Game recommendation system.
Project Proposal
Mihail Kenarov

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1. Introduction

1.1 What is the goal of our recommendation system?

The goal of this project is to create a recommendation system that allows a user to find similar video games to the one they have chosen. This will be determined by some of the features of the choice they have made and show other games that they may find interesting to get as well.

1.2 Why would we create such a system?

Let us start with this statement:

[(NVIDIA, n.d.)](#)

"Recommender systems are highly useful as they help users discover products and services they might otherwise have not found on their own."

But let us dive deeper into the "why" are they so useful and "how" is that a useful system that we use and helps us in our everyday lives.

Recommendation systems are everywhere around us and we use them in our everyday lives. They allow us to find more options of the similar things we like. This makes us, as the consumer, find more enjoyable products that can help us in our lives or show us services similar to the one we have chosen, which we can find useful. Most of the time when we buy a product we combine it with another one. For example when we buy a t-shirt. When we take on this action the recommendation system pops up and shows us a pair of jeans for example, that would go along well with it. This way, it helps us not only just buy a random product, but a pair that we would enjoy to wear.

Not only that but when it comes to the businesses that implement these kinds of systems it can bring in more customers, because of the joy from being multiple quality products all together, while also brining in more revenue. This helps a company grow and make more either products or services for the customer, while also making sure to have enough resources to have increase the quality of their products.

1.3 Who would be interested in this project?

People who enjoy playing various kinds of video games may find this project useful, for future recommendations based on their interests. It goes not only for people who spend a lot of their time playing video games, but also for people who are interested in trying some new games in their busy schedules. With the creation of such s system, they can quickly find another game, similar to the one they like – quickly.

1.4 When will the project be constructed?

- Phase 1 – Research and planning
    - Research about the project will be conducted in the first couple of weeks of the semester, to get a better understanding of recommendation systems and what would be the most suitable approach in our case.
- Phase 2 – Development
    - During that time the data will be edited and structured properly for the selected algorithm, which will also be chosen during this time, based on what currently matches our expectations.
- Phase 3 – Delivery and evaluation
    - After the creation and testing of the project it will be evaluated to see if it matches up to our expectations.

1.5 How will the project be created?

We will first get a suitable dataset that would give us the necessary information to help us create such a system. There are many ways or places to find one – Kaggle, Maven Analytics or even just Google Dataset Search. Afterwords we will see which recommendation algorithm works best in our case and find a suitable model to train. Finaly, inferencing will be done as a way of testing out the project and seeing if the recommendations work as expected. The idea of the project is to see 5 games that are similar to the one that has been chosen

2.Domain understanding

We all know what video games are, but not many of us know what exactly a recommendation system is and what it consists of, which brought me to create research of my own.

2.1 What is a recommendation system?

A recommendation system is a sophisticated tool designed to analyse user behaviour, preferences, and interactions with items to predict what the user might like or need. These systems are integral to many online platforms, including e-commerce websites, streaming services, and social media, where they help users discover new content, products, or services that align with their interests. The goal of a recommendation system is to enhance user experience by providing personalized suggestions, thereby increasing engagement, satisfaction, and potentially sales or conversions.

2.2 What about some history of the recommendation systems?

(Apáthy, 2024)

Recommendation systems have been with us since the creation of human time. It started exactly from us – the humans, spreading general ideas while talking to friends, family, or people we just enjoy being with, about things we would say go well together or we would like the people close to us to experience. These were the first ever recommendations that were ever given out and we still use them to this day.

With the evolution of technology, we even received even the first recommendation system, which was made by humans and operated on its own – "Grundy." It was a system for the recommendation of books based on the users' inputs. With time it started being criticized as all things in our world, especially in technology.

Today, we are surrounded by recommendation systems everywhere around us -from the online shops that we visit, to the talks we have with friends. We could say that they have "integrated" into our lives, considering the fact that they with us, no matter what we do – having a discussion with a friend, buying clothing online or just ordering food for home.

2.3 How does a recommendation system work?

Recommendation systems are sophisticated algorithms designed to enhance user experience by predicting their preferences based on an analysis of historical data. This data encompasses a variety of user interactions, including ratings given to products or services, browsing habits, purchase history, and even social interactions with other users on the platform.

