Trading Recommendations System for Non-fungible Tokens

Project Proposal

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Acronyms

AI Artificial Intelligence. 9

DL Deep learning. 9

ERC Ethereum Request for Comments. 1

GUI Graphical User Interface. 13

ML Machine Learning. 9, 19

NFT Non-fungible Token. 1
NLP Natural Language Processing. 11

P@K Precision at K. 16

1 Introduction

In recent months, the Non-fungible Token (NFT) market has been growing exponentially as it appears to be the most widely accepted business application of Blockchain technology (Dowling, 2021b), since the introduction of crypto. Even though many people have got into purchasing NFTs, one of the major problems that owners, as well as potential customers face, is that they're unable to find NFTs that are worth trading their current NFTs to. In this research project, the author tries to identify the required features to be considered for an NFT-trading Recommendations System and introduce a new Ensemble Architecture for Recommendations that can be applied in other related domains as well. The proposed architecture will try to automate several decision-making steps that a user would otherwise need to go through to find the best possible trade.

This document defines the problem, the research value, and the research strategy that the author wishes to follow over the next few months. The necessary proofs of the problem, as well as previous research interests, are also reviewed. Finally, the expected plan of the deliverables of the project is presented in the Work Plan.

2 Problem Domain

2.1 Non-fungible Tokens (NFTs)

Non-fungible Tokens (NFTs) are provably scarce unique digital assets that can be used to represent ownership (*ERC-721 Non-Fungible Token Standard* 2021). They can be one of a kind rare artworks, collectable trading cards, and other assets with the potential to increase in value due to scarcity (Conti, 2021; Fairfield, 2021). While being digital assets, they also can be used to represent physical assets. A digital certificate of land/ qualification can be identified as a couple of examples. The biggest winners in the NFT space over the last few months have been digital artists who were able to sell art worth over $2.5 Billion (*Off the chain* 2021).

NFTs were introduced by Ethereum (Wood, 2014) as an improvement proposal (*EIP-2309* 2021; *ERC* 2021) in the Ethereum Request for Comments (ERC)-721 standard (*ERC-721 Non-Fungible Token Standard* 2021). This allows anyone to implement a Smart Contract with the ERC-721 standard and let people mint NFTs as well as, keep track of the tokens produced by it. This allows the created tokens to be validated. Furthermore, the standard 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.

Each of these created tokens is unique from the other tokens created by the same Smart Contract, unlike fungible tokens which were introduced with cryptocurrencies and are denoted by the ERC-20 standard (*ERC-20 Token Standard* 2021) on the Ethereum network. One Bitcoin can be swapped to another Bitcoin, but each NFT will be unique. Then, the deployed Smart Contract will be responsible to keep track of the tokens created by it on the network. A Smart Contract is a program that resides on the Ethereum network with a collection of code & data (*Introduction to smart contracts* 2021).

For each NFT, the contact address & unit256 tokenId are globally unique on any blockchain. This allows Decentralized Applications (DApps) (Frankenfield, 2021; *Decentralized applications (dapps)* 2021) to take the tokenId and present the image/ asset that is identified by the particular NFT.

"To put it in terms of physical art collecting: anyone can buy a Monet print. But only one person can own the original." (Clark, 2021)

While a digital file can be copied regardless of whether it's an NFT or not, what this technology provides is the ownership of the digital asset. That is something that cannot be copied or taken from the owner. If an NFT that contains your certificate/ domain is held under your wallet on the Blockchain, no one else can get it from you unless they have your digital wallet's private key. Similar to a deed. But, anyone can see, validate and admire what you own.

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).

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.

2.2 NFT Marketplaces

OpenSea, which was the first NFT marketplace is also considered to be the largest. In the attempt to become the "Amazon of NFTs", OepnSea raised $23 million in a Series A (Hackett,

