Informatics Institute of Technology

In Collaboration With

University of Westminster, UK

University of Westminster, Coat of Arms

Trading Recommendations System for Non-fungible Tokens

A dissertation by

Mr. Dinuka Ravijaya Piyadigama

w1742104 / 2018373

Supervised by

Mr. Guhanathan Poravi

May 2022

Submitted in partial fulfilment of the requirements for

the BSc (Hons) Computer Science degree at

the University of Westminster.

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

ACRONYMS

AI Artificial Intelligence.
API Application Programming Interface.

ERC Ethereum Request for Comments.

LSTM Long short-term memory.

MAE Mean Absolute Error.
ML Machine Learning.
MLP Multilayer Perceptron.
MSE Mean Squared Error.

NFT Non-fungible Token.
NLP Natural Language Processing.

P@K Precision at K.

RMSE Root Mean Square Error.
RNN Recurrent Neural Network.

CHAPTER 1: INTRODUCTION

CHAPTER 2: LITERATURE REVIEW

2.1 Chapter Overview

As mentioned in the introduction chapter, Non-fungible Token (NFT)s have been a very popular application of Blockchain in the recent months. In this chapter, the author critiques on related work with respect to the application of Recommendation Systems while further exploring what, why & how NFTs have been making the headlines and pulling in investors from around the globe. Furthermore, the author has brought-forward possible improvements that may open up possibilities of providing expected recommendations in the NFT-space.

2.2 Concept Map

After conducting a literature survey across a wider-scope, the scope to be covered in this literature review was broken down in a concept graph. The concept graph was created to ensure that all required literuture to be covered would be identified under the areas of problem domain, existing work, technologies, evaluation approaches as well as limitations in each of these sections. The graph can be found in **Appendix A - Concept Graph**.

2.3 Problem Domain

Blockchain has been one of the highest sought after fields in the current day and age. NFTs have made the biggest buzz after cryptocurrencies out of the applications of Blockchain technology. With more and more people expected to enter connected digital environments such as the meta-verse (Casey Newton, 2021), it is clear that NFTs will play a huge role in tomorrow's internet (Peter Allen Clark, 2021) due to it's ability to make digital items have scarcity, uniqueness, and proof of ownership, similar to physical items (*Non-fungible tokens (NFT)* 2021).

2.3.1 ERC Standards

There're many Ethereum Request for Comments (ERC) standards that have been brought forward by the Etheruem (Wood, 2014) development community that are meant to help maintaining standard in smart contracts that are created on the Blockchain with the desired functionalities.

The ERC-721 standard, which is the first standard that introduced NFTs; implements functionalities to transfer tokens from Blockchain accounts, to get the current token balance of an account, to get the owner of a specific token, the total supply of tokens available on the network, etc. Apart from the item itself, the creator can include metadata such as their signature in the NFT. What began on the Ethereum Blockchain with the ERC-721 standard has since been adopted by other Blockchains.

Some of the notable ERC standards that can be identified related to the domain of this research can be compared as below.

Table 2.1: Comparison of ERC standards

Standard	ERC-721	ERC-777	ERC-1155	ERC-20
Name	Non-fungible tokens	Non-fungible tokens (Dafflon, Jordi Baylina, and Thomas Shababi, 2017)	Semi-fungible, Non-fungible fungible tokens	Fungible tokens
Description	Each token is completely unique	A richer standard for fungible tokens, enabling new use cases and building on past learnings. Backwards compatible with ERC20.	Tokens begin trading as fungible tokens, then may end up being non-fungible in the long run	All coins of one kind are equivalent and hold the same value
Examples	CryptoKitties (CryptoKitties, 2021)		Concert tickets, gift vouchers, coupons	Cryptocurrencies - Bitcoin, ETH

This research focuses on the ERC-721 and ERC-1155 (Prathap, 2021) standards.

2.3.2 Benefits of NFTs for creators, collectors & buyers

NFTs have a feature to allow a creator to make a certain percentage as royalty whenever the NFT is transferred to a new buyer. Since the items can be verified on the Blockchain, it also ensures that the original creator of the NFT can be tracked down and given due credit, any date in the future, no matter how many wallets it gets passed through (Chevet, 2018). Apart from the fact that a buyer can claim the right of ownership of the original item, they also get to financially support the creator. Ultimately, NFTs may gain value over time due to their scarcity. This gives collectors an additional advantage of being able to sell it for a higher price later on.

Creators of NFTs can also create "shares" for their NFT. This allows investors and fans to own a portion of an NFT without having to purchase the entire thing (*ERC-721 Non-Fungible Token Standard* 2021).

2.3.3 Recent news trends & sales related to NFTs

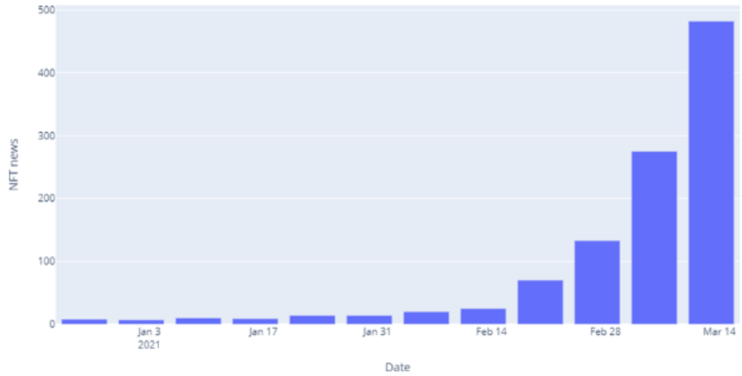

Figure 2.1: News trends in 2021 related to NFTs (Dowling, 2021a)

The above figure shows the increase in news trends related to NFTs since the start of 2021. It has been exponentially increasing and hitting headlines around the globe on a daily basis.

There is almost no brand in the world right now that hasn't either introduced NFTs into their marketing efforts or are working on doing so. *Nike's CryptoKicks* (Beedham, 2019) is one such example.