By scrutinizing this data, recommendation systems unearth valuable patterns and correlations, discovering insights into user behaviour that might otherwise remain hidden. These insights serve as the foundation for predicting future preferences accurately.

However, the functionality of recommendation systems extends beyond mere prediction. They also excel in identifying similarities between products or services that align with a user's interests. This capability enables them to offer recommendations not only based on explicit user preferences but also on implicit preferences inferred from past behaviour.

Sometimes it is even possible that a recommendation system is a little bit misguided. There have been times when a model for example is fed information in the form of 'To see later' or 'Wishlist', just for it to be something different from what their interests are. In that case, it is highly possible to differentiate the difference between what a user thinks they would like versus what they are actually interested in and follow.

In essence, recommendation systems operate as intelligent assistants, leveraging the power of data analysis to tailor suggestions that cater to individual tastes and preferences. Through continuous learning and refinement, these systems strive to deliver personalized recommendations that resonate with users, trying to enhancing their overall experience and satisfaction, although it is possible that sometimes it takes a bit more time.

2.4 What types of recommendation systems are there?

1. ***Content-Based Filtering*** - This type of recommendation system suggests items to users based on the characteristics or attributes of the items themselves. It analyses the features of items that a user has interacted with in the past and recommends similar items. For example, if a user has watched action movies in the past, a content-based filtering system might recommend other action movies with similar themes or actors.

2. ***Collaborative Filtering*** - Collaborative filtering recommends items to users based on the preferences or behaviour of similar users. It identifies users who have similar tastes or interests and suggests items that those users have liked or interacted with, but the current user has not. Collaborative filtering can be further divided into two subtypes:

   2.1. ***User-based collaborative filtering:*** It finds users who are similar to the target user based on their interactions with items and recommends items that those similar users have liked.

   2.2. ***Item-based collaborative filtering:*** It identifies items that are similar to the ones the user has interacted with and recommends those similar items.

3. ***Hybrid Recommendation Systems*** - Hybrid recommendation systems combine multiple recommendation techniques to provide more accurate and diverse recommendations. By leveraging both content-based and collaborative filtering methods, hybrid systems can overcome the limitations of individual approaches and offer improved recommendation quality.

4. ***Matrix Factorization*** - Matrix factorization techniques model the relationship between users and items by decomposing the user-item interaction matrix into lower-dimensional matrices. These methods are particularly useful when dealing with sparse data, such as user-item interactions in large-scale recommendation systems.

5. ***Context-Aware Recommendation*** - Context-aware recommendation systems take into account additional contextual information, such as time, location, device, and user activity, to provide more personalized recommendations. By considering the context in which recommendations are made, these systems can offer more relevant and timely suggestions to users.

6. ***Demographic-Based Recommendation*** - Demographic-based recommendation systems recommend items to users based on demographic information such as age, gender, location, and occupation. These systems can tailor recommendations to specific user segments or demographics, enhancing the personalization of the recommendation process.

2.5 What are some machine learning algorithms used in recommendation systems?

1. **Collaborative Filtering Algorithms:**

    (Wikipedia, 2024)
    1.1. K-Nearest Neighbours (KNN): This algorithm finds users or items that are most similar to the target user or item and recommends items or users that those similar entities have liked or interacted with.

    The usage of kNN is understandable in this case. This is because the fact that it is an algorithm that is used for the purposes of classification, but in this case, it would be used not on a certain features of the items only, but the users as well, while seeing how well does it go into the

    (Kacaman, 2022)
    1.2. Matrix Factorization: Techniques like Singular Value Decomposition (SVD) and Alternating Least Squares (ALS) are used to decompose the user-item interaction matrix into lower-dimensional matrices. These decompositions can then be used to predict missing ratings or to recommend items.

    This way it is even easier to visualize the difference between the different ratings of the user and the item. By doing so we can have a better understanding of what is up to their interests and what did they previously enjoy.

2. **Content-Based Filtering Algorithms**

    (Turing, 2024)

    2.1. Cosine Similarity: This algorithm measures the cosine of the angle between two vectors to determine how similar they are. In the context of recommendation systems, it can be used to compare the content of items to a user's profile to recommend similar items.

    Not only that but it can be useful when it comes to comparing not only the features of a user to an item, but items to other items in general. This way, it can be more suitable for a content-based recommendation systems, since the items will be the ones which are similar to one another, not only to the user. The more features that are similar – the better.