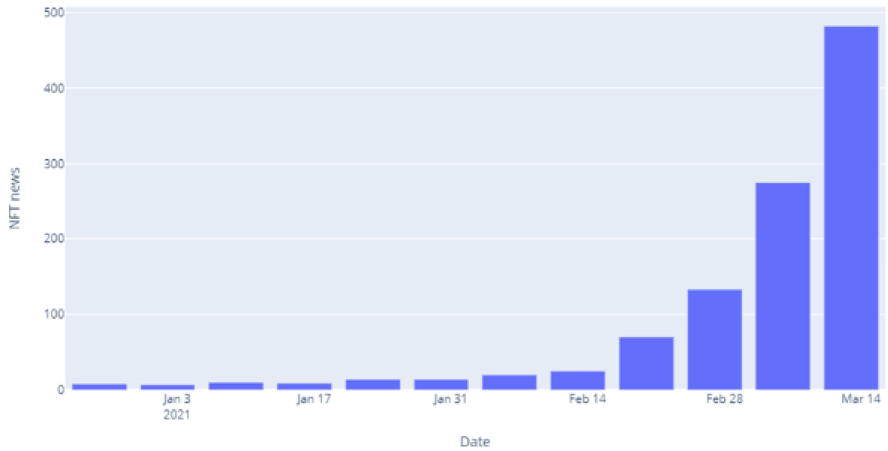

Figure 2.1: News trend in 2021 related to NFTs (Dowling, 2021a)

2021), following a $100 million raise in a Series B round, ended the company in a valuation of $1.5 billion (dfinzer, 2021; Matney, 2021). Open Sea saw nearly $150 million in sales in the month of June.

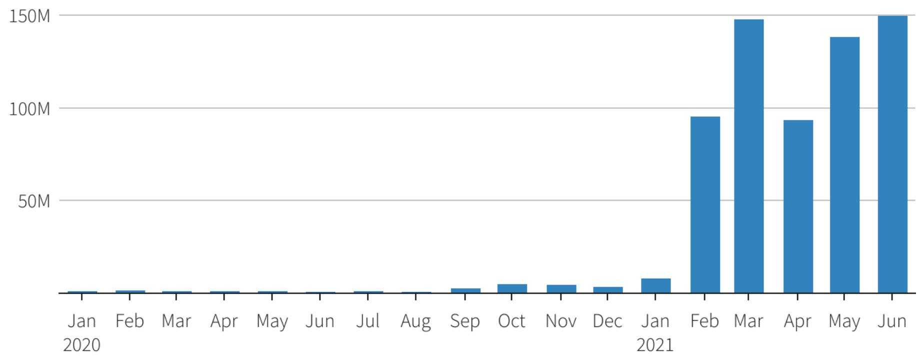

Figure 2.2: Monthly Ethereum-based NFT token sales volume on the OpenSea marketplace, in USD (Howcroft, 2021)

These marketplaces are set to increase access to the digital goods industry.

An NFT purchased on an Ethereum marketplace can be traded on any other Ethereum marketplace for a completely different NFT. Creators don't necessarily need to sell their NFT on a market. They can do the transaction peer-to-peer, completely secured by Blockchain. No one is needed to intermediate and an owner isn't locked onto any platform (*ERC-721 Non-Fungible Token Standard* 2021).

2.3 Recommendation Systems

Recommendation Systems have been driving engagement and consumption of content as well as items on almost every corner of the internet over the last decade.

Recommendation Systems help users identify relevant items on an online platform. When users are recommended with relevant items, it enables businesses in growing their revenue. 35% of Amazon's revenue (Naumov et al., 2019) & 60% of watch time on YouTube (*Recommendations* 2021) comes from recommendations.

3 Problem Definition

Currently, there is no way of identifying possible tradable NFT assets, unless manually browsing through the internet. Marketplaces allow searching for NFTs by keywords, categories & pricing, but don't provide personalized recommendations of trending items. This applies to someone who wants to purchase an NFT that shows similar characteristics to another NFT that has already been purchased by a previous buyer or oneself. Since there can be only one owner for an NFT at a time, recommendations using standard collaborative filtering is also not entirely ideal. Content-based approaches won't help identify trending items.

In order to help with the exploration of these digital assets, it's identified that several steps that the user has to follow in order to identify trending items that are timely, popular among the community and may have an expected value can be automated.

3.1 Problem Statement

It is difficult to find NFTs of comparable value that is trending among the community, timely and relevant to the user's identified interest or the NFT that the user currently owns.

4 Research Motivation

The problem identified in this proposal applies to both people who have a lot of domain knowledge about NFTs and people who have no idea how valuable items are in relation to their interests. Whoever it is, there's no solution that would mimic the exact thinking pattern of a person who is searching for a suitable NFT.

