore* with the signature of Skadoodle was traded for 61 thousand dollars. *(We discussed Souvenir skins in Section 3.2.5.)*

However, championships are not the only esports-related factors that can influence the market. In 2019 rumors started spreading, that the Polish *CS:GO* team called Virtus.Pro will terminate all player contracts – these rumors later turned out to be true. As the team has broken up, stickers with the autographs of its players skyrocketed, as they would become discontinued. This resulted in a 40% rise in Virtus.Pro sticker prices, shown in Figure 9.

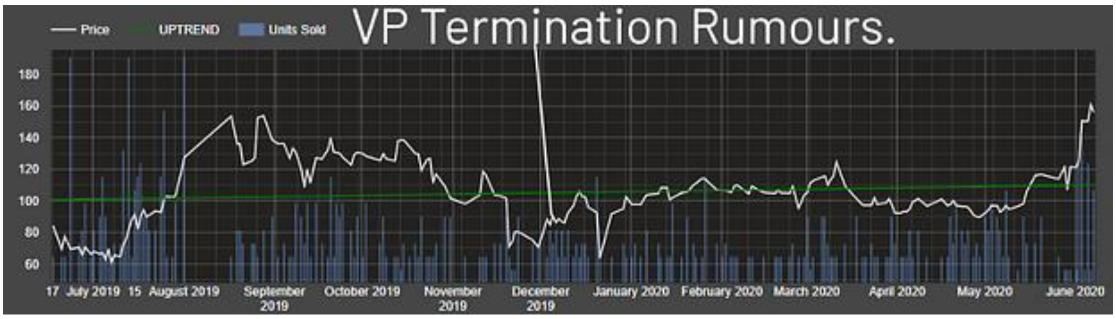

Figure 9: Virtus.Pro sticker prices skyrocket as rumors of the team's termination turn out to be true [74].

3.4.4 Steam sales

Steam sales are platform-wide promotions happening multiple times a year, where games could be bought with discounts up to 95%. During Steam sales the skin market supply usually rises, lowering prices, as players are trying to earn Steam Wallet credits that they can spend on the discounted games.

3.4.5 Announcement and release of Counter-Strike 2

Valve surprise-announced *Counter-Strike 2* on March 22, 2023. Some items' prices started rising after, as players speculated which skins will look better with the new graphical engine of *CS2*. However, when *CS2* released on September 27, player reception was not positive [78][79]. Many users communicated their dissatisfaction by writing negative reviews on the game's Steam page mentioning multiple problems: *CS2* dropped MacOS support, lacked maps and game modes found in *CS:GO*, had performance issues and was in the absence of an effective anti-cheat system, letting hackers overrun the game. But the biggest pain-point was that this way *CS:GO* became unplayable – however the positive reviews for *CS:GO* stayed on the store page, making players call out Valve for dishonesty. This series of events made *CS2* Valve's lower rated game ever, causing investors fear that their items would use value because of the controversy, making them flood the market, causing skin prices to drop.

4 Building prediction models

After getting to know the market and the factors influencing the prices of skins, we can begin to build the prediction model. During this section we will define the goal of the prediction as well as gather data and build prediction models. Throughout our work we will use the programming langue Python[1], with tools such as NumPy[2], pandas[3], Matplotlib[4], scikit-learn[5], XGBoost[6] and Keras[7].

4.1 Goal of the prediction

There are some works already in the field of *CS:GO* skin price prediction, like the thesis of Emma Taylor, who used machine learning algorithms to show the difference in the precision of predictions between using the skin attributes as features versus price history statistics [80].

In our work we wanted to test the viability of neural network prediction compared to traditional machine learning techniques in this extraordinary market. We have decided to build a model, that based on the data of the first half year after an item’s release, tries to predict the price change in the following year and classifies items into one of the different price change categories. The break-even point for the items would be a price increase of 17.65% due to the 15% Steam tax after each transaction, mentioned in Section 3.3.2. Price increases within a 5% proximity should be viewed as stagnating to give a safer estimate of which skins are profitable and which are not. Based on these statements, the three classes would be the following:

- **Non-profitable items**: less than 12.65% price increase.
- **Stagnating items**: between 12.65% and 22.65% price increase.
- **Profitable items**: more than 22.65% price increase.

These classes later would be the basis of our target. The features would be generated from the statistical data from the first half year and the attributes of the items.

[1] Python: https://www.python.org/
[2] NumPy: https://numpy.org/
[3] pandas: https://pandas.pydata.org/
[4] Matplotlib: https://matplotlib.org/
[5] scikit-learn: https://scikit-learn.org/
[6] XGBoost: https://xgboost.readthedocs.io/
[7] Keras: https://keras.io/

4.2 Data collection

The Steam platform has a public Application Programming Interface *(API)*, that can be used to collect data about games, users, and Community Market listings. Although the Community Market differs from third party platforms – as Steam Wallet credits could not be exchanged for real money – we argue that behaviors observed on the marketplace are generic among platforms. The API gives cumulative data for each item type: this means that all *AK-47 Asiimov Factory New* skin sales are summarized; however, in the following section we will reference to this cumulative data for a specific item type as one **item** to make it simpler to understand.

For data collection we used a Python script, building on the script of Dr. Blake Porter [81] by extending it to collect additional data such as the item name color, the image URL and to emit the whole raw data instead of processing the data right-away – this way later we can generate different values without sending requests to the server again. We also fixed some minor issues, causing the server terminating connection because of the frequent requests. This could be caused by API limit changes introduced since the 2019 creation of the original script. The script first collects all the items on the Community Market in batches of 100 – as this is the maximum requestable item count per request – and saving their names and text colors. After that the names can be used to request the cumulative price history of the items. The price history for each item is given in daily frequency although only dates with at least one transaction are given. A price history data on an exact date for an exact item contains the daily median sale price and the volume of transactions on the given date.