2.2. TF-IDF (Term Frequency-Inverse Document Frequency): This technique is used to reflect how important a word is to a document in a collection or corpus. It can be used to represent items in a way that highlights their most notable features, which can then be used to recommend similar items.

It can be used to not only look into the features of a game as in the columns, but we could dive deeper into the 'description' that a certain game has been given. This way it can look not only for the characteristics of the product, but also the keywords that are associated with it.

3. Hybrid Algorithms

Hybrid Recommender Systems: These systems combine collaborative filtering and content-based filtering to leverage the strengths of both approaches. They can provide more accurate recommendations by considering both the similarity between users and the similarity between items. Not only that but they do deal well with the other problem that can occur when it comes to for example the collaborative filtering – the 'Cold Start'. This is the problem happens at the beginning. Because of the lack of knowledge that an algorithm has about you it will recommend you things that are not that close to you liking, but by creating a hybrid model, it does eliminate this problem.

4. Deep Learning Algorithms

4.1. Neural Networks: Deep learning-based recommendation systems, such as those using Convolutional Neural Networks (CNNs) for image-based recommendations or Recurrent Neural Networks (RNNs) for sequence-based recommendations, have shown great promise in capturing complex patterns in data.

4.2. Autoencoders: These are used for dimensionality reduction and can be particularly effective in recommendation systems where the data is high-dimensional. They can learn to represent items in a lower-dimensional space, making it easier to identify similarities.

5. Ensemble Methods

Ensemble Recommendation Systems: These systems combine predictions from multiple recommendation algorithms to improve the overall recommendation quality. Techniques like bagging and boosting can be used to combine the strengths of different algorithms.

6. Graph-Based Algorithms

Graph Neural Networks (GNNs): These are used in recommendation systems to model the relationships between users and items as a graph. GNNs can capture the complex relationships between entities, making them suitable for recommendation tasks.

2.6 What about pros and cons, limitations, and possible ethical problems?

2.6.1 Advantages:

[(Holewa, 2023)](#)

1. Revenue Boost - One of the critical benefits of recommendation systems is their potential to drive revenue growth using data filtering tools. You can increase cross-selling and upselling opportunities by presenting personalized and relevant recommendations. That is why customers are more likely to discover and purchase additional products or services that align with their interests, leading to increased sales and revenue generation.

2. Enhanced Customer Satisfaction - Recommender systems can elevate customer satisfaction levels, leading to increased customer retention. Recommendations that resonate with a particular user's preferences may change their perception of the platform as attentive and responsive to their needs. This, in turn, may result in heightened satisfaction and a positive overall user experience.

3. Personalisation at Scale - Recommendation systems excel at delivering personalised experiences. That is because the recommendation engine processes data to create individual profiles and offer tailored recommendations to each customer. This level of personalisation increases the likelihood of conversions because customers may appreciate the platform's ability to curate products specifically for them.

4. Controlled Retailing - Controlled retailing enables you to showcase new or underexposed items, manage inventory, and drive sales in trending directions. You can influence purchasing behaviour and promote specific offerings by strategically guiding customers towards particular products or services.

   Overall the advantages of recommendation systems come in the form of their convenience for the businesses to be able to sell out their stock, while also providing the user with similar items that they would like to buy. It might not even be a physical item, but also a service.

Sometimes a recommendation is even the new post that we see in our feed on the different social media platforms that we use, while we do not even realise that it is happening.

(Macmanus, 2009)

1. Lack of Data - The biggest issue facing recommender systems is that they need a lot of data to effectively make recommendations. It is no coincidence that the companies most identified with having excellent recommendations are those with a lot of consumer user data: Google, Amazon, Netflix, Last.fm. The more item and user data a recommender system must work with, the stronger the chances of getting good recommendations. But it can be a chicken and egg problem – to get good recommendations, you need a lot of users, so you can get a lot of data for the recommendations.

2. Changing Data - Recommendation systems face challenges in adapting to changing data, particularly in industries like fashion where trends evolve rapidly. As highlighted by Paul Edmunds and David Reinke, relying solely on past behaviour or algorithmic approaches may not suffice due to the dynamic nature of preferences and attributes. Social recommenders offer a promising avenue for addressing these complexities, emphasizing the need for adaptive and context-aware recommendation strategies.

