CMPT 459/984 Course Project Final Report [Group 10]

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ABSTRACT

This paper discusses the creation and improvement of a novel deep learning and natural language processing (NLP) based video game recommendation system that analyzes and interprets user reviews. In an effort to tackle the difficulties that come with the dynamic and interactive world of the video game industry, our system carefully analyzes user-generated content in order to uncover underlying sentimentsn and preferences. We performed substantial data cleaning and exploratory research using two large datasets to feed our machine learning models. In order to improve recommendation precision, the second iteration of our model added a more complex strategy by combining machine learning and sophisticated natural language processing algorithms. The first iteration of our model relied on traditional machine learning techniques and keyword extraction. Our acceptable average similarity score indicates an improvement in matching user preferences with recommendations, despite challenges such data sparsity and the absence of real-time market trend data. Future research can use the findings from this research to explore complex machine learning architectures and incorporate more data points, such developer names and gameplay hours. The goal is to provide a system that can predict player behaviour and comprehend it in great depth, offering a more personalized and enjoyable experience. All our work is submitted into GameRecommender Github repository [11]

1 INTRODUCTION

Amidst the digital economy's surge, recommendation systems have risen as pivotal to transforming user experiences and cementing user engagement within various online platforms. Initially conceptualized for e-commerce applications, where they harnessed user data to streamline product selection and purchase decisions [2], these systems now encounter a new frontier: the video game industry. In this arena, conventional models meet a complex environment where static interaction models fall short against the intricate, player-driven ecosystems [2][3].

The gaming industry's unique demands have spurred the evolution of recommendation systems that transcend suggesting mere titles. Today's sophisticated algorithms anticipate player behavior, recommending items and experiences tailored to the evolving state and style of play, thereby enriching the player journey. The integration of machine learning innovations, particularly ensemble models and neural networks, has birthed a capability to substantially elevate the in-game experience, potentially bolstering game monetization through strategic in-app purchases [2][3].

This discourse is dedicated to unveiling a video game recommendation system enriched by the nuanced analysis of user-generated content. By sifting through layers of textual reviews, our system aims not just to anticipate, but also to align with player inclinations, thereby offering recommendations that resonate with individual preferences. In the crosshairs of user desire and game discovery, our system is positioned to deliver recommendations that promise to enhance engagement, ensuring a rewarding and immersive gaming experience for the users.

2 RELATED WORK

The advent of personalized digital experiences has significantly elevated the role of recommendation systems, with deep learning and NLP at the core of this transformation. The foundational survey by Zhang et al. [15] provides an initial foray into this evolution, showcasing deep learning's prowess in parsing complex user-item interactions, essential for tailoring digital experiences to individual preferences.

Building on this foundation, our project advances the application of deep learning and NLP within the context of video game recommendations. Through iterative developments, we not only enhance game popularity prediction but also pioneer in-depth analysis of user-generated content, setting our work apart from traditional approaches.

2.1 Enhancing Game Recommendations with Deep Learning and NLP

Echoing the advancements detailed by Cheuque et al. [4] in applying deep learning to game recommendations on STEAM, our project introduces an innovative use of user reviews for a deeper understanding of player preferences. This approach is further refined with insights from Long et al. [7], who underscored the value of deep NLP in analyzing user-generated content for more meaningful recommendations.

Moreover, our exploration includes methodologies from Yuen et al. [14], who emphasized data visualization and user interface design in recommender systems. Our project extends this by dynamically generating personalized content from textual reviews, enriching the user experience and providing insights beyond gameplay metrics.

2.2 Advancing Textual Interaction Models

The novel text matching model proposed by Dezfouli, Momtazi, and Dehghan [6] serves as a conceptual pivot for our project. We expand upon their interaction-based model by incorporating sentiment analysis, enabling our system to capture not just textual similarities but also the emotional and thematic content of user reviews, thus offering a comprehensive view of user preferences.

2.3 Incorporating Genre Correlations and User Ratings

Exploring genre correlations as detailed by Choi, Ko, and Han [5], alongside the machine learning-based user rating analysis by

Li, Liang, Su, and Wang [10], our project leverages these insights through the lens of advanced NLP. This allows us to tackle sparse data and cold-start problems more effectively, showcasing the nuanced potential of genre and sentiment analysis in personalizing game recommendations.