The collected data contained 20275 individual items, with the whole dataset having price history entries between the dates April 26, 2013, and July 10, 2023. The first and last price history entries for each item vary, as not all skins are released at the same time, and not all skins have daily transactions.

4.3 Data processing

4.3.1 Generating features

After collecting the data, we generated the features based both on attributes of the item and the first half year’s statistical data after the release of the skin. The features can be seen in Table 3.

Table 3: Feature names with the corresponding descriptions.

Feature name	Description of feature
`rarity`	The rarity of the item, known from the text color of the item. See rarity categories in Section 3.2.1.
`condition`	The condition of the item, obtained from the name of the item as float values are not public on the market. See condition categories in Section 3.2.2.
`isWeapon`	1 or 0 depending on if the item is a weapon or not. Gloves are categorized as weapons as they are like weapons in functionality and attributes.
`hasStatTrak`	1 or 0 depending on if the item has a StatTrak counter or not. Read about StatTrak in Section 3.2.3.
`firstPrice`	The first known daily median price of the item.
`firstVol`	The volume of transactions on the first day.
`halfYearPrice`	The first daily median price of the item after the 182^{nd} day since released.
`halfYearVol`	The volume of transactions on the first day after the 182^{nd} day.
`priceChangeToDate`	$\frac{halfYearPrice - firstPrice}{firstPrice} = priceChangeToDate$
`minPrice`	Minimum price in the first half year.
`minPriceVol`	The volume of transactions on the minimum price day.
`maxPrice`	Maximum price in the first half year.
`maxPriceVol`	The volume of transactions on the maximum price day.
`meanPrice`	Mean price in the first half year.
`medianPrice`	Median price in the first half year.
`week_<X>_min`	The minimum price on week ***X***. ***X*** is in the range of 0 to 25.
`week_<X>_max`	The maximum price on week ***X***. ***X*** is in the range of 0 to 25.

`week_<X>_mean`	The mean price on week ***X***. ***X*** is in the range of 0 to 25.
`week_<X>_median`	The meadian price on week ***X***. ***X*** is in the range of 0 to 25.
`minVol`	Minimum volume of transactions during the first half year.
`maxVol`	Maximum volume of transactions during the first half year.
`meanVol`	Mean volume of transactions during the first half year.
`medianVol`	Median volume of transactions during the first half year.
`totalVol`	Total volume of transactions during the first half year.
`dateCountToDate`	The number of days when at least one 1 transaction happened in the first half year.
`firstYearMin`	Minimum price in the year after the half year mark.
`firstYearMax`	Maximum price in the year after the half year mark.
`firstYearMean`	Mean price in the year after the half year mark.
`firstYearMedian`	Median price in the year after the half year mark.
`medianPriceChange`	$\frac{firstYearMedian - firstPrice}{firstPrice} = \text{medianPriceChange}$
`priceChangeCategory`	Price change classes labeled with [0, 1, 2] for non-profitable, stagnating, and profitable based on the definitions in Section 4.1.

Due to the nature of the generation of statistical values, all item's that had no value in the first one and a half year have been dropped. The feature ***priceChangeCategory*** calculated from the ***medianPriceChange*** will be our target later.

4.3.2 Data analysis and cleaning

After generating the features, it was time for the data analysis and cleaning. We eliminated the entries that are outliers by the ***medianPriceChange***. We did this by discarding the items with values below the 5^{th} or above the 95^{th} percentile. After that we visualized the data from different perspectives.

First, we looked at the data grouped by condition labels. As shown in Figure 10 there are a lot of entries with no condition labels, which is an expected outcome as only weapons and gloves have conditions. Additionally, Figure 11 shows, that the price changes among the non-conditioned items are more volatile, while the items with conditions are more subtle.

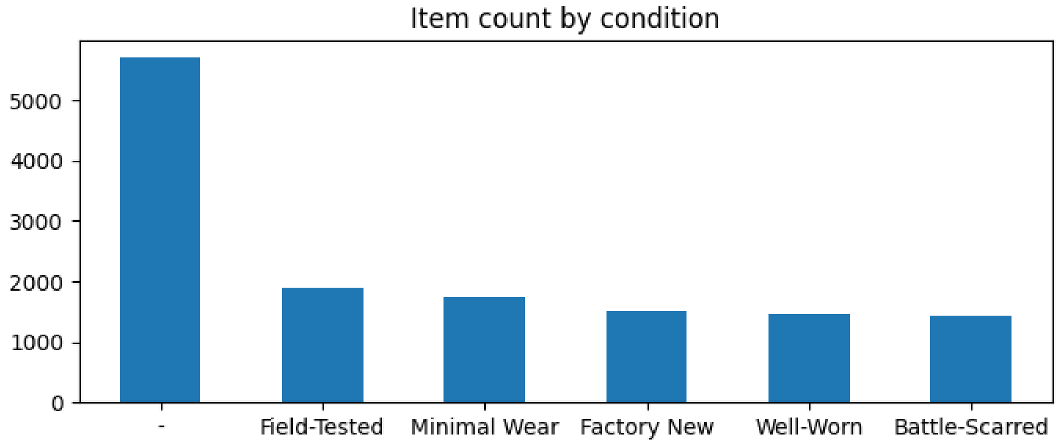

Figure 10: Item counts in each condition category.