3. Changing User Preferences - Paul Edmunds highlights the challenge of changing user preferences in recommendation systems, where browsing intentions can vary from day to day. For instance, a user might search for personal items one day and look for gifts the next. These issues underscore the importance of dynamic recommendation algorithms that adapt to evolving user preferences.

4. Unpredictable Items – "In our post on the Netflix Prize, about the $1 Million prize offered by Netflix for a third party to deliver a collaborative filtering algorithm that will improve Netflix's own recommendations algorithm by 10%, we noted that there was an issue with eccentric movies. The type of movie that people either love or hate, such as Napoleon Dynamite. These types of items are difficult to make recommendations on, because the user reaction to them tends to be diverse and unpredictable."

(Azati, 2022)

5. Information variability - Recommendation engines rely on historical or current data, which can become outdated quickly, especially in rapidly changing industries like media, online gaming, and marketing. This reliance on "old data" can result in less relevant or even irrelevant suggestions. One solution is to continuously retrain the neural network with fresh data after each period, ensuring recommendations stay up-to-date and accurate.

Overall recommendation system do operate mainly on data, but sometimes if some if it is not there or changing rapidly – the algorithms do seem to start missing the whole point and cannot keep up with what the user is actually interested in, which is after all the whole point

of the system. So it is quite possible that the algorithm may start lacking which is fixable with time, but with the ever so changing nature of the human, it would be quite difficult to do so.

2.6.3 Ethical Problems:

- After reviewing some of the problems previously mentioned, we can see that data plays a crucial role in the creation of a recommendation systems and how it functions. While gathering all of the data it is possible that because of the "slow start", we are given products or services which are not to our liking and not only that, but it is highly possible that because of data that is not clean, a bias develops.

- While talking about data, it is also important to mention some of the privacy concerns:

"The more the algorithm knows about the customer, the more accurate its recommendations will be. However, many customers are hesitant to hand over personal information, especially given several high-profile cases of customer data leaks in recent years. However, without this customer data, the recommendation engine cannot function effectively. Therefore, building trust between the business and customers is key.

Many businesses are thriving thanks to recommendation engines. While they do bring enormous opportunities, it is vital to be aware of the many challenges inherent to the technology in order to utilize it to the fullest. We would not recommend anything less." (7 Critical Challenges of Recommendation Engines)

- Sometimes another problem is that the human factor of creativity and change of interest can occur, but the system could not recognise such changes or it finds it difficult to adapt to them. This will make the algorithm irrelevant or it might the possibility of a user to "broaden their horizon". (7 Critical Challenges of Recommendation Engines)

But let us be honest, if it is created by someone, there is a reason for it. Who uses recommendations systems nowadays and who has the most accurate ones – big companies like Netflix, Amazon, Spotify or even Bol. They make large investments into these algorithms so that the users find the most suitable product, but why do they do so – profits, after all, everybody is interested it. The problem comes a bit from the fact that the companies likely do not experience any kind of concern for the user as a person, but more so as a consumer. This does impact the way they work, since most of the time they are not as interested in the wellbeing of their customers, but more so to keep you hooked in to continue using their products and what does that do to the person – many things but let's say that they forget one thing which is very important – the responsibilities and the health of the person who uses them

2.7 Who is most affected by the usage and creation of recommendations systems?

Users

Users are the primary beneficiaries of recommendation systems. They receive personalized recommendations that help them discover new products, content, or services that match their preferences and interests. By receiving relevant suggestions, users can save time, make informed decisions, and enhance their overall experience on platforms such as e-commerce websites, streaming services, social media platforms, and more.

Businesses

Businesses that implement recommendation systems benefit from increased user engagement, retention, and conversion rates. By providing personalized recommendations, businesses can improve customer satisfaction, loyalty, and revenue generation. Recommendation systems also enable businesses to gather valuable insights into user behaviour and preferences, which can inform marketing strategies, product development, and inventory management.

Advertisers

Advertisers benefit from recommendation systems through targeted advertising opportunities. By analysing user data and preferences, recommendation systems can deliver personalized ads to users who are more likely to be interested in the advertised products or services. This targeted approach can improve ad relevance, click-through rates, and return on investment for advertisers.