Two factors can be depicted by this. One; is that NFTs are gaining more and more public attraction and acceptance. The second is that since there's a huge buzz among the public on social media and numerous web-sites, it makes sense to consider the opinions that are shared online by them.

2.3.4 Value-driving factors in NFTs

When considering ownership desire of NFTs, it is understood that the increase in price of an NFT has the possibility of being a factor to be considered when making a purchase.

> *"The value of an NFT is entirely determined by what someone else is willing to pay for it."*
>
> (Conti, 2021)

The value of an NFT has been identified to be heavily reliant on the public's acceptance of the item. Demand is expected to drive price rather than technical, or economic indicators which are the usual factors that affect stock prices and investor demand.

> *"Ultimately owning the real thing is as valuable as the market makes it. The more a piece of content is screen-grabbed, shared, and generally used the more value it gains. Owning the verifiable real thing will always have more value than not."*
> (*ERC-721 Non-Fungible Token Standard* 2021)

In addition to gaining value, due to the "non-fungible" nature of the item, it cannot be replicated. Similar to a Mona Lisa painting, popularity helps improve the value of the original and only the original is identified as the truly original painting with immense value, even though anyone can Google and get a copy of the painting.

2.3.5 NFT Market places & what they offer

The money pumped into NFTs & the most popular NFT market, ***OpenSea*** has exponentially increased in 2021 (Matney, 2021). Similar to OpenSea, there're many other NFT market places such as *Foundation, Rarible, Nifty Gateway, Litemint etc*. Some of them built on the Ethereum Blockchain, while some others built on Blockchains such as *Solana (community, 2021; Staff, 2021), Stellar (Fred Rezeau et al., 2021), etc*.

2.3.6 Data mining NFTs

One recent study done on data mining and visualizing has made use of the OpenSea Assets & Events APIs using Python & Pandas to collect, visualize & analyse NFT data on Meebits (Larva Labs, 2021) NFT sales (Adil Moujahid, 2021). The author of this thesis expects to expand on analyzing features beyond those that have been extracted in the data mining and Analysis done on Meebits NFT sales.

2.3.7 Blockchain & AI

Artificial Intelligence (AI) & Blockchain are bound to be extremely important technologies for businesses moving forward. There're already many applications that bring these two technologies together (Gwyneth Iredale, 2021).

The very first study done examining the pricing of NFTs suggests that *"prospects for future studies are potentially limitless, as at the beginning of any new market"* (Dowling, 2021a). As a future study, the author has suggested identifying if there's a fundamental model that drives the price determination in NFTs. Since NFTs are originating from Blockchain; which is a technology that comes from the field of Computer Science, it's important to understand the factors that affect the pricing and market created by them.

Why create a Recommendations System for NFTs?

In 2018 it was estimated that 35% of Amazon's revenue Naumov et al., 2019 is driven by Recommendation Systems. 75% of Netlfix viewer activity Vanderbilt, 2021 was also said to come from recommendations back in 2013. Therefore, it is clear that the use of a recommendation system that is catered toward the needs of potential NFT owners will help increase sales of NFTs, driving forward the adoption of this technology.

2.3.8 Proposed architecture of a Recommendations System for NFTs

By the requirements identified to purchase & own NFTs, the author has proposes the following architecture to be followed in order to achieve the aim stated to be achieved in this research.

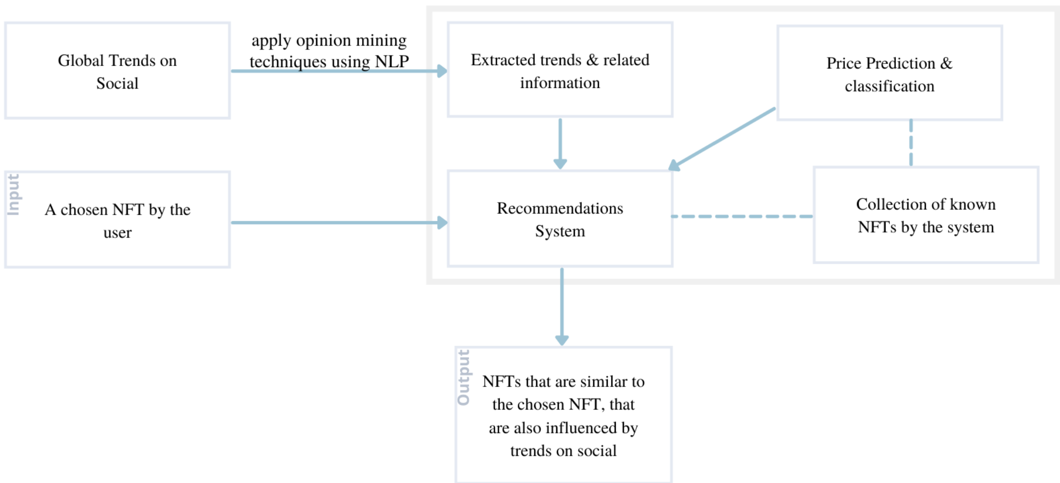

Figure 2.2: Proposed architecture of a Recommendations System for NFTs *(self-composed)*

As shown in figure 2.2, the proposed architecture is expected to make use of global trends extracted using social Application Programming Interface (API)s. These can be from Twitter, Reddit, Google Trends or any other source that the user wishes to use. Once extracting relevant information using Natural Language Processing (NLP), the Recommendation System can then use this information to predict items that are relevant to the chosen item by the user and also those that have a possibility of getting influenced by trends on social.

2.4 Existing Work

2.4.1 NFT Recommendations Systems

There is only one study previously done with related to recommending NFTs and that study also comes in the form of a blog article on *OpenSea* (*What are you missing? Using basic machine* *learning to predict and recommend NFTs with OpenSea data - OpenSea Blog* 2020). The article considers the use of a basic Machine Learning (ML) technique called **Multiple Regression** with data gathered from OpenSea.