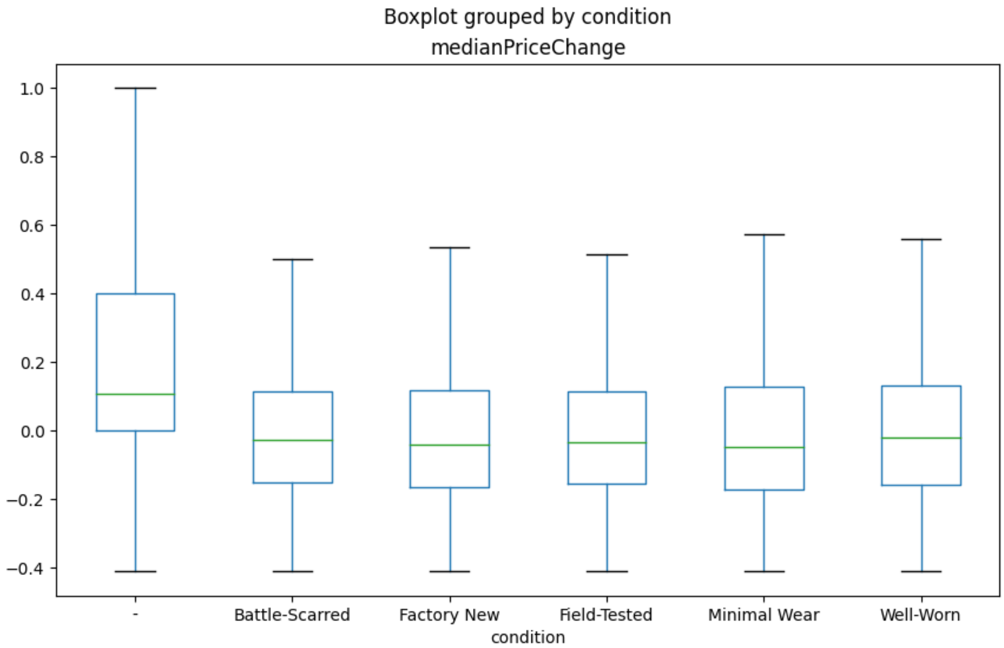

Figure 11: Price changes by condition category.

After that we looked another important attribute, rarity. Figure 12 shows us that most of the items have Consumer Grade rarity, which is expected because these items are dropped for free – as mentioned in Section 3.2.1 – meaning the only cap on supply are player hours. However, things get interesting as we look further into the plot: from the eight rarity categories only four are present and the Contraband rarity has a lot of items, while as we know only one skin, the *M4A1 Howl* has this rarity. This means that something with the data is off.

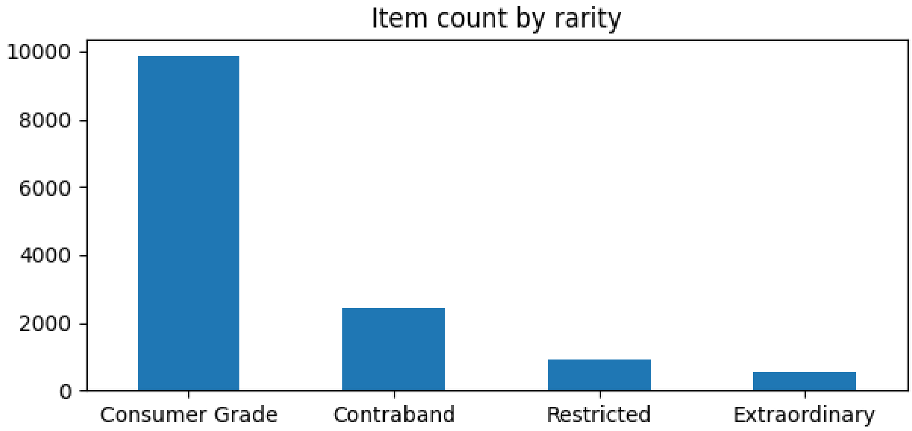

Figure 12: Number of entries by rarity.

Upon inspection we realized that there are in fact only four text colors *(supposed equivalents of rarity)* in the data set. A light grey, a purple, a gold and an orange color. However, these colors do not represent the rarity. The rarity color-coding of the items are only shown in case descriptions. After taking a look at the search options of the Steam Community Market it was clear that these colors represent the categories shown in Figure 13. Although this way we cannot assume the rarities of items, we can use these colors later to generate new features.

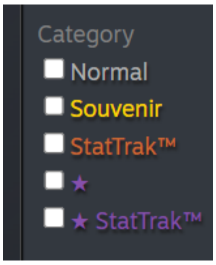

Figure 13: Color-coding of special item categories on the Steam Community Market.

After that we eliminated the 10 entries, that had a price increase between 17.6% and 17.7% as these entries have a profitability rate near 0%. This is because Steam collects a 15% tax on each transaction – as mentioned in Section 3.3.2 – which means, that the user must sell the item with a margin more than 17.65% to be profitable. After that we plotted the items by profitability shown in Figure 14. There are 3574 profitable, 1130 stagnating and 9006 non-profitable items by the definitions provided in Section 4.1.

Figure 15 shows us the price change distribution of these 13710 entries that remain after all of the previously mentioned eliminations have been applied.