At first it does seem kind of random from where we might have gotten the information from, but this is because we needed to ask a more… "core" question to begin with. And this is the one:

2.8 Where are recommendation systems used?

There are many different platforms and places where the recommendation systems are used for a variety of purposes, having a large affect the market. They are used in the online sphere to help customers find things that are of similar interest to the things they like.

For a change of pace, how about we ask a GPT like bot as well:

(Royzen and Wei, n.d.)

2.8.1 Phind's Answer

E-commerce and Retail

- Online Shopping Platforms: Amazon, eBay, and Alibaba use recommendation systems to suggest products based on a user's browsing history, past purchases, and the purchases of similar users.
- Clothing and Fashion Retailers: Stores like ASOS, Zara, and Nordstrom use recommendation systems to personalize clothing and accessory suggestions for their customers.
- Electronics Retailers: Companies like Best Buy and Newegg recommend products based on customer reviews, product specifications, and customer purchase history.

Streaming Services

- Music Streaming Platforms: Services like Spotify, Apple Music, and Pandora use recommendation systems to suggest songs, playlists, and artists based on a user's listening history and preferences.
- Video Streaming Platforms: Netflix, Hulu, and Disney+ recommend movies, TV shows, and series based on a user's viewing history, ratings, and the viewing habits of similar users.

Social Media

- Facebook and Instagram: These platforms use recommendation systems to suggest friends, groups, and content that a user might find interesting based on their interactions and the interactions of similar users.
- LinkedIn: Recommends job postings, companies, and networking opportunities based on a user's professional background, skills, and interests.

Online Advertising

- Google Ads: Google uses recommendation systems to suggest ads to users based on their search history, website visits, and the content of the websites they visit.
- Amazon Advertising: Amazon uses recommendation systems to suggest products to advertisers based on the products that similar users have viewed or purchased.

Travel and Hospitality

- Airbnb: Recommends accommodations based on a user's search history, past bookings, and the preferences of similar users.
- Booking.com: Suggests hotels, flights, and car rentals based on a user's search history, past bookings, and the preferences of similar users.

News Aggregators

- Google News: Recommends news articles based on a user's reading history and the reading habits of similar users.
- Reddit: Recommends subreddits and content based on a user's browsing history and the browsing habits of similar users.

Education and Learning Platforms

- Coursera, Udemy, and Khan Academy: Recommend courses, tutorials, and learning paths based on a user's past enrolments, ratings, and the enrolments of similar users.

Healthcare and Wellness

- Fitbit and MyFitnessPal: Recommend workout plans, diet plans, and health tips based on a user's activity data, dietary habits, and the habits of similar users.

Although asking a Chatbot is quite possible to give us a bias answer, this does give us many examples of where and how the recommendation systems are used. However, since it is possible that the information may be subjective it would be a good idea to see some other sources and see if any of these statements are supported elsewhere.

We do see however see other sources that do align with what we were given:

2.8.2 Support for "The statement of 'Phind'" A
[(Michael, 2024)](Michael, 2024)

"Recommendation systems have a wide range of use cases across several industries, including:

eCommerce: Recommendation systems are widely used in eCommerce to provide personalized product recommendations to customers based on their past behaviours and preferences. Learn more about recommendation systems in eCommerce (coming soon)

Entertainment: Recommendation systems are used in entertainment, such as music and video streaming services, to recommend content that is likely to be of interest to users.

News and media: Recommendation systems are used in news and media platforms to recommend articles, videos, and other content that is relevant to a user's interests.

Social media: Recommendation systems are used in social media to recommend friends, groups, or posts that are likely to be of interest to users.

Healthcare: Recommendation systems are used in healthcare to provide personalized recommendations for treatments, medications, and other healthcare services.

Finance: Recommendation systems are used in finance to provide personalized recommendations for investments, credit products, and other financial services.

Advertising: Recommendation systems are used in advertising to provide personalized recommendations for ads and offers that are likely to be of interest to users.

E**ducation:** Recommendation systems are used in education to provide personalized recommendations for courses, programs, and other educational content."

"What are the use Cases and applications of recommendation system.

E-Commerce

A recommendation system is very helpful for E-Commerce platforms, it helps provide relevant suggestions to users based on their previous purchases. Recommendation systems help provide personalized offers, product recommendations and recommendations for users with similar tastes.