As mentioned in the work of Cheng and Lin (2020), Recommendation Systems play a significant role in the resolution of the problem of information overload. In order to provide ideal recommendations to a user, it is important to understand the user's thought process as well as other factors that affect a decision to trade.

Since the Recommendations domains are highly important for many business use-cases and the NFT domain is seeing a booming acceptance with a bright future ahead, this work is expected to add value to the progression of advancements & accessibility related to the domains of NFTs, Blockchain & Recommendation Systems.

5 Existing Work

5.1 Recommendation Systems

Research	Year	Technique Used	Improvements	Limitations
Amazon's Deep Learning-based movie recommendations model (Larry, 2019)	2019	Autoencoder, trained on chronologically sorted movie-viewing data	Outperformed item-to-item collaborative filtering the bestseller list	*Critique: The timeline doesn't consider overlapping of movies at various points in time, which will be necessary for trends.* Tested only on movie recommendations.
A hybrid recommender system for the mining of consumer preferences from their reviews (Cheng and Lin, 2020)	2020	A framework that integrates collaborative filtering with opinion mining sentiment analysis on users' reviews that is used to create preference profiles.	Effective in dealing with insufficient data and is more accurate and efficient than existing traditional methods. The quality of recommendations can be improved regardless of whether the dataset is rich or sparse.	The semantic strategy of opinion extraction is generic. This may not be ideal to identify different aspects in varied genres. Slang, irony or sarcasm isn't considered in the current framework. It's very dependent on text mining of user reviews. *Critique: A person has to have placed reviews on previous movies in order to create a preference profile.*

User Rating Classification via Deep Belief Network Learning and Sentiment Analysis (Chen and Hendry, 2019)	2019	A deep learning model to process user comments and to generate a possible user rating for user recommendations have been used. A Deep Belief Network and Sentiment Analysis (DBNSA) achieves data learning for the recommendations.	Outperforms baseline models in training loss value, precision, and recall on the Yelp and Amazon data sets. In the Trip-Advisor data set, DBNSA has the best MSE training loss value and recall. DBNSA saves more time than the other baseline methods.	At present, the proposed method is not suitable for real-time testing. This method is required to be tested with a fast Deep Learning algorithm. Sarcastic comments have not been considered in user comments.

Cross-domain recommendations based on a hybrid approach (PES University/Department of Computer Science, Bangalore, 560085, India, Ayushi, and Badri Prasad, 2018)	2018	A hybrid approach of combination of content-based recommendation, user-to-user collaborative filtering and personalized recommendation techniques.	Address the limitations of single domain analysis such as data sparsity and cold start problem. Integration of several domains is further capable of generating higher accuracy in suggestions. Twitter sentiment analysis over the recommended entities generated by the model to help the user in decision making by knowing the positive, negative and neutral polarity percentage based on tweets done by people.	*Critique: Sentiment analysis based on Twitter sentiment is calculated and shown after showing recommendations.* *It's ironic to recommend something and say if it's good/ bad by the system itself. Better if only positive sentiment-based items are recommended.*

A LSTM-Method for Bitcoin Price Prediction(Ferdiansyah et al., 2019)	2019	LSTM (Long short-term memory).	The proposed model with time series techniques can predict the price for the next days with split the data to train and test.	The result is not good enough regarding the RMSE (Root Mean Squared Error). Future work: modified LSTM layers, adding dropout and modified number of epochs, and using different instability data-sets to test how good the prediction results are or *try to use sentiment analysis combined with LSTM method* to see the impact of the uncertainty in value bitcoin.
Using basic machine learning to predict and recommend NFTs with OpenSea data (*What are you missing? Using basic machine learning to predict and recommend NFTs with OpenSea data - OpenSea Blog* 2020)	2021	Multiple Regression	This considers past purchase patterns, NFTs saved in wallets to predict if another wallet containing a similar combination will be likely to own an NFT from a specific category (eg: Cryptokitties, ENS domain, etc) in the future.	Recommends NFT categories that a user may be interested in. Doesn't recommend specific NFTs. The user needs to either manually input preferences or provide his wallet key that contains all his owned assets. *Critique: This won't consider current trends. It won't consider the recognition of the creators (eg: NFT made by Beeple).*

Table 5.1: Related work in Recommendations Systems

5.2 Understanding factors that affect NFT Markets

It is understood that the pricing of NFTs is moved by the changes in the pricing of cryptocurrencies, but appears to have comparatively less volatility. But the spillover between NFT markets has been identified to be very low compared to the high spillover effect among individual crypto markets (Dowling, 2021b).