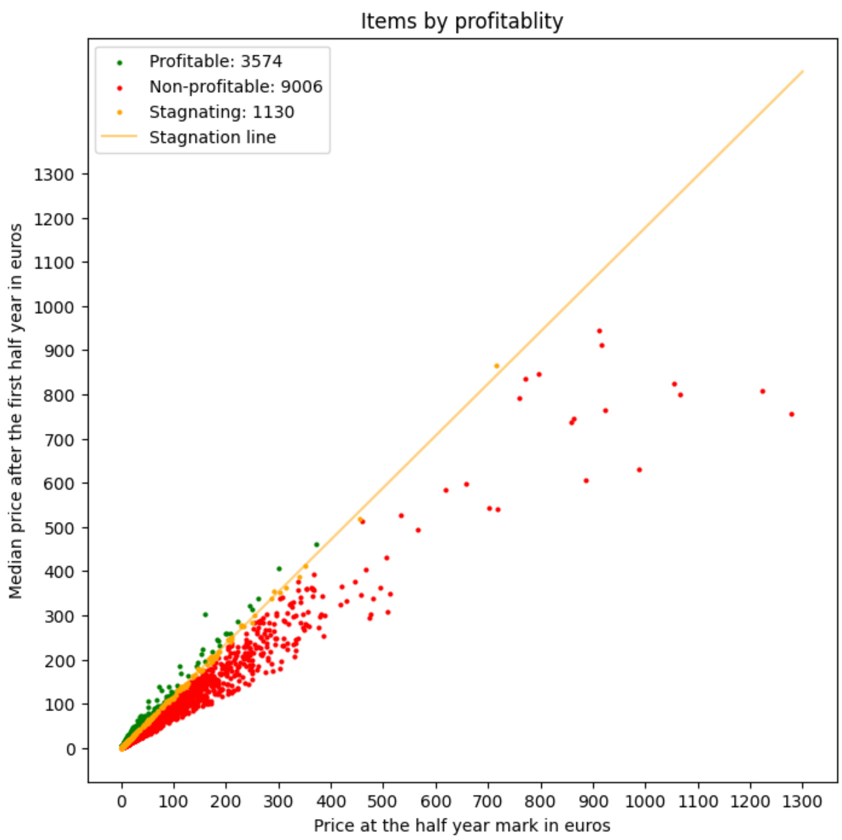

Figure 14: Comparison of items' prices at the half year mark and the median prices of the same items in the following year.

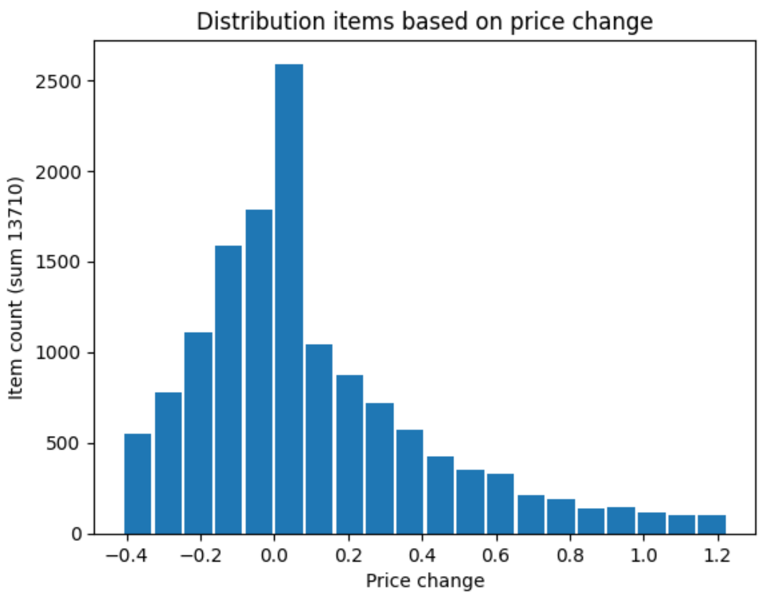

Figure 15: Distribution of items by price change in the year following the first half year.

4.3.3 Generating extra features based on the analysis

After the analysis we created new features shown in Table 4 to help in the improvement of the predictions.

Table 4: The features created after the data analysis.

Feature name	Description of feature
`hasStar`	1 or 0 depending on if the item name starts with a star or not. The star indicates that the item is a knife or gloves. Indicated by the purple text color.
`isSouvenir`	1 or 0 depending on if the item is a Souvenir skin or not. Indicated by the golden text color.
`condition_<name>`	The condition categories after one-hot encoding [82]. For each category a new feature is created which is 1 or 0 depending on if the item is the given category or not.

4.4 Creating the models

Neural networks have been in the spotlight in the past few years, as the progress in information technologies and the increasement of computational power made the usage of the technology more available than ever before. In this section we will build a neural network and other models to generate predictions.

4.4.1 Selected features

From all the features created in Section 4.3, ***priceChangeCategory*** has been selected as the target, and the following 131 attributes – consisting of 21 statistical and characteristic features, 4 statistical values for each of 26 weeks and 6 categories of condition – were selected as inputs for the models:

```
[isWeapon, hasStatTrak, firstPrice, firstVol, halfYearPrice, halfYearVol,
priceChangeToDate, minPrice, minPriceVol, maxPrice, maxPriceVol, meanPrice,
medianPrice, minVol, maxVol, meanVol, medianVol, totalVol, dateCountToDate,
hasStar, isSouvenir,
{week_<X>_min, week_<X>_max, week_<X>_mean, week_<X>_median; X ∈ [0,25]},
{condition_<name>; name is "none" or a condition (Section 3.2.2)}]
```

4.4.2 The baseline model

As discussed in Section 4.1, our work focuses on the viability of neural networks in *CS:GO* item price prediction. For this we have created an estimator to measure the precision of our neural network against. We have selected a logistic regression model. Logistic regression uses a sigmoid function to condense the output of a linear equation between 0 and 1. If the value is closer to 1 than 0 then the item is in the given class. For binary classification the algorithm is simple, as if the item is not in class A, then it must be in class B. In a multiclass classification model, the sigmoid function is calculated for each class, then the item is categorized into the class that has the highest corresponding value. Figure 16 shows an example for a sigmoid function.