Entertainment

Recommendation Models can analyse and understand consumer behaviour to detect patterns that can help provide content suggestions to the users. This way a recommendation system is very likely to provide suggestions that will match the user's needs.

This is what Netflix does, by analysing the user's tastes and preferences it helps come up with more recommendations for the user.

Social Media

Social media platforms that have been growing rapidly with millions of active users also use recommendation systems. Social media platforms use recommendation systems to understand the user's interests, and analyse their data, to suggest other users with similar interests.

Travel & hospitality

Recommendation systems are also used to enhance the travel and hospitality platform. It provides the users with personalized travel options and hotel recommendations. Along with that it also helps provide destination suggestions, travel packages and itineraries".

As we can see, from the small examination of the given spheres of interests in the world, we can comfortably say that recommendation systems are big factor in the way that businesses expand and also the users are experiencing used to seeing them everywhere – no matter is if it is a digital or an actual holdable product.

2.9 Stakeholder Involvement.

When it comes to the creation of such a system we all need a stakeholder – an expert is a great choice since it also provides a person who can give you some guidance as well as be able to tell you more about what are some of the limitations of a system and things to pay attention to, however, it can also be just a random person from class or a good friend of yours who is interested in the topic. In my case it is the last one.

For this manner I have contacted an old friend of mine who is interested in the subject of AI as well as its creation and the ways in which it can be used – Svetlomir Ivanov. Not only that but he is surrounded by it due to the fact that he is currently undergoing his internship.

The following is a transcript of an interview that we conducted on the topic withing the start of the semester, discussing AI, the ways that he uses them, what is his opinion on the topic and how we discussed the idea of a video games recommendation system.

The interview:

Mihail Kenarov:

First off, good afternoon, and second, do you mind if I record this conversation?

Svetlomir Ivanov:

Hello, good afternoon. No, no, I don't mind.

Mihail Kenarov:

Okay, so, do you mind introducing yourself?

Svetlomir Ivanov:

Hello, my name is Svetlomir Ivanov, and I currently live in Breda. I study in Avans university of applied sciences, and my major is international business. Also, I am doing an internship in the port of Rotterdam, and in a company that is called 'PortXL'. (PortXL, n.d.)

Mihail Kenarov:

So, considering that we are currently in the 21st century and I have the opportunity talk with you on this topic, do you mind if we discuss more about AI? Are you similar with AI in the current day and age, and is it part of your day-to-day life?

**Svetlomir Ivanov:**

Yeah, I've seen a lot of things about AI, and I think that it is both fascinating and a little bit scary, and I think that it can be used both in a good and a bad way, and it really depends on the people using it. I see a lot of good applications in my work, because what we do is we search for innovative companies in the maritime industry that have AI, implemented in their technologies. Most of the time I see people using AI for good things and as a way to improve their system. The bad side that I've seen is from the media platforms, like TikTok or Instagram, where people use AI to manipulate information, as we know with deepfakes, which is bad because it can have a negative effect on society as well as the whole, in my opinion. And when it comes to the question, 'Do I use it in my daily, in my day-to-day life?' - Yes, I do, and I mainly use it as a way to summarize information, to understand a topic that I'm not familiar with, or to get inspiration, ideas or brainstorm about a certain task that I've been given. And I believe that if it is 'right', you can have a big impact with it.

**Mihail Kenarov:**

Alright, so is there a way that you would like to use AI in your free time that you have currently not used it, or you want to be more familiarized with?

**Svetlomir Ivanov:**

Yeah, yeah. For example... In my free time, when I get off work and I come home, I play games, but for some time now, I've been playing the same games, and it's getting a little bit boring, and I would like to explore new fields of gaming, so I can, for example, experience something new and find out some new concepts, but I don't have the time to search for such games, so yeah, I've been just playing the same old stuff.

**Mihail Kenarov:**

Would you say that you're satisfied with what you're given on the mainstream platforms or would you say that they're a little bit 'too personalized' or 'too mainstream'?

**Svetlomir Ivanov:**

Yeah, I think that they're pretty mainstream because the games they get recommended usually are similar to the games they play but in a big way they're not really, they don't have that key element in common, if I can say it like this.

Mihail Kenarov:

So would you like to have a recommendation system that's a little bit on the content -based side where there is a room for let's call it diversity, because of the lack of specialization?