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.

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

"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)

These statements prove that the demand for investment in NFTs will be heavily reliant on the public's acceptance of the item is.

6 Research Gap

Based on previous work done related to Recommendation Systems, the literature doesn't identify integrating all the factors that affect the desirability of owning relevant, timely & trending NFTs (items) to a recommendations model. This project focuses on an Empirical gap in the NFT domain as well as Theoretical and Performance gaps in Recommendations Systems.

Collaborative filtering, which has been a standard baseline technique for Recommendations for over a decade, can't be taken as the only recommendations model because, by the time one NFT is viewed many times by other users, it may already be too late for another user to purchase that item.

7 Research Contribution

The author's research contribution can be summarized as follows:

- **Recommendations Systems**: Data Engineering + Data Science [Machine Learning (ML) + Deep learning (DL)] + Ensemble models
- **NFT Trading**: Recommendations + Artificial Intelligence (AI) + Automation + Data Analysis

7.1 Technological Contribution

A Hybrid Recommendations technique that attempts to use public trends in a way that hasn't been attempted in previous research will be explored in order to facilitate the recommendation of relevant, trending and timely items. Automation of several decision-making steps that a user would otherwise need to go through to find the best possible trade will be integrated into the Recommendations Architecture. It is hypothesized that this novel recommendations architecture will be able to be applied to other items as well in order to give enhanced recommendations based on trends.

7.2 Domain Contribution

The information in an NFT that has an effect on a user's desire to be owned will be identified, when attempting to provide suitable recommendations. Looking at the success of Recommendation Systems across multiple systems for over a decade, it is understood that a Recommendation System would help users identify NFTs that they would be interested in trading. This will in return help in increasing sales on NFT Marketplaces and wider adoption of the technology.

NFTs are a result of the advancement of the application of techniques related to Blockchain, while Recommendation Systems are a result of Data Science advancements over the last few decades. Both the domains considered in this research can be identified to be originated from the field of Computer Science.

8 Research Challenge

NFTs is a new domain, which has very less research done related to preferences and factors considered when purchasing NFTs. Therefore, it is first important to identify the data points (features) & external factors that affect the value/ desirability of owning NFTs to suggest trading recommendations of NFTs to a user.

"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)

NFTs are identified to be more challenging to be recommended to users using traditional recommendation methods due to the uniqueness of each item together with the traditions brought forward with the crypto community. Similar to cryptocurrencies, it has been identified that NFTs too have an impact on the general public opinion & trends (Dowling, 2021a).

Currently, available Recommendation Systems haven't had the necessity to consider trends as much as with related to the desirability of owning NFTs. Furthermore, scarcity of items opens another challenge of the inability to keep recommending items that are not available for sale or have already been purchased by an interested buyer. But that alone can't be considered due to the time-tested & proven baseline recommendation techniques being highly effective in multiple domains. Using the identified factors to be considered, a suitable recommendations architecture needs to be implemented.

9 Research Questions

RQ1: What are the features of NFTs & external factors that affect the desirability of owning NFTs?
RQ2: How can a system predict the most relevant, trending, timely & worthy NFTs for trading purposes?
RQ3: What are the recent advancement in recommendation models & architectures that can be taken into consideration when building a hybrid Recommendation Architecture, using ensemble techniques?

10 Research Aim

The aim of this research is to design, develop & evaluate a novel Recommendation Architecture that will provide relevant, trending, timely, and worthy NFTs for trading purposes by automating some of the decision making steps that the user would otherwise have to do manually.

To elaborate on the aim, this research project will produce a system & architecture that can be used to recommend trending items with respect to a chosen item in a specific data set. The focus will be laid on the recommendation of NFTs. In order to achieve this several public channels of trends will be required to be streamed into the recommendations architecture together with the automation of several decision-making steps that a user that is interested in purchasing NFTs would have to manually go through, in order to make the best possible trade. The use of Data Mining techniques, Natural Language Processing (NLP) techniques, Data Analysis, hybrid, content-based, collaborative filtering & Deep Learning methods will be researched to make the best possible recommendations.