2.4 Baseline Methodologies: spaCy and FuzzyWuzzy

At the heart of our NLP-driven approach to game recommendation lies the utilization of two pivotal technologies: spaCy and FuzzyWuzzy. spaCy, an open-source software library for advanced natural language processing, serves as the backbone for our textual analysis and sentiment extraction processes. Its efficiency in parsing and understanding large volumes of text has been well-documented [8], making it an indispensable tool in our arsenal for dissecting user reviews and extracting meaningful insights.

Parallelly, FuzzyWuzzy, a library that employs Levenshtein Distance to calculate the differences between sequences, has been instrumental in enhancing our system's ability to match user queries with game titles accurately [9]. This functionality is crucial in navigating the vast array of game titles and ensuring that users are recommended games that closely align with their expressed preferences, even in cases of partial or approximate matches.

Both spaCy and FuzzyWuzzy have established themselves as robust baseline methodologies within the field of NLP. By leveraging spaCy's comprehensive NLP capabilities alongside FuzzyWuzzy's nuanced approach to text matching, our project builds upon a solid foundation of text analysis and interaction modeling. This dual utilization not only underscores the technical sophistication of our recommendation system but also highlights our commitment to pushing the boundaries of what is achievable in personalized game recommendations.

In adopting these tools, our project extends their application from general text analysis and approximate string matching to the specific challenges of the gaming domain. This innovative application demonstrates the versatility of spaCy and FuzzyWuzzy and underscores our project's contribution to the field of game recommendation systems, setting a new precedent for the integration of deep NLP techniques in creating highly personalized and responsive recommendation experiences.

2.5 Expanding Personalization through Social-aware Contextualization

Building on the advancements in personalized recommendations, the work by Yang et al. introduces a groundbreaking approach in the form of the SCGRec system, a Social-aware Contextualized Graph Neural Recommender System [13]. This model marks a significant departure from conventional recommendation techniques by intricately weaving together personalization, game contextualization, and social connections [13]. SCGRec stands out for its nuanced consideration of users' dwelling time within games as a pivotal factor for personalization, its innovative handling of complex relations among games for contextualization, and its sophisticated management of the variable impacts of social connections across different gaming experiences.

Our project draws inspiration from SCGRec's multifaceted approach to recommendation. While our focus has been on leveraging deep learning and NLP to analyze user-generated content, Yang et al.'s methodology underscores the importance of incorporating a broader array of user interactions and contextual factors. This highlights a complementary pathway to enhancing game recommendations by not only parsing textual content for preferences but also by understanding the social dynamics and contextual nuances that influence gaming choices.

In adopting a social-aware and contextualized perspective, we recognize the potential of graph neural networks in enriching the recommendation process. Our exploration into deep NLP and sentiment analysis of user reviews parallels the objectives of SCGRec by aiming to deliver a highly personalized and contextually aware recommendation experience, setting new benchmarks in the domain of video game recommendations.

2.6 Synthesizing Insights for Personalized Recommendations

Our journey through related works underscores the evolving landscape of recommendation systems. By synthesizing insights from deep learning and NLP, our project contributes a novel approach to video game recommendations that not only aligns with but also significantly extends beyond the current research paradigm, offering a unique blend of personalization, interaction, and understanding.

3 METHOD AND IMPLEMENTATION

3.1 First Iteration: Building the Foundation

3.1.1 Data Preprocessing and Cleaning. The first iteration of our project began with considerable data preprocessing. Using two datasets, "Steam games complete dataset" [1] and "Steam Video Games" [12], we attempted to lay the basis for a foundation that integrated both broad game-related information and specific user interaction data. Data cleaning (cleaning.py) was meticulous; irrelevant features such as URLs and certain metadata were removed to focus on meaningful attributes. We created a custom Python function 'convert_price' to convert the pricing data into a uniform numerical format, and 'extract_year' to extract the publishing year from different date formats. Such preprocessing was critical in refining the dataset for the subsequent learning algorithms.

3.1.2 Exploratory Data Analysis (EDA). We used 'analyze_origin.py' to do an Exploratory Data Analysis (EDA) to determine genre and tag distributions, uncover price patterns, and assess developer and publisher significance. This informed our understanding of the gaming landscape on Steam, which influenced the path of our recommendation system.