This takes into account previous purchase patterns and NFTs held in wallets to predict whether another wallet carrying a similar combination is likely to own an NFT from a certain category in the future. The categories considered here are mostly collections created by specific well-known creators. Cryptokitties and ENS domains are a couple of examples for collections that have been taken into consideration.

As a final recommendation, this system is capable of presenting NFT categories. Since users can't purchase an entire category, they will have to go back to the process of picking which NFT to purchase in the recommended collection.

This doesn't take into consideration of current global trends and it will not take into account the creators' recognition. An NFT minted by Beeple or a major league like NBA are bound to capture more attention of buyers compared to an NFT minted by a person who hasn't gained any reputation in this space. The major concern with regarding this system is that the user must either enter his preferences manually or provide his wallet key, which holds all of his owned assets, in order to get a recommendation from the system. Although, getting a users' public key can by no means cause any threat of loosing the NFTs, it can be lead to lack of privacy, which is a tradition that the people into crypto-related assets have a tendancy to be concerned about.

> *"Crypto has a founding tradition of emphasizing freedom and privacy. Maybe because of this prevailing cultural trend, the NFT space does not have many recommender systems."*
> (*What are you missing? Using basic machine learning to predict and recommend NFTs with OpenSea data - OpenSea Blog* 2020)

As mentioned in the same blog post, this tradition is also been identified as a reason to why we have not yet seen much development related to Recommendation Systems in this space. Another reason could be because of the very recent spark in interest this domain has seen in recent times, as mentioned in the Problem Domain.

2.4.2 Crypto recommendations

Since NFTs have a distant relationship with crypto assets, it is expected to be of help to understand how crypto assets are evaluated when opted for selection to comprehend how NFT assets could be evaluated. A study done related to a modelling framework that exposes this area of research (Bartolucci and Kirilenko, 2020) assumes that two main features, namely security and stability can be used to determine the user-desire to own a specific crypto asset.

Investor's attitudes towards assets' features, information about the adoption trends, and expected future economic benefits of adoption have been simulated in order to predict the features of the assets that will most likely be adopted. The preference of investors are collected from an app, which calculates the overall state of the 'market'. Then, the app recommends to the user which crypto assets proposed by the user would be a sensible investment. Information about the adoption choice of other investors is considered when making this recommendation.

The number of assets, investors and assets' features and investor preferences were fixed within the period of analysis. In a normal use-case scenario, it's highly likely that all these would fluctuate and evolve with the asset's adoption probabilities and expected returns. This revelation clarifies the fact that crypto related assets have a tendency to change with time, social acceptance and trends. Therefore, it is important to consider these factors when building a crypto-related Recommendations System.

2.4.3 Opinion mining & sentiment extraction based Recommendation Systems

"Catching opinions from social media could be a cheap, fast and effective way to collect feedbacks from users"

(Zhang, Xu, and Jiang, 2018)

When the above fact is looked at in a more generalized form, it is clear that exploiting user trends that build-up of opinions from social media can lead to better quality recommendations, while (Hu et al., 2020) expresses how sentiment analysis of user reviews can be used to point in the direction of personalized recommendations.

A **hybrid Recommendations System** (Cheng and Lin, 2020) which utilizes **opinion & sentiment extraction techniques from user reviews** to create preference profiles for movie recommendations, to enhance the quality of recommendations regardless of the rich or sparse nature of the dataset has been identified as one of the recent researches done towards pushing the limits of baseline recommendation models. The framework that has been designed here uses Collaborative Filtering as the base Recommendations model. The contribution of this research is applicable to the feature engineering stage of the system.

Sentiment analysis is applied on user-reviews to detect user-opinions about movies that were watched and reviewed by users. This data is used to create a user's preference profile, similar to what's created in Content-based filtering. The user's sentiment is identified as a step beyond traditional preference ratings.

Due to its capability of dealing with insufficient data, the framework is able to produce recommendations that are more accurate and efficient than existing baseline methods. This proves that using public opinion in the feature engineering stage can enhance the quality of recommendations.

Due to the fact that the semantic strategy of opinion extraction being generic, it is understood that it may not be ideal to identify different aspects in varied genres. Examples mentioned are, quality of sound may be of greater interest in action movies, while the story-line in dramas. Slang, irony & sarcasm haven't been taken into consideration when extracting user opinion. A major limitation identified in most systems that rely on similar opinion mining systems is that they are very dependant on the text mining technique used. Another identified drawback in this research by the author is that, to establish a preference profile, a person must have posted reviews on previous movies. If not, those users won't be able to get recommendations. This can be identified as a concern in systems that are dealing with user's who care about their privacy.

A **Deep Belief Network and Sentiment Analysis (DBNSA)** has been introduced to achieve data learning for recommendations (Chen and Hendry, 2019) to enhance recommendations produced by baseline-recommendation techniques. This deep learning model processes user comments to generate a possible user rating for user recommendations.

"Users usually transmit their decisions together with emotions."

(ibid.)

This research paper emphasizes the necessity of using user comments for recommendation systems since these comments contain a variety of emotional information that can influence the correctness and precision of recommendations.

Once applying sentiment analysis, a feature vector is created for the input nodes. A noise reduction procedure has been integrated into the system that deletes short comments, comments with no expression and false rating comments. This is used to improve the classification of user ratings. Finally, the DBNSA accomplishes data learning for the recommendations.

The paper published claims to outperform baseline models in training loss, precision and recall when tested on Yelp & Amazon datasets. When tested on the Trip-Advisor dataset, DBNSA had the best Mean Squared Error (MSE) training loss value & recall. The research also mentions that DBNSA saves more time, while producing results with better accuracy compared to other baseline models.

The main drawback that this paper points out is that the proposed system is not suitable & ready for real-time testing. The authors of the paper have also shown interest in testing the proposed method with a faster Deep Learning algorithm. Similar to the previously mentioned system, sarcastic user-comments have not been taken into consideration here as well. Out of the two recommendations models that were tested, *libSVM* was identified to have higher accuracy value, Mean Absolute Error (MAE) and F-score, while the Multilayer Perceptron (MLP) had the highest precision value.