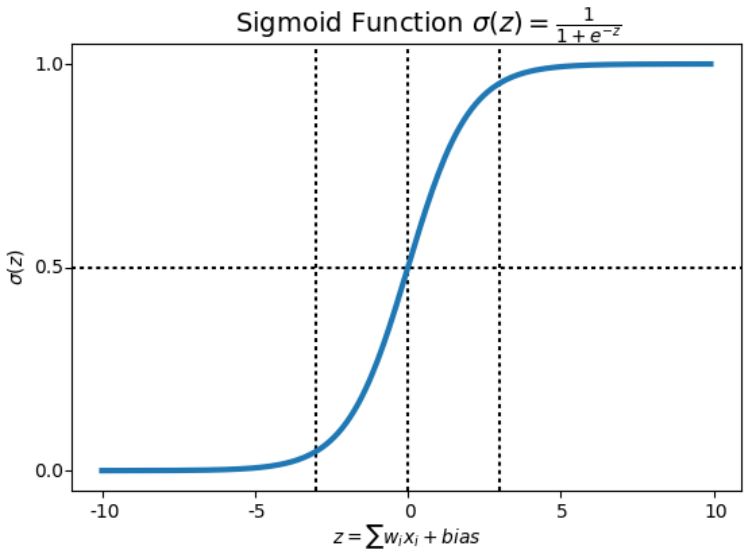

Figure 16: The graph of a sigmoid function, where w_i is the weight for input x_i [85].

4.4.3 The proposed neural network model

4.4.3.1 What is a neural network?

The inspiration for artificial neural networks come from the world of biology [83]. The human brain consists of a network of neurons, which consist of receptors *(dendrites)* and effectors *(axons)*. The neuron detects signals via dendrites, generates new signals based on them and distributes it through the axons. The artificial neural network is an imitation of this system: the neuron accepts multiple inputs and assigns a weight to each, then summarizes the weighted inputs with a bias value. After this linear transformation, the neuron applies a non-linear evaluation called an activation function, then propagates the result through the network. This process is shown in Figure 17.

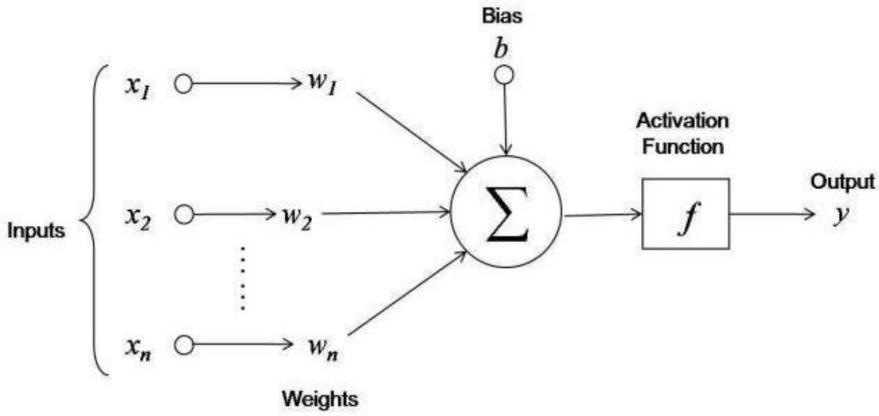

Figure 17: The processing in an artificial neuron [84].

The artificial neural network consists of layers: layer ***n***'s neurons' input values are the output values of layer ***n-1***, and layer ***n***'s output values are the inputs for layer ***n+1***. The two exceptions being the first layer *(the input layer)* where the data is injected in the model, and the last layer *(the output layer)* where results are emitted. We call all layers between the first and last layers hidden layers, as they are not perceived from the outside. A neural network's architecture is shown in Figure 18.

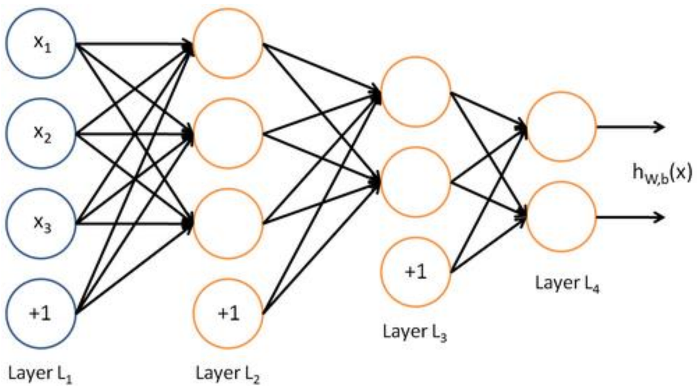

Figure 18: The architecture of a neural network. Layer L_1 is the input layer and layer L_4 is the output layer [84].

In our work we will not discuss the technology of neural networks in greater depth, for more details the interested reader can refer to the article *Introduction to Artificial Neural Network*, by A. D. Dongare, R. R. Kharde and Amit D. Kachare in *International Journal of Engineering and Innovative Technology* [83].

4.4.3.2 Building the neural network

We used the Keras library to create the neural network. The first task was to convert the target feature with one-hot encoding [82]. This way the neural network will predict the class of an item similarly to a sigmoid function. However, using a normal sigmoid activation function should be avoided for multiclass classification as sigmoid functions give independent predictions for each class. The solution is using the SoftMax activation function in the output layer, which returns the probability distribution between all classes. The difference between the two functions is shown in Figure 19.

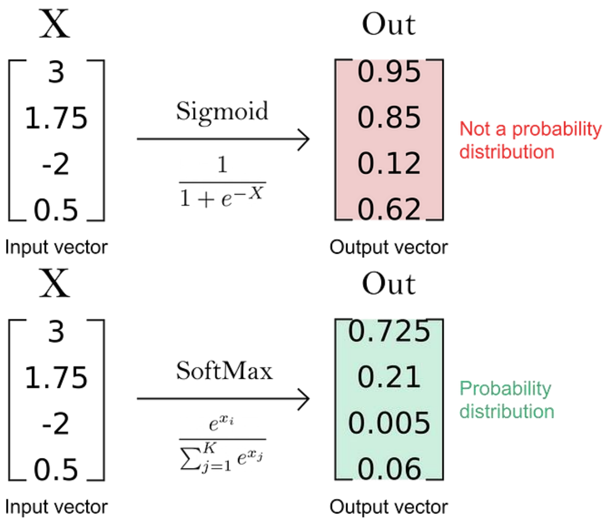

Figure 19: Difference between the outputs a Sigmoid and a SoftMax activation function [86].