The required knowledge will be studied and researched, components will be developed and the performance will be evaluated in order to validate or invalidate the chosen hypothesis. The system will be able to run in a local browser for personal use or in a hosted server for public use. The data science models & their code will be available for further research and use in a public repository that is easy to get up and running with ease. A review paper will be published with knowledge gathered from the survey of Literature. A research paper will be published on the outcome of the findings in the research project.

11 Research Objectives

The Aims and Research Questions mentioned above are expected to be achieved and answered with the completion of the following Research Objectives. These objectives are milestones that will be expected to be met in order for the research to be completed successfully.

Objective	Description	Learning Outcomes
Problem Identification	Identifying a suitable and valuable problem domain to contribute towards, with identified research gaps suitable for a research project	LO5
Literature Review	Read previous work to collate relevant information on related work and critically evaluate them	LO4, LO2, LO5
Project Methodology	Choosing the Research, Development and Project Methodologies that can be followed. Creating a project plan with expected activities and scheduled times for the time-frame allocated for the project	LO3, LO7
Requirement Specification	Specifying the requirements of the project using appropriate techniques and tools in order to meet with the expected research gaps & challenges to be addressed	LO1, LO2, LO5, LO7
Data Gathering and Analysis	Collecting and analysing data used in previous related research and any domain-specific data required to solve the research problem	LO1, LO5
Research Design	Designing architecture and a system that is capable of solving the identified problems with recommended techniques.	LO1
Implementation	Implementing a system that is capable of addressing the gaps that were aimed to be solved.	LO1, LO5, LO6
Testing and Evaluation	Testing the created system & Data science models with appropriate data and evaluating them with baseline techniques identified in literature	LO4
Documenting the progress of the research	Documenting and notifying the continuous progress of the research project and any faced obstacles.	LO8, LO6

Publish Findings	Producing well-structured documentation/ reports/ papers that critically evaluate the research. • Publishing a review paper on related work. • Publishing evaluation & testing results identified from the research. • Making the code or models created in the research process available for future advancements in research. • Making any modified data-sets or re-creation strategies available to the public, to train & test models related to similar use cases of utilized data.	LO4, LO8

Table 11.1: Research Objectives

12 Project Scope

The scope is defined as follows based on the project objectives and a review of existing products with consideration to the granted time period for this research project.

12.1 In-scope

The following is a list of the project's scope:

- A system that is capable of recommending NFTs to users based on a specific NFT chosen by a user.
- Creation of a Recommendations System that integrates public trends on social media.
- Creation of a Recommendations System that is capable of providing better rending recommendations compared to baseline techniques.
- Testing the requirement of integrating public trends into a Recommendations architecture with the use of Content-based filtering, collaborative filtering & Deep Learning techniques.
- Graphical User Interface (GUI) that allows a user to provide the tokenId of a chosen NFT by the user & to view the results given by the Recommendations System.
- Automation techniques with related to Smart Contracts will be directly applicable only to selected Blockchains.

12.2 Out-scope

The following are the parts that will not be covered by the project:

- Recommending items that haven't been seen previously by the system.
- Creating a Recommendations System that utilizes less computational power & resources compared to baseline techniques.
- GUI with options to tune the Recommendations System.
- All automation techniques to cover every available Blockchain.

12.3 Prototype High-Level Architecture Diagram

13 Proposed Methodology

13.1 Research Methodology

The quality of any project is governed by three key factors: cost, time, and scope, all of which must be managed efficiently throughout the project's lifetime. As a result, methodologies are required. Saunders Research Onion Model (Writers, 2019) has been used to deduce the methodologies. The methodologies chosen as appropriate for the project are listed in the table below.

Research Philosophy	The philosophy of research influences data collection & data analysis since it is related to the nature of reality being investigated. Positivism, Interpretivism & Constructivism are philosophies that could be used to approach this research. Out of these, **Positivism** was chosen since the research is expected to be replicable with similar **quantifiable** results.
Research Approach	The approach that a researcher may use when conducting the research is the approach. A **Deductive** approach was chosen over an Inductive approach since this is expected to be a **quantitative** research that aims to **test & prove** the **hypothesis** at hand.