Since user relationships and timeline comments also affect the user's decision making, these can be used to find information from relatable timelines to solve the cold start problem.

A **hybrid approach that combines techniques from content-based filtering, user-to-user collaborative filtering and personalize recommendations** (Ayushi and Prasad, 2018) has been introduced to address the limitation of single domain analysis. Data sparsity and cold start problem have been pointed out as the addressed limitations. Movie domain knowledge has been used to generate recommendations for books & music. After considering an array of supervised learning algorithms, the authors came to a conclusion that the Decision Tree classifier was found to give the highest accuracy.

The use of data from multiple domains allows the system to generate higher accuracy in suggestions. Twitter sentiment has been used to present the user with an analysis of the recommendations produced, to help users in their decision making process.

The drawback identified in the Recommendations System developed here is that Twitter sentiment is analysed, calculated and displayed only after showing the user recommendations.The author's suggestion is that only the items with positive sentiment could've been presented, at least results could've been bias towards positive sentiment.

2.4.4 Price prediction using social-media trends

As mentioned under the Problem Domain section of this literature review, it is understood that NFTs have very little spill-over with other Crypto assets. However, knowing Crypto price prediction models is important since Wavelet coherence analysis indicates a co-movement between these two markets (Dowling, 2021b). These models can be used separately on each NFT asset to anticipate the pricing with related to time, sales & bids. The author finds this research to be related to address the research gap in this thesis since an appropriate price prediction could be used to enhance NFT recommendations to users.

Past research suggests **a model which employs time series techniques, can predict the price for the next few days** by splitting the data into train and test runs (Ferdiansyah et al., 2019).

In terms of Root Mean Square Error (RMSE), the result is insufficient. The authors of this research have shown interest in testing out this method with modified Long short-term memory (LSTM) layers by adding dropout and modifying the number of epochs. Using different instability data-sets can also be tried out to test how good the prediction results could get. Furthermore, sentiment analysis is also proposed as future work to be combined with the LSTM method. This could be used to identify how public sentiment causes the value of crypto to adjust, with related to past price-fluctuations.

2.5 Technological Review

Recommendations Systems allow users to identify trending items among a community, while being timely and relevant to the user's expectations. When the purpose of various Recommendation Systems differ, the required type of recommendations also differ from each use case. While one Recommendation System may focus on recommending popular items, another may focus on recommending items that are comparable to the user's interests. Content based filtering, user-to-user & item-to-item Collaborative filtering and more recently; Deep Learning methods have been brought forward by the researches to achieve better quality recommendations.

Even though each of these methods have proven to perform well, there have been attempts to push the boundaries of their limitations. Following a wide range of methods, researches have tried to expand on the capabilities of standard recommendation systems in order to provide the most effective recommendations to users while being more profitable from a business's perspective. This has been achieved by taking a hybrid approach when building models and architectures for Recommendation Systems.

2.5.1 Machine Learning based recommendation techniques

There are several baseline techniques of Recommendations Systems that have been used by the biggest data-driven companies around the world. Among the many types of recommendation systems, **item-to-item Collaborative filtering** (G. Linden, B. Smith, and York, 2003) has been the most successful technique for an extended period of time (Brent Smith and Greg Linden, 2017), while user-to-user Collaborative filtering and Content based filtering have also had their own upsides. In order to take advantage of the relevant advantages of each method, Hybrid recommendation systems (Geetha et al., 2018) were introduced.

2.5.2 Deep Learning based recommendation techniques

In 2019, **Facebook** open-sourced a new categorical data-driven **Deep learning-based recommendation engine** (Naumov et al., 2019; *We are open-sourcing a state-of-the-art deep learning recommendation model to help AI researchers and the systems and hardware community develop new, more efficient ways to work with categorical data.* 2019). This recommendation model was developed from the two perspectives of recommendation systems and predictive analytics. It made use of embeddings, two MLPs, one sigmoid function (Freudenthaler, Schmidt-Thieme, and Rendle, 2011) and a parallelization scheme to support large-scales of data.

In recent research done by **Amazon** (Larry, 2019) it is understood that when a timeline is considered for recommendations, an ***Autoencoder*** **Deep Learning model** is capable of Recommending the best possible combination of movies to users.

2.5.3 Concerns about progress in Recommendation Systems

In several research & review papers, it has been brought to sight that Deep learning techniques in the area of recommendation systems have failed to live up to the expectations compared to the advancements in Computer Vision, Speech Recognition & Natural Language Processing domains (Choi et al., 2021). The results that have been published presenting advancements in the Recommendation Systems domain using Deep learning techniques have not been very convincing for the majority of use cases. Many standard Machine learning & regression techniques have been able to outperform systems created using Deep learning models in terms of recommendations. As highlighted in past reviews (Dacrema, Cremonesi, and Jannach, 2019) it is understood that Deep learning models have been used as baseline methods for evaluating new Deep learning models. Thus, when looking back at older Machine learning techniques, they haven't been making any improvement in many cases. As a result, many of the work related to Recommendation Systems using Deep learning techniques have been giving poorer recommendations, for higher computational power.

A study conducted in 2019 questioned if we are really making any progress with Deep Learning models in the domain of Recommendations (ibid.). In a more recent study researches tried to understand similarities and advantages of using **MLP (Multi Layer Perceptron)** versus **dot product** (Rendle et al., 2020). Similar to many Deep learning approaches, it was understood that MLP weren't necessary unless the dataset was too large or the embedding dimension was very small. A dot product was identified as a better choice since it was efficient to a satisfactory extent.

2.5.4 How to choose the ideal algorithm for a Recommendations System?

A general application of a Recommendation System will come in a business use case, where companies focus on maximizing profits for minimum expenses. In a scenario like that, it would make more sense to choose a cheaper model that gets the job done to a satisfactory level. Dot products offer a significant advantage over MLPs in terms of inference cost due to the availability of efficient maximum inner product search algorithms. Since MLPs are too costly to use in production environments, the better default choice in most cases would be the dot product approach that uses Machine Learning techniques with Matrix Factorization.

$$< x, y >= \sum_{i=1}^{d} x_i y_i \tag{2.1}$$

$$y = \varphi(\sum_{i=1}^{n} w_i x_i + b) = \varphi(w^T x + b) \tag{2.2}$$

where w denotes the vector of weights, x is the vector of inputs, b is the bias and phi is the non-linear activation function.