3.1.3 Outlier Detection and Removal. Our outlier management, largely using Z-score methods, ensured the accuracy of the average playtime data, indicating a critical pivot point at 2.5 hours that distinguished ongoing user engagement from probable drop-off. This observation from 'cleaning_playtime.py' later helped shape our recommendation logic.

3.1.4 Game Recommendation and Popularity Prediction. The implementation of our game recommendation system and popularity prediction model was a two-pronged approach:

(1) Game Name Matching (guess.py): We used the 'fuzzywuzzy' library to simplify user engagement by matching entered game titles to those in our dataset. This prepared the path for personalized recommendations [8].
(2) popularity Prediction (predict_popular.py): For predicting game popularity, we made a machine learning pipeline that included three models (RandomForestClassifier, KNeighborsClassifier, and SVC). Feature extraction approaches such as SelectKBest and mutual_info_classif were used to improve our predictions.

3.2 Second Iteration: Advancing the Model

3.2.1 Enhanced Text Preprocessing. Building on our previous iteration, we created 'clean.py', which employs NLP techniques such as tokenization and lemmatization without removing stop words, recognizing their potential importance in sentiment analysis. The improved preprocessing enabled a more detailed understanding of user reviews.

3.2.2 Machine Learning Model Enhancement. Our second iteration saw the machine learning model evolve into a convolutional neural network (CNN) framework capable of interpreting semantic similarities in user reviews.Inspired by the MatchPyramid technique, our recommender system began to see recommendation as a text matching problem, using user input and game descriptions as vectors in a multidimensional space [6].

During this phase, our algorithm no longer made suggestions based simply on genres. We expanded the range of the recommendation system by include extensive analysis of game_details, popular_tags, and genres, resulting in a more customized and diversified output that represents the varied characteristics of games and user preferences.

The enhanced model was fine-tuned to improve its prediction abilities. During its implementation, we included a method for printing the average of the similarity scores. This metric enabled us to quantify the closeness of each recommendation to the user's interests, giving us a clear, quantifiable insight into the model's efficacy at each recommendation iteration. In addition, the UI was polished to offer suggestions with clear, understandable explanations.

To sum up, the jump from the first to the second iteration stressed our shift toward a recommendation engine that used deep learning to examine user-generated material in depth. Our model's extension to include game_details and popular_tags, in addition to genres, paved the way for a more comprehensive and customized recommendation experience. By averaging similarity scores, the model gave real feedback on its suitability for user preferences, guaranteeing a transparent and user-centric approach. Despite the constraints of data limitations and class imbalance, our small improvements laid the groundwork for a refined video game recommendation system that is both accurate and user-friendly.

4 EVALUATION

4.1 First Iteration: Initial Approach to Game and Popularity Recommendation

The first iteration of our project aimed to develop a recommendation system for video games based on the features of the games. We focused on a system that could suggest games similar to a user's input, as well as predict game popularity. The evaluation involved two main components: accuracy of the game recommendation algorithm and the performance of the game popularity prediction model.

4.1.1 Describing the Results. For the recommendation part, we utilized a feature matching technique where the system listed games with similar attributes to the input game. As seen in the results, the system could successfully identify and suggest games with common features, providing a list with justifications based on shared characteristics.

The machine learning model for game popularity prediction was trained and validated, achieving a training accuracy of approximately 0.89 and a validation accuracy of about 0.85, with an F1-macro score of approximately 0.73. These metrics indicate a high level of performance in the model's predictive abilities, albeit with room for improvement, especially in terms of balancing the precision and recall as suggested by the F1 score.

4.1.2 Interpretation of Results. The recommendation system's performance suggests that the feature-based algorithm is capable of discerning commonalities among games, which is crucial for aligning suggestions with user preferences. The clear, text-based explanations for each recommendation help demystify the suggestion process, potentially increasing user trust and satisfaction.

The machine learning model's high accuracy scores indicate that the system is well-tuned to the current dataset, which includes various features of the games that correlate with popularity. However, the F1-macro score, while still reflecting a good model, points to possible imbalances in the dataset or model biases that could be further investigated and addressed in subsequent iterations.