Research Strategy	The strategy focuses on the data collection methods that will be used to answer the research questions. **Survey, Archival Research** & **Ethnography** were the strategies chosen to address the research questions. These strategies were chosen as they would compliment each other while providing relevant data that is enough for the research. While Survey seems to be the primary strategy, Archival Research & Ethnography is expected to allow the **qualitative aspect** expected in the approach taken to the solution, which will finally affect the **quantitative results**, to be addressed.
Research Choice	Choice of the methodology identifies if the research is concerned with the qualitative and quantitative aspects of the research. **Multi-method** was chosen since although **quantitative results** are the primary perspective, it is identified that **qualitativeness** of the data used by the system to be developed will also be an important consideration that will affect the quantitative results.
Time Horizons	**Longitudinal** was chosen as the time horizon for the research since data will be gathered and used for evaluation and testing over a long period of time.
Techniques and procedures	Data collection and analysis techniques are considered here. Mediums such as online news, statistics & trends from social media, observations, conversations, reports, surveys, documents, secondary tabular data, organizational records will be used.

Table 13.1: Research Methodology

13.2 Development Methodology

13.2.1 Life cycle model

Agile Software Development Life-cycle was chosen as the research development method since iterative development is needed. **Prince2** was chosen as the product development methodology. It allows the author to develop the product in controlled environments in logical compartmentalized units.

13.2.2 Design Methodology

Object-Oriented Analysis and Design were chosen as the Design Methodology by the author to support an incremental methodology that can be used to extend the system with the ability to reuse system components.

13.2.3 Evaluation Methodology

As identified in recent advancements in literature (Larry, 2019), Precision at K (P@K) score has been identified as a suitable method of bench-marking a recommendations system for evaluation purposes. Therefore, it will be used to compare the novel solution that is to be developed against baseline models.