A variation that combines the MLP with a weighted dot product model, named ***neural matrix factorization (NeuMF)*** is also explored in this research. But, that too is deemed to be outperformed by the dot product method.

One of the major limitations identified related to dot product in this study is that, learning a dot product with high accuracy for a large embedding dimension required a large model capacity. This may also require more computational resources. Therefore, it would be advisable for Data Science engineers to consider both approaches based on the requirements & data of the system that they're planning to work on.

2.5.5 Architectures of Recommendation Systems that integrate opinion mining techniques

There have been many attempts to expand the capabilities of Recommendations by making use of public opinion. Collaborative Filtering was one approach to achieve that. Another identified approach was to make use of user-data on social media. This has been integrated into Machine Learning-based Hybrid Recommendation Architectures in many ways. In the figure 2.3, the author tries to elaborate on the possible technical contribution brought forward in this research.

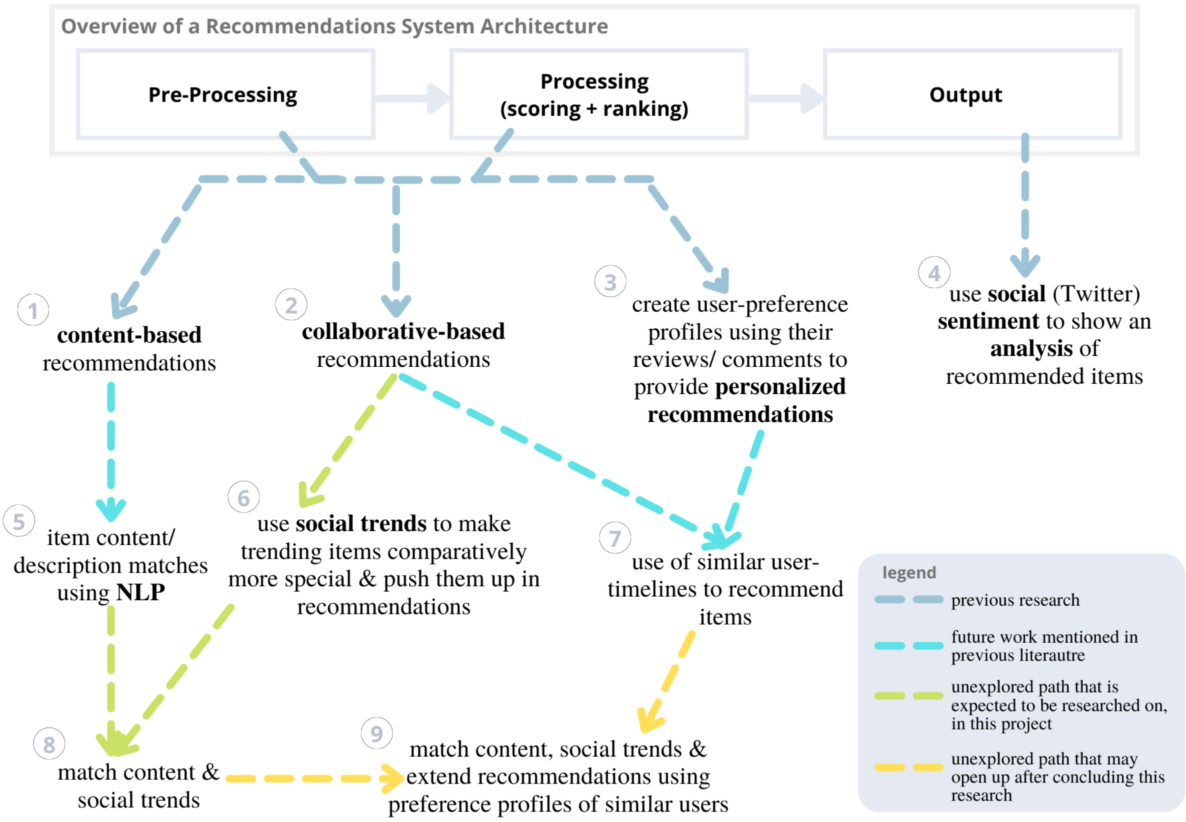

Figure 2.3: Enhancements done to Recommendation Systems using opinion mining techniques *(self-composed)*

The figure 2.3 shows the identified possible points of integration of opinion mining techniques to a Recommendations System. 1, 2 (G. Linden, B. Smith, and York, 2003; Larry, 2019), 3 (Cheng and Lin, 2020) & 4 (Ayushi and Prasad, 2018) techniques have been already applied as identified in past literature, while the 7th technique has been mentioned as a possible future work from the 3rd technique (Chen and Hendry, 2019). Method 5 hasn't been explicitly attempted in recent literature with respect to Recommendation Systems, but the data science models used aren't expected to require a lot of tweaking to achieve it, after the feature engineering step is being taken care of.

Method 6 has not been identified in previous literature and is expected to align better with the desires circulating the NFT market-space. This can be extended to method 8. Finally, if methods 7 & 8 turn out to give promising results, method 9 would be the next step to provide a completely new personalized recommendations architecture that integrates social media trends that are related to the content of the items.

2.5.6 NLP techniques that can be applied to support integration of opinion mining into Recommendation Systems

The main NLP techniques that were identified to be useful to be implemented in a system that requires data-mining & opinion mining techniques are were Sentiment Analysis, Named Entity-Recognition, Tokenization, Stemming & Lammetization; the latter 4 techniques being required for pre-processing scraped data from opinion-mining techniques.

In order to apply these techniques, many past literature (as mentioned in Existing Work), points in the direction of using industrial-grade libraries that utilize **Recurrent Neural Network (RNN) architectures** such as *SpaCy and NLTK*. The most state-of the-art models & techniques that make use of **Transformer architectures** can be found in the *Hugging Face* library (Wolf et al., 2020).