Another common practice is to normalize the inputs of the neural network. This not only helps to lower the required computational power and thus calculation time, but it also lowers the estimation errors [87]. We used Keras's implemented Normalization layer as the input layer for this task.

For the hidden layers we chose the commonly used ReLU *(Rectified Linear Unit)* activation function: $y = \max(0; x)$. Additionally, we considered using the Swish activation function: $y = x \times \text{sigmoid}(\beta x)$ [88]. This function gained popularity since its 2017 proposal, as for in many neural networks it outperformed ReLU, but unfortunately not in our case. Figure 20 shows ReLU and Swish together.

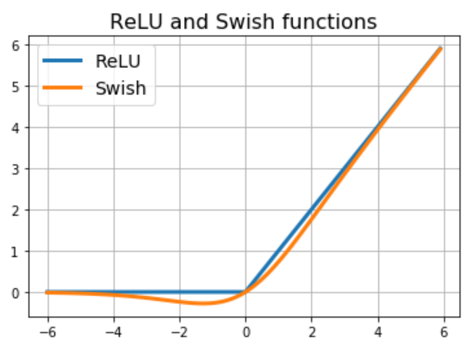

Figure 20: ReLU and Swish functions visualized [89].

Then, for the model compilation we had to provide a loss function and an optimizer. For neural networks using logistic regression the common practice is to use categorical cross entropy – shown on Figure 21 – as the loss function [90].

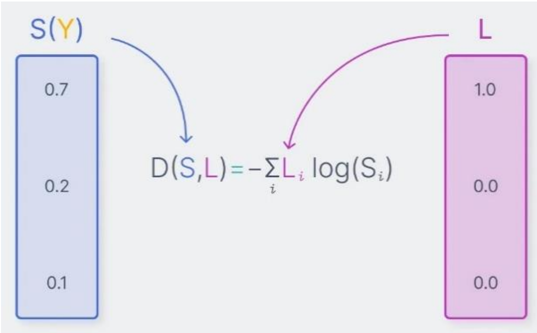

Figure 21: Cross entropy calculates the difference between the predicted probability distribution and the true class [91].

After experimenting with the optimizers ***SGD***, ***RMSprop***, ***Adam***, ***Adadelta***, ***Adagrad***, ***Adamax***, ***Nadam*** and ***Ftrl***, the default ***Adam*** proved to be the best for the task [92]. For the learning rate and other hyperparameters such as the number of hidden layers the output shape for the hidden layers and the batch size during fitting, we used Keras's ***GridsearchTuner***. A hyperparameter grid search exhaustively tests all combinations of the given hyperparameter values and returns the best one [93]. The final hyperparameter values are shown in Table 5.

Table 5: Hyperparameter values after the grid search.

Learning rate	0.0031623
Hidden layer count	5
Hidden layer output count	128
Batch size	64

Lastly, we should tackle the problem of overfitting. Overfitting is when the model is too closely fitted to the training data, giving good estimates for the that set, but underperforming in the prediction of the test set. To avoid this, we used 20% of the training data as a validation set during fitting with a callback function, that measures the validation set's loss after each epoch. If the validation loss has not decreased in the last 7 epochs it stops the training and restores the best weights. Figure 22 shows the change of the validation loss and accuracy values for a fitting of 60 epochs, and a fitting when the early stopping callback is used. One can see that the validation loss starts to increase after the 28th epoch. The fitting procedure with early stopping stops at this point, while the one without it begins overfitting.

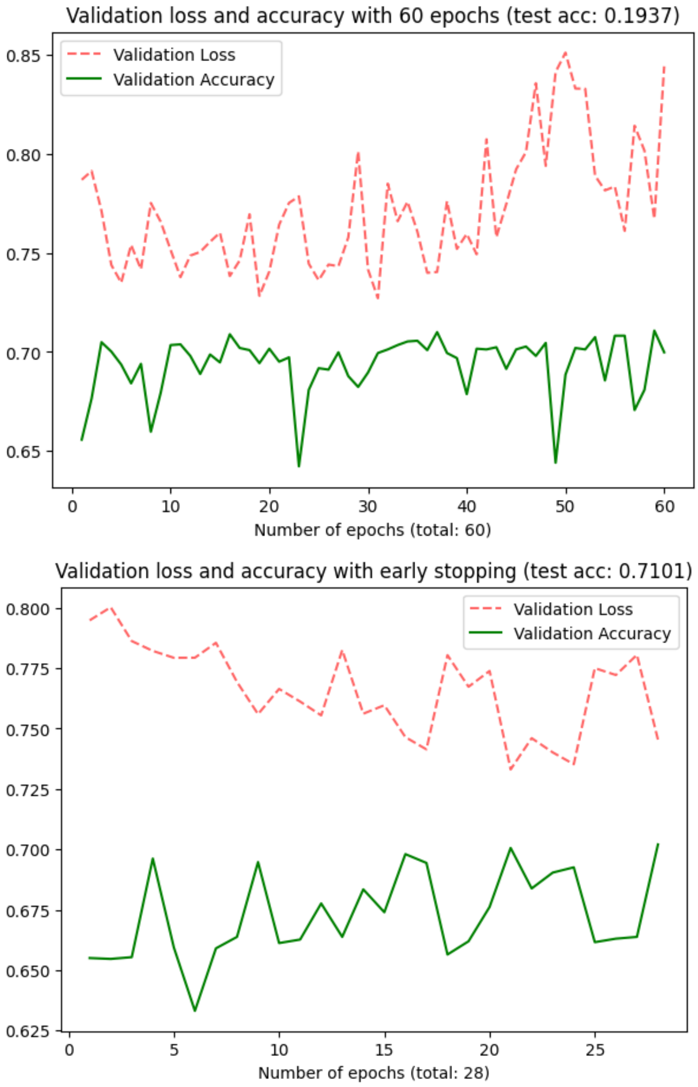

Figure 22: The validation loss and accuracy of the neural network fitted for 60 epochs and fitted with an early stopping callback.