13.3 Project Management Methodology

13.3.1 Scheduled Timeline

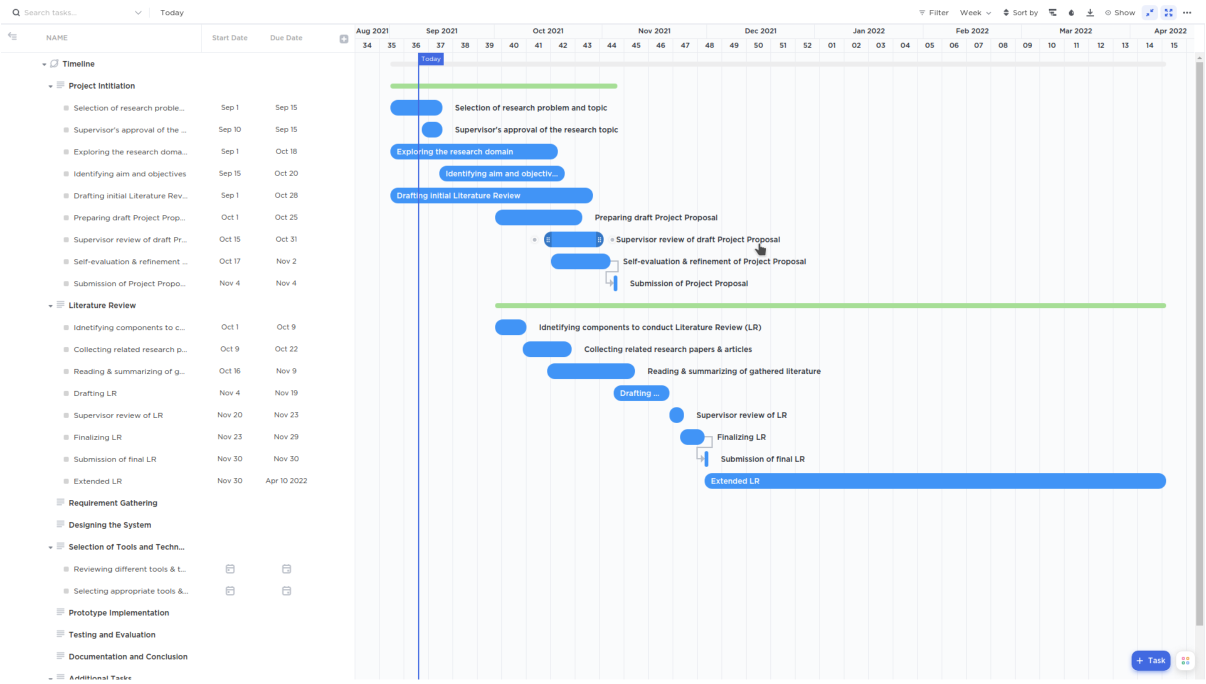

Figure 13.1: Gantt Chart

13.3.2 Deliverables

Deliverable	Date
Project Proposal Document The initial proposal of the project	4th November 2021
Literature Review Document The Critical review of existing work and solutions	11th December 2021
Software Requirement Specification The document specifying requirements to be satisfied and developed as the final prototype and means of collecting data	15th December 2021
System Design Document The document specifying the design developed for the Recommendations System and overviews of the algorithms to be developed.	1st December 2021
Prototype The prototype with main core features functional	1st February 2022
Thesis The final report documenting the project and research process and decisions	15th March 2022
Review Paper A review paper reviewing existing systems in the Recommendations domain published in a journal/ conference	1st March 2022
Manuscript Paper A research paper introducing the concepts and design developed as part of this project	31st December 2021
Final Research Paper A research paper introducing the Recommendations System developed at the end of this project	1st April 2021
Public project library A publicly accessible project library/ repository to set up, test and use the developed Recommendations System	1st April 2021

Table 13.2: Deliverables and dates

13.3.3 Resource Requirements

The resources required to complete the project are identified based on the objectives, expected solutions, and deliverables. The following are the software, hardware, and data resource requirements.

Software Requirements

- **Operating System(Linux/ macOS/ Windows 10)** - Linux will be the default choice for development since of the ease of support for multiple development tools and performance benefits. macOS/ Windows will be used for research documentation & study purposes.
- **Python** - The language that will be used to create the Machine Learning & Deep Learning models. Python is an all-purpose language that has been used in many projects that integrate with data science.
- **Tensorflow/ Scikit learn Python packages** - Libraries that will be used to support model development, training & testing.
- **Golang/ NodeJS** - The Application Programming interface that will be used to communicate with the ML backend and the front-end. Golang will allow the application to support concurrency and multi-threaded communications while being extremely lightweight and fast. This will be used to avoid any bottlenecks that could occur at this point in the system. NodeJS will be kept as a secondary option in the case of requiring any pre-built features that are not directly supported by Golang & aren't directly relevant to the research.
- **JavaScript (React)** - The front-end of the application, where recommendations will be shown. This is also an important part of the project since it will be the users' point of interaction with the system.
- **PyCharm/ VSCode/ GoLand** - Development environments to support development of the project.
- **Google Colab** - Cloud development environment to build, train & test ML & Deep Learning models.
- **Zotero** - Research management tool to save and backup research artifacts & manage references.
- **Overleaf/ MS Office/ Google Docs/ Canva/ Figma** - Tools to create reports, figures & documentations.
- **Google Drive/ GitHub** - To backup files & code related to the project
- **Docker** - To make the ensemble system's setup process as simple as possible.

Hardware Requirements

- **Core i7x Processor(8th generation)** - To be able to perform high resource intensive tasks.
- **Nvidia 1050Ti GPU** - To manage training processes of data science models.
- **16GB RAM** - To manage data-sets & development environments.
- **Disk space of 40GB or above** - To store data & application code.

Data Requirements

- **Non-fungible Token data** - From OpenSea open-API.
- **Twitter data** - From Twitter developer API.

- **Google Trends data** - From Google Dataset Search & unofficial Google Trends Python API (Pytrends).
- **Ethereum Smart Contract data** - From Etherscan
- **User Preference Profiles data** - From Amazon, Yelp, Kaggle open datasets. May be needed for testing purposes.

Skill Requirements

- Creation of required Recommendation Systems.
- Ability to create optimized Machine Learning & Deep Learning models.
- Research writing skills.

13.3.4 Risk Management

The following are the risks identified prior to starting the project with possible mitigation steps.

Risk Item	Severity	Frequency	Mitigation Plan
Loose access to on going development code	5	2	Keep all code backed up on GitHub & external backup
Corruption of documentation	4	4	Follow a cloud-first documentation approach and backup on a weekly basis
Inability to complete all expected deliverables within the allocated time	4	2	Work on deliverables on a priority basis.
Inability to explain the research work done due to illness	2	1	Have a recording of demonstration and detailed documentation with explanation

Table 13.3: Risk Mitigation Plan

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