2.5.7 Practices to be followed to optimize the usage of gathered opinions

When considering multiple opinions related to a specific topic/ item, they can be combined into one document and processed rather than processing each opinion one by one (Zhang, Xu, and Jiang, 2018). When doing so, it would be good to have an impact score of each document to make sure that recommendations are biased appropriately towards the opinions of the majority with consideration of the users' opinions.

2.6 Review of Evaluation Approaches

When evaluating Recommendation Systems, we may examine the outcomes produced by the system in two ways. The first way would be identifying if the system is capable of recommending items that a user may use. The second method would be to identify if the system is capable of recommending items that a user will choose/ use.

The first way to evaluating the outcome can be done utilizing current data and pre-identified conditions. For the second approach, the evaluation algorithm would require feedback from the public. This can be done by having open beta testing. It would take more time & effort, but it will be capable of evaluating a system qualitatively on the final goal instead of a possibility.

If we look at evaluating this system from an expected-output performance point of view, *Precision at K (P@K)*, also identified as *Top-N strategy* in several literature is the most common method of evaluating a Recommendations System. This measure and the metrics that have been mentioned below can be used to **quantitatively** evaluate Recommendation Systems.

Table 2.2: Benchmarking techniques for Recommendation Systems

Measure	Description	Objective Orientation
MAE	Measures the average absolute deviation between a predicted rating and the user's true rating, overall the known ratings.	Negatively oriented. Lower, the better.
RMSE	A variant of MAE emphasizes large errors by squaring them.	
Precision	The percentage of items in the recommended list that are assessed to be relevant to the user (i.e. it represents the probability that a selected item is relevant).	Positively oriented. Higher, the better.
Recall	The ratio of relevant items presented by the system to the total number of relevant items available in the items in the system.	

MAE & RMSE are used to measure the accuracy of predicted user-ratings (1-5 star ratings) per item, per user. Precision & recall are used to measure if the system successfully predicts which items the user will select or consume (Dayan et al., 2011).

Since the goal of the Recommendations System is to provide the user with multiple options, it is better if the system can produce options across a diverse range. To evaluate the diversity of items across the produce recommendations, *Aggregate diversity* can be measured.

Apart from these metrics, quality-of-service measures such as CPU & Memory usage can be considered for evaluation as well.

In the review questioning the advancements of Recommendation Systems, (Dacrema, Cremonesi, and Jannach, 2019) the author mentions that the lack of used datasets and code-bases hinder the ability to properly benchmark and evaluate new research related to Recommendation Systems. The importance of reproducibility of research related to Recommendations Systems have future been elaborated in reviews that follow (Dacrema, Boglio, et al., 2021; Ferrari

Dacrema et al., 2020; Dacrema, Cremonesi, and Jannach, 2020).

2.6.1 Benchmarking

A common test dataset is required in order to consider the results produced by these methods to be valid. Since there's no previous NFT Recommendation System found in research, the author will not be able to conduct a comparative benchmark analysis on the proposed system. Therefore, a **Baseline-Benchmarking** strategy will be followed.

The evaluation benchmark results produced by this system will be made available public together with the used datasets in order to allow future researchers to evaluate new Recommendation Systems in this domain.

2.7 Chapter Summary

CHAPTER 3: METHODOLOGIES

CHAPTER 4: SOFTWARE REQUIREMENTS SPECIFICATION

REFERENCES

Adil Moujahid (June 28, 2021). *Data mining Meebits NFTs using Python and OpenSea API // Adil Moujahid // Data Analytics and more*. URL: http://adilmoujahid.com/posts/2021/06/data-mining-meebits-nfts-python-opensea/ (visited on 10/09/2021).

Ayushi, Smriti and Badri Prasad (Nov. 8, 2018). "Cross-Domain Recommendation Model based on Hybrid Approach". In: *International Journal of Modern Education and Computer Science* 10.11, pp. 36–42. ISSN: 20750161, 2075017X. DOI: 10.5815/ijmecs.2018.11.05. URL: http://www.mecs-press.org/ijmecs/ijmecs-v10-n11/v10n11-5.html (visited on 07/12/2021).

Bartolucci, Silvia and Andrei Kirilenko (Aug. 12, 2020). "A model of the optimal selection of crypto assets". In: *Royal Society Open Science* 7.8. Publisher: Royal Society, p. 191863. DOI: 10.1098/rsos.191863. URL: https://royalsocietypublishing.org/doi/full/10.1098/rsos.191863 (visited on 07/07/2021).

Beedham, Matthew (Dec. 10, 2019). *Nike now holds patent for blockchain-based sneakers called 'CryptoKicks'*. TNW | Hardfork. Section: hardfork. URL: https://thenextweb.com/news/nike-blockchain-sneakers-cryptokick-patent (visited on 07/19/2021).

Casey Newton (July 22, 2021). *Mark Zuckerberg is betting Facebook's future on the metaverse - The Verge*. The Verge. URL: https://www.theverge.com/22588022/mark-zuckerberg-facebook-ceo-metaverse-interview (visited on 11/20/2021).

Chen, Rung-Ching and Hendry (June 2019). "User Rating Classification via Deep Belief Network Learning and Sentiment Analysis". In: *IEEE Transactions on Computational Social Systems* 6.3. Conference Name: IEEE Transactions on Computational Social Systems, pp. 535–546. ISSN: 2329-924X. DOI: 10.1109/TCSS.2019.2915543. (Visited on 05/25/2021).

Cheng, Li Chen and Ming-Chan Lin (Oct. 2020). "A hybrid recommender system for the mining of consumer preferences from their reviews". In: *Journal of Information Science* 46.5, pp. 664–682. ISSN: 0165-5515, 1741-6485. DOI: 10.1177/0165551519849510. URL:

http://journals.sagepub.com/doi/10.1177/0165551519849510 (visited on 07/16/2021).