The model summary with the parameter count for each layer is the following:

```
 Layer (type)                Output Shape              Param #
=================================================================
 normalization (Normalization)    (None, 131)              263
 dense (Dense)                    (None, 128)              16896
 dense_1 (Dense)                  (None, 128)              16512
 dense_2 (Dense)                  (None, 128)              16512
 dense_3 (Dense)                  (None, 128)              16512
 dense_4 (Dense)                  (None, 128)              16512
 dense_5 (Dense)                  (None, 3)                387
=================================================================
Total params: 83594 (326.54 KB)
Trainable params: 83331 (325.51 KB)
Non-trainable params: 263 (1.03 KB)
```

4.4.4 Gradient boosted decision tree model

During our research we found that many times decision trees prove to be more precise than neural networks for structured data that lacks special elements, such as images or voice data [94] [95]. Therefore, we decided to create a tree model as well to try it out on our dataset. We used XGBoost's XGBClassifier, which is an implementation of the gradient boosted decision tree model, that combines multiple weak-learner decision trees to generate a more precise prediction [96].

The classifier's *plot_importance()* function gives us an insight about the importance of different features, the top 20 features shown in Figure 23. The relative importance of each feature to the outcome, is measured by the average information gain of all splits on the attribute. Information gain is the most relevant metric to interpret the relative importance of a feature in tree models. The interested reader can refer to [97] for further details.

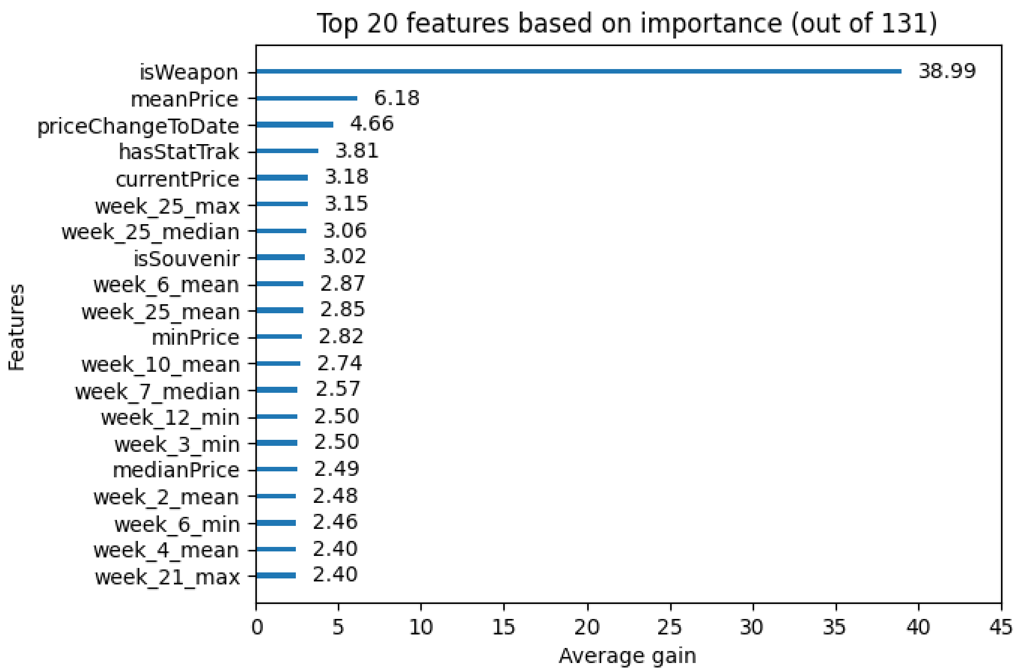

Figure 23: The average information gain of the top twenty features in the gradient boosted tree model.

The high gain of the feature ***isWeapon*** seems odd at first, however, as shown previously in Figure 11 items with no condition are way more volatile than items with a condition. And as we know, only weapons and gloves have condition labels, so it is a rather important decision point to increase the precision of the model. Additionally, it is worth noting that the importance values coincide with the results of Emma Taylor, as she only investigated weapon skins, where statistical features showed to be dominant [80]. In our case, after the ***isWeapon*** feature there are also mostly statistical values.

4.5 Comparison of the models

After creating the baseline model, the neural network, and the gradient boosted decision tree model, we conducted a comparison of them. The cleaned dataset with 13710 entries were used, that we created in Section 4.3.2, allocating 80% of the set for training and 20% of it for testing. When splitting the dataset preserving the distribution of the target classes in both sets was kept in mind. For scoring the accuracy metric was used:

$$Accuracy = \frac{Correct\ predictions}{All\ predictions}$$

In Figure 24 we investigated the accuracy of the models. As shown, both the neural network and the gradient boosted decision tree model outperformed the baseline model. Our example confirms that for a task with structured data decision tree models could perform well, even better than neural networks [94] [95]. One cause might be, that neural networks have huge number of hyper- and normal parameters – as shown in Section 4.4.3.2 – and finding the optimal setup is rather hard.