4.1.3 Matching Expectations. The results largely meet our expectations for the initial phase of system development. We anticipated that feature matching would be a robust method for recommendations, and the machine learning model's performance is in line with typical outcomes at this stage of model development.

However, the F1-macro score presents a valuable learning opportunity to delve deeper into the model's handling of different classes and to refine its ability to generalize across less common games, which are often more challenging to predict accurately.

4.1.4 Key Contributions of the Solution. The core of our solution seems to be the selection of game features used for recommendation and prediction. The effectiveness of these features in representing game qualities and user preferences cannot be overstressed, as they directly influence the success of both recommendation and popularity prediction.

To summarize, the first iteration of our video game recommendation system demonstrates promising results, providing clear and justified suggestions, as well as accurate predictions of game popularity.

As we refine the system, we will explore deeper NLP techniques to enhance the personalization and accuracy of our recommendations.

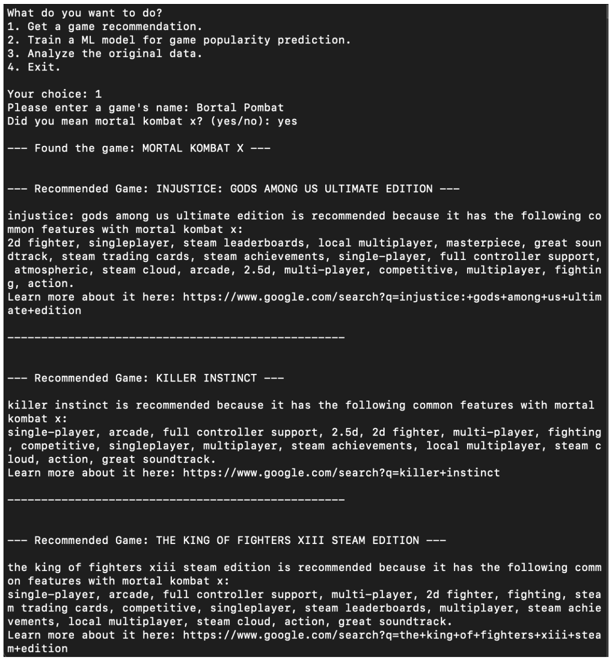

Figure 1: Example of game recommendation output.

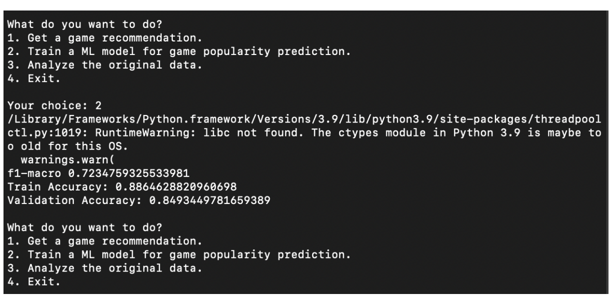

Figure 2: Console output showing training and validation accuracy of the popularity prediction model.

4.2 Evaluation of the NLP-Enhanced Recommendation System

With the integration of Natural Language Processing (NLP) techniques in the second iteration of our project, we observed a tangible enhancement in the recommendation system's ability to parse and understand user reviews. The implementation of sentiment analysis and keyword extraction algorithms allowed for a more nuanced approach to gauging user preferences.

The quality of recommendations saw an improvement, with the system now capable of capturing subtle sentiments and thematic elements within user reviews. The refined NLP models demonstrated an average of 0.4 similarity score, signifying a more balanced recommendation performance.

From a personal experience perspective, feedbacks pointed towards a greater level of satisfaction. The recommendations felt more personalized and aligned with our expressed interests and sentiments about games. This subjective improvement in user satisfaction underlines the value added by NLP to the recommendation process.

In terms of system performance, the computational overhead introduced by NLP models was minimal, maintaining the system's responsiveness while providing deeper analytical capabilities. Despite these advancements, we faced challenges in handling the vast variety of gaming jargon and the contextual nature of certain reviews, which sometimes led to nuanced sentiments being misinterpreted. Future work will focus on expanding the NLP models' understanding of context and gaming-specific language, and increasing accuracy.