Chevet, Sylve (2018). "Blockchain Technology and Non-Fungible Tokens: Reshaping Value Chains in Creative Industries". In: *SSRN Electronic Journal*. ISSN: 1556-5068. DOI: 10.2139/ssrn.3212662. URL: https://www.ssrn.com/abstract=3212662 (visited on 04/18/2021).

Choi, Minjin et al. (Mar. 8, 2021). "Local Collaborative Autoencoders". In: *Proceedings of the 14th ACM International Conference on Web Search and Data Mining*. WSDM '21. New York, NY, USA: Association for Computing Machinery, pp. 734–742. ISBN: 978-1-4503-8297-7. DOI: 10.1145/3437963.3441808. URL: https://doi.org/10.1145/3437963.3441808 (visited on 05/18/2021).

community (Nov. 18, 2021). *Solana Ecosystem*. Solana. URL: https://solana.com/ecosystem/# (visited on 11/20/2021).

Conti, Robyn (Apr. 29, 2021). *What You Need To Know About Non-Fungible Tokens (NFTs)*. Forbes Advisor. Section: Investing. URL: https://www.forbes.com/advisor/investing/nft-non-fungible-token/ (visited on 07/19/2021).

CryptoKitties (2021). *CryptoKitties | Collect and breed digital cats!* CryptoKitties. URL: https://www.cryptokitties.co (visited on 11/20/2021).

Dacrema, Maurizio Ferrari, Simone Boglio, et al. (Jan. 6, 2021). "A Troubling Analysis of Reproducibility and Progress in Recommender Systems Research". In: *ACM Transactions on Information Systems* 39.2, 20:1–20:49. ISSN: 1046-8188. DOI: 10.1145/3434185. URL: https://doi.org/10.1145/3434185 (visited on 11/14/2021).

Dacrema, Maurizio Ferrari, Paolo Cremonesi, and Dietmar Jannach (Sept. 10, 2019). "Are We Really Making Much Progress? A Worrying Analysis of Recent Neural Recommendation Approaches". In: *Proceedings of the 13th ACM Conference on Recommender Systems*, pp. 101–109. DOI: 10.1145/3298689.3347058. arXiv: 1907.06902. URL: http://arxiv.org/abs/1907.06902 (visited on 05/30/2021).

— (July 9, 2020). "Methodological Issues in Recommender Systems Research (Extended Abstract)". In: Twenty-Ninth International Joint Conference on Artificial Intelligence. Vol. 5.

ISSN: 1045-0823, pp. 4706–4710. DOI: 10.24963/ijcai.2020/650. URL: https://www.ijcai.org/proceedings/2020/650 (visited on 11/14/2021).

Dafflon, Jacques, Jordi Baylina, and Thomas Shababi (Nov. 20, 2017). *EIP-777: Token Standard*. Ethereum Improvement Proposals. URL: https://eips.ethereum.org/EIPS/eip-777 (visited on 11/19/2021).

Dayan, Aviram et al. (2011). "Recommenders benchmark framework". In: *Proceedings of the fifth ACM conference on Recommender systems - RecSys '11*. the fifth ACM conference. Chicago, Illinois, USA: ACM Press, p. 353. ISBN: 978-1-4503-0683-6. DOI: 10.1145/2043932.2044003. URL: http://dl.acm.org/citation.cfm?doid=2043932.2044003 (visited on 10/16/2021).

Dowling, Michael (Apr. 29, 2021a). "Fertile LAND: Pricing non-fungible tokens". In: *Finance Research Letters*, p. 102096. ISSN: 1544-6123. DOI: 10.1016/j.frl.2021.102096. URL: https://www.sciencedirect.com/science/article/pii/S154461232100177X (visited on 07/17/2021).

— (Apr. 29, 2021b). *Is non-fungible token pricing driven by cryptocurrencies? | Elsevier Enhanced Reader*. DOI: 10.1016/j.frl.2021.102097. URL: https://www.sciencedirect.com/science/article/pii/S1544612321001781?via%3Dihub (visited on 06/23/2021).

ERC-721 Non-Fungible Token Standard (2021). ethereum.org. URL: https://ethereum.org (visited on 07/19/2021).

Ferdiansyah, Ferdiansyah et al. (Oct. 2019). "A LSTM-Method for Bitcoin Price Prediction: A Case Study Yahoo Finance Stock Market". In: *2019 International Conference on Electrical Engineering and Computer Science (ICECOS)*. 2019 International Conference on Electrical Engineering and Computer Science (ICECOS), pp. 206–210. DOI: 10.1109/ICECOS47637.2019.8984499. (Visited on 07/15/2021).

Ferrari Dacrema, Maurizio et al. (Oct. 19, 2020). "Critically Examining the Claimed Value of Convolutions over User-Item Embedding Maps for Recommender Systems". In: *Proceedings of the 29th ACM International Conference on Information & Knowledge Management*. CIKM '20. New York, NY, USA: Association for Computing Machinery, pp. 355–363.

ISBN: 978-1-4503-6859-9. DOI: 10.1145/3340531.3411901. URL: https://doi.org/10.1145/3340531.3411901 (visited on 11/14/2021).

Fred Rezeau et al. (Apr. 15, 2021). *NFTs on Stellar - Stellar Development Foundation*. Stellar Events. URL: https://stellar.org/events/nfts-on-stellar?locale=en,%20https://stellar.org/events/nfts-on-stellar?locale=en (visited on 11/20/2021).

Freudenthaler, C., L. Schmidt-Thieme, and Steffen Rendle (2011). *Factorization Machines Factorized Polynomial Regression Models*. URL: https://www.semanticscholar.org/paper/Factorization-Machines-Factorized-Polynomial-Models-Freudenthaler-Schmidt-Thieme/10e8617b6c58d599b8d17b3a60047a599bfe5e72 (visited on 08/27/2021).