Svetlomir Ivanov:

Yeah, that would be perfect in my case. If it's not so personalized because most of the gaming services they use, they usually strive to provide recommendations that are more personal.

Mihail Kenarov:

You would like it a little bit more abstract, I take it.

Svetlomir Ivanov:

Yeah, now that you think of it, that might be ideal in my case.

Mihail Kenarov:

Okay, and is there a specific thing that you would like to be shown, for example, a picture of the game, the descriptions or something else?

Svetlomir Ivanov:

I've thought about this, but I think that it is enough for me to be able to see the title of the game. other games that I'm being suggested and then in turn I would do my research myself. So no, I wouldn't want a picture. The title as text is sufficient.

Mihail Kenarov:

Okay, so you would say that you're pretty much satisfied if you're able to receive a content -based recommendation system that will allow you to see like top three, top five or top ten games? How many games would you like?

Svetlomir Ivanov:

Yeah, I would like it if the output provides a couple of diverse options and I think five games would be ideal for me.

Mihail Kenarov:

Okay, so let's take that into conclusion I would say and let's say five games with the title, and then whatever more information you would need to do, you would like to do it yourself?

Svetlomir Ivanov:

Yeah, that's right, exactly.

Mihail Kenarov:

Okay so thank you very much for your time and i hope that the product that i will show you will satisfy these requirements.
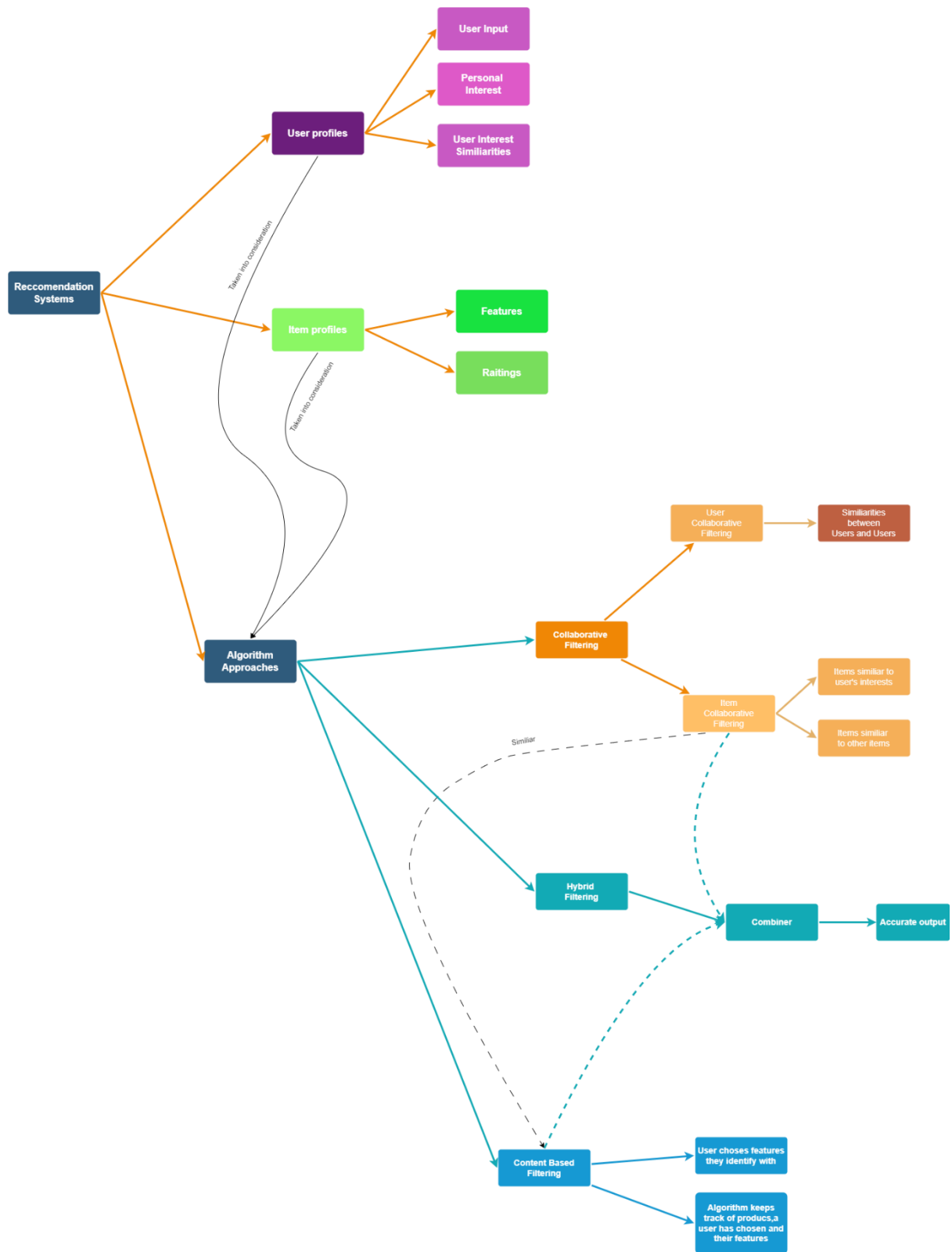
Svetlomir Ivanov:

Thanks for having me and i wish you good luck with delivering of the system

Mihail Kenarov:

Thank you very much. Goodbye!

Svetlomir Ivanov:

Goodbye!

3. Data Sourcing

3.1 Objective

Considering that the mission of the project is to create a recommendation system, which will give us some video games, we will need a dataset that has some. It would be great if the dataset is vast with a mix of older games and newer ones.

3.2 Data Requirements

We need the dataset to contain a lot of data about the games such as the name, genres, ratings possibly and descriptions. Not only that but it would be good to not exclude older games for the people, who do find them interesting. As of now, it will be good to have these:

   Text Data: Name, Genres, Description

   Numerical Data: Ratings

3.3 Data Sources

Publicly available dataset:
https://www.kaggle.com/datasets/gsimonx37/backloggd/data?select=games.csv

Actual source of the dataset:
https://www.backloggd.com/

"*Backloggd*" is like a personal game shelf online. It gives you a place where you can log all your games, from any system. It also give us the opportunity to compare certain games with your friends and see what they are playing. It helps you keep track of what you're playing now and what you want to play next. Think "Goodreads" for books or "Letterboxd" for movies, but for games.

3.4 Data Legality and Ethics

The data that is offered on Kaggle is mentioned to be obtained using a program on Backloggd.

When it comes to the data that is offered on the actual site of "Backloggd", It does seem to be some general characteristics about the games that have been published in previous years. They give us a the name of the game, a small description of it, the platforms where it is possible to be played on and also the genres, which are some good indicators. We are also shown a certain ratings on the site for the games.

1. Games Dataset - basic data:

    id - video game identifier (primary key)

    name - name of the video game.

    date - release date of the video game.

    rating - average rating of the video game.

    reviews - number of reviews.

    plays - total number of players.

    playing - number of players currently.

    backlogs - the number of additions of a video game to the backlog.

    wishlists - the number of times a video game has been added to "favourites".

    description - description of the video game.

2.Developers dataset - developers (publishers):

    id - video game identifier (foreign key)

    developer - developer (publisher) of a video game.

3.Platforms dataset - gaming platforms:

    id - video game identifier (foreign key)

    platform - gaming platform.

4.Genre's dataset - game genres:

    id - video game identifier (foreign key).

    genre - video game genre.

5. Scores dataset - user ratings:

    id - video game identifier (foreign key).

    score - score (from 0.5 to 5 in increments of 0.5).

    amount - number of users that gave this score.

3.6 Version Control

A history of the project and the processing of the data will be kept on a Git repository in case of an incident and as a way for a version control.

The link to the git repository:

- https://git.fhict.nl/I509460/video-game-reommendation.git

3.7 Iterative Process

The model will be check for its performance after the iterations. Depending on the results, if they are found are satisfactory or not, changes will be made either to the model or the preparation of the data.

4.Analytic Approach

The target is to give the user the titles of multiple games which can interest them for them to buy. This will be done by finding similar games to the one they have selected and based on the features of the game, find other ones that will be similar to it.

The model that is currently selected are is the TF*IDF model. With it we are able to find out the amount of times a certain word has been mentioned withing the selected from us feature – the description. By doing this, we are able to find precisely which games are connected to each other by the words they are associated with. For example we can use the batman series – if a game is connected to the franchise via the main character, we are shown the other games that are connected to it and can enjoy them.

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