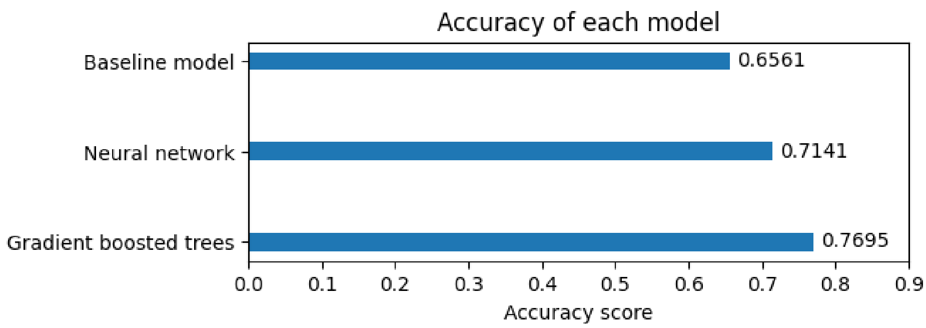

Figure 24: Accuracy of the models using the whole cleaned dataset.

Additionally, we decided that it would be interesting to see how the models perform on just the weapons and just the non-weapon items. For this the cleaned dataset has been split by the ***isWeapon*** value – which feature then got removed – resulting in a set of 8045 entries of weapon skins and a set of 5665 non-weapon items. Like for the whole dataset, these two sets were also divided into a training and test set in proportions of 80% and 20%, respectively. Figure 25 shows, that predicting only weapon skins improves all the models, while the classification of non-weapon items falls below the previous scores. This is expected, as discussed in Section 4.3.2, the items without condition values – thus being not weapons – have price changes more volatile, which is harder to estimate.

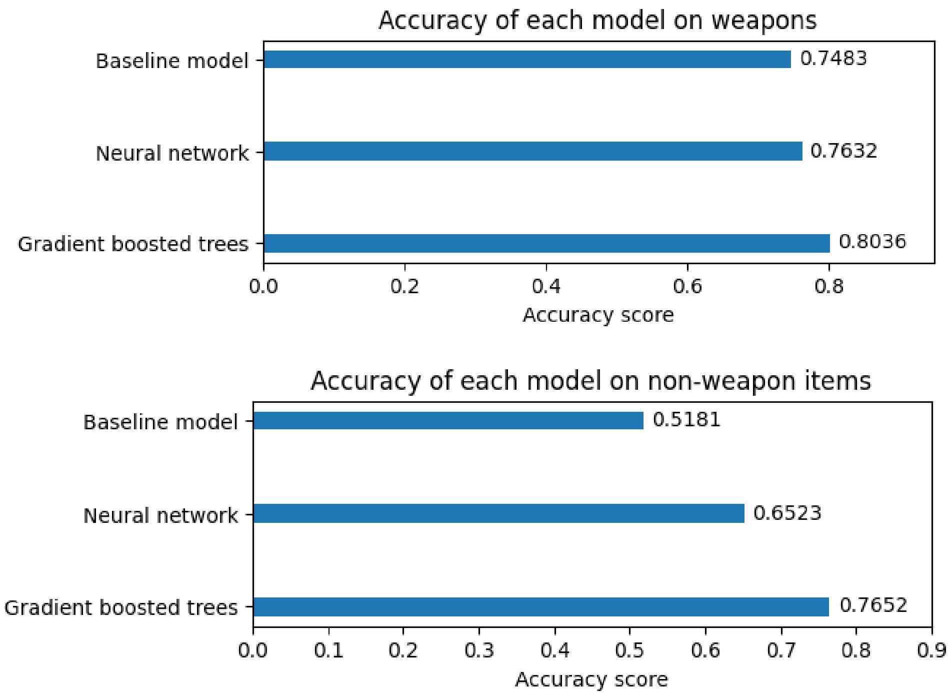

Figure 25: Accuracy of the models on weapons and non-weapon items.

Additionally, we can see that the order of the models by accuracy does not change based on the dataset, but the difference of the scores decreases in the case of weapons and increases for non-weapon items. This shows us, that the gradient boosted decision tree model is the most robust, having a score difference less than 0.04 between the worst and best scenario. Table 6 shows that in this aspect our neural network is also positioned in the middle.

Table 6: The scores of the models on the different datasets, and the greatest differences between the estimation scores for each model.

	All data	Weapons	Non-weapon	Greatest diff.
Baseline model	0.6561	0.7483	0.5181	0.2302
Neural network	0.7141	0.7632	0.6523	0.1109
Gradient boosted trees	0.7695	0.8036	0.7652	0.0384

Based on these results it can be stated that for the structured data, gathered and processed in this work, can be best estimated by a decision tree model, as it achieves the best scores and is the most robust model.

5 Conclusion

In our work we had dived into the current microtransaction systems, their psychology, methodologies, and perception by the players. We particularly explored the scene of *CS:GO* item trading, investigating the specific features of items populating this market, the means of trading, and the different external factors influencing the market. We collected characteristics and statistical data about these items through the Steam Community Marketplace.

In our work we measured the viability of machine learning practices – including neural networks – that are commonly used for speculating and predicting different markets. We built three prediction models to categorize the items of this unique market based on their profitability. Based on the fine score our neural network achieved on the weapon skin dataset, we see potential in refining the model for this specific market, as neural networks have many desirable aspects. They can work well on differently- or non-structured data, recognizing patterns and making assumptions based on them. For time-series analysis long short-term memory neural networks are proven concepts that could be used for the prediction of individual item price changes based on their price history, while deep learning image processing could help predict the price change of items based on visual features [98] [99]. However, as of now we suggest using the decision tree model as it proved to be the most effective, versatile, and robust on all datasets.

We think there is more work to do in this field, as the demand is present: players want to be able to sell and exchange microtransaction items that they do not need. The *CS:GO / CS2* skin trading market offers a solution while also being a unique trading scene, that worth paying attention to. Valve pioneered the player-to-player trading systems, continuously building on it, and showing an example for the whole video game industry. The skin market has already changed and developed much in the past 10 years, and with the popularity of *Counter-Strike* and the release of *CS2* further evolution is inevitable.

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