Geetha, G. et al. (Apr. 2018). "A Hybrid Approach using Collaborative filtering and Content based Filtering for Recommender System". In: *Journal of Physics: Conference Series* 1000. Publisher: IOP Publishing, p. 012101. ISSN: 1742-6596. DOI: 10.1088/1742-6596/1000/1/012101. URL: https://doi.org/10.1088/1742-6596/1000/1/012101 (visited on 04/29/2021).

Gwyneth Iredale (June 29, 2021). *Are Blockchain and AI a Perfect Combination?* 101 Blockchains. URL: https://101blockchains.com/blockchain-and-ai/ (visited on 07/23/2021).

Hu, Shigang et al. (2020). "Reviewer Credibility and Sentiment Analysis Based User Profile Modelling for Online Product Recommendation". In: *IEEE Access* 8. Conference Name: IEEE Access, pp. 26172–26189. ISSN: 2169-3536. DOI: 10.1109/ACCESS.2020.2971087.

Larry, Hardesty (Nov. 22, 2019). *The history of Amazon's recommendation algorithm*. Amazon Science. Section: Latest news. URL: https://www.amazon.science/the-history-of-amazons-recommendation-algorithm (visited on 05/25/2021).

Larva Labs (2021). *The Meebits*. URL: https://meebits.larvalabs.com/ (visited on 11/20/2021).

Linden, G., B. Smith, and J. York (Jan. 2003). "Amazon.com recommendations: item-to-item collaborative filtering". In: *IEEE Internet Computing* 7.1, pp. 76–80. ISSN: 1089-7801. DOI:

10.1109/MIC.2003.1167344. URL: http://ieeexplore.ieee.org/document/1167344/ (visited on 05/18/2021).

Matney, Lucas (July 20, 2021). *NFT market OpenSea hits $1.5 billion valuation*. TechCrunch. URL: https://social.techcrunch.com/2021/07/20/nft-market-opensea-hits-1-5-billion-valuation/ (visited on 07/23/2021).

Naumov, Maxim et al. (May 31, 2019). "Deep Learning Recommendation Model for Personalization and Recommendation Systems". In: *arXiv:1906.00091 [cs]*. arXiv: 1906.00091. URL: http://arxiv.org/abs/1906.00091 (visited on 04/29/2021).

Non-fungible tokens (NFT) (2021). ethereum.org. URL: https://ethereum.org (visited on 11/20/2021).

Peter Allen Clark (Nov. 15, 2021). *What is the Metaverse? Here's Why It Matters | Time*. Time. URL: https://time.com/6116826/what-is-the-metaverse/ (visited on 11/20/2021).

Prathap, Madana (Oct. 22, 2021). *Semi-fungible tokens — coins that travel between the worlds of cryptocurrency and NFTs*. Business Insider. URL: https://www.businessinsider.in/investment/news/what-is-a-semi-fungible-token-sft/articleshow/87205941.cms (visited on 11/19/2021).

Rendle, Steffen et al. (Sept. 22, 2020). "Neural Collaborative Filtering vs. Matrix Factorization Revisited". In: *Fourteenth ACM Conference on Recommender Systems*. RecSys '20. New York, NY, USA: Association for Computing Machinery, pp. 240–248. ISBN: 978-1-4503-7583-2. DOI: 10.1145/3383313.3412488. URL: https://doi.org/10.1145/3383313.3412488 (visited on 07/20/2021).

Smith, Brent and Greg Linden (May 2017). "Two Decades of Recommender Systems at Amazon.com". In: *IEEE Internet Computing* 21.3. Conference Name: IEEE Internet Computing, pp. 12–18. ISSN: 1941-0131. DOI: 10.1109/MIC.2017.72.

Staff, Daily Hodl (Nov. 4, 2021). *Solana Becomes Fourth-Biggest NFT Blockchain As SOL Overtakes Cardano*. The Daily Hodl. URL: https://dailyhodl.com/2021/11/04/solana-becomes-fourth-biggest-nft-blockchain-as-sol-overtakes-cardano/ (visited on 11/20/2021).

Vanderbilt, Tom (2021). “The Science Behind the Netflix Algorithms That Decide What You’ll Watch Next”. In: *Wired* (). Section: tags. ISSN: 1059-1028. URL: https://www.wired.com/2013/08/qq-netflix-algorithm/ (visited on 08/27/2021).

We are open-sourcing a state-of-the-art deep learning recommendation model to help AI researchers and the systems and hardware community develop new, more efficient ways to work with categorical data. (Feb. 7, 2019). URL: https://ai.facebook.com/blog/dlrm-an-advanced-open-source-deep-learning-recommendation-model/ (visited on 05/15/2021).

What are you missing? Using basic machine learning to predict and recommend NFTs with OpenSea data - OpenSea Blog (Jan. 30, 2020). URL: https://opensea.io/blog/analysis/predict-and-recommend-nfts/ (visited on 08/27/2021).

Wolf, Thomas et al. (Oct. 2020). “Transformers: State-of-the-Art Natural Language Processing”. In: *Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing: System Demonstrations*. Online: Association for Computational Linguistics, pp. 38–45. DOI: 10.18653/v1/2020.emnlp-demos.6. URL: https://aclanthology.org/2020.emnlp-demos.6 (visited on 11/19/2021).

Wood, Dr Gavin (2014). “ETHEREUM: A SECURE DECENTRALISED GENERALISED TRANSACTION LEDGER”. In: p. 39. (Visited on 07/15/2021).

Zhang, Wenping, Mengna Xu, and Qiqi Jiang (2018). “Opinion Mining and Sentiment Analysis in Social Media: Challenges and Applications”. In: *HCI in Business, Government, and Organizations*. Ed. by Fiona Fui-Hoon Nah and Bo Sophia Xiao. Vol. 10923. Series Title: Lecture Notes in Computer Science. Cham: Springer International Publishing, pp. 536–548. ISBN: 978-3-319-91716-0. DOI: 10.1007/978-3-319-91716-0_43. URL: http://link.springer.com/10.1007/978-3-319-91716-0_43 (visited on 07/12/2021).

APPENDIX A - CONCEPT GRAPH

Figure 1: Concept Map *(self-composed)*