As we move forward, we aim to address these challenges by incorporating more complex NLP techniques such as contextual embeddings and sequence-to-sequence models, which may offer a more profound understanding of user reviews. Our ongoing commitment is to refine the system further, always with an eye towards enhancing the gaming experience through intelligent and sensitive recommendations.

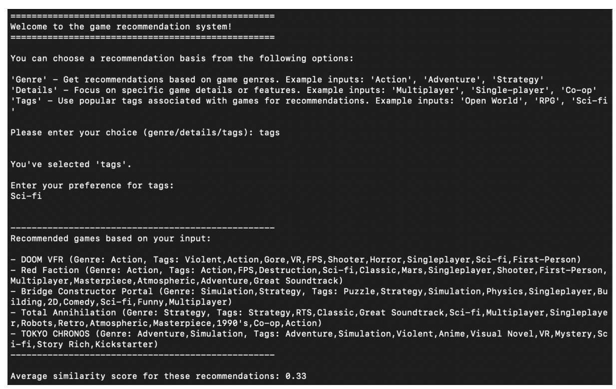

Figure 3: Sample output for NLP Method.

5 DISCUSSIONS

5.1 Limitations of Current Work

Although significant, the progress we have achieved on the project has highlighted a number of areas that need more analysis. A primary limitation is the extent of our data. Even though we have made great progress in understanding user preferences, our dataset is still limited since certain potentially important variables, like comprehensive user demographic data or contextual information that might affect game recommendation are not included. Furthermore, the datasets we used to build our current model mostly contained information that may not fully represent the complex and dynamic gaming landscape.

The use of textual analysis alone offers another drawback. Although the incorporation of genres, game details, and popular tags has expanded the range of our recommendation criteria, it is not sensitive to the constantly evolving nature of gaming trends or real-time market fluctuations that may impact the level of popularity and subsequent success of games.

Furthermore, even with our increased average similarity score, it is still unclear how this relates to real user satisfaction. Although quantitative measurements are important, they fall short of capturing the complex and highly subjective experience of enjoying and liking a game. The lack of a strong feedback loop from a wide range of users limits our understanding of how recommendations are taken into account in real-world scenarios.

5.2 Future Work

Our future path is well-defined and bold. We want to incorporate additional different data points into our model in order to solve the restrictions related to data depth. For instance, adding gameplay hours would offer insight into player engagement beyond initial preference, providing a proxy measure for sustained interest in a game. In the same way, adding developer names could allow us to find out how developer history or brand reputation affect game popularity.

We intend to look into complex models that can capture the temporal dynamics of the gaming industry in order to push the limits of our machine learning abilities. Recurrent neural networks (RNNs) or transformers, which can handle sequential data, may be used in this process in order to provide predictions that take trends and changes in the market into consideration.

Finally, we want to analyze the feature extraction module by an ablation study. We can determine the relative relevance of every feature in detail by systematically analyzing how it affects the model's performance. This will increase the precision of our recommendations and provide insightful information about games.

In conclusion, the work we have done so far has established a solid foundation for a dynamic and sophisticated video game recommendation system. To build a system that provides individualized, timely, and profoundly meaningful game suggestions, we will continue to grow our dataset, integrate user feedback, and use advanced machine learning algorithms.

6 CONCLUSION

The development of our video game recommendation system has been a journey of technical evolution, marked by a transition from basic machine learning techniques to the advanced interpretive power of deep learning and natural language processing (NLP). We have delved into extensive datasets, extracting insights and refining our approach to offer more personalized game recommendations and predict game popularity with increased accuracy.

Despite our system's demonstrated proficiency, evidenced by the jump in similarity scores, we acknowledge the limitations of our current iteration. The absence of real-time analytics and comprehensive user data points to the necessity for broader datasets and a more dynamic analytical approach.

Looking ahead, our roadmap includes the integration of additional data elements like gameplay hours and developer reputation to enrich our predictions. We aim to leverage more complex machine learning models capable of adapting to the ever-evolving gaming industry trends.

In conclusion, our efforts thus far have laid a solid foundation, but the quest for an optimal recommendation system is ongoing. Our future endeavors will focus on perfecting a system that not only understands but anticipates user needs, refining the gaming experience to be as engaging and satisfying as the games themselves.

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