**A Flask Application for Fashion Recommendation System using ResNet50 CNN Model**

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**Abstract.** The core functionality of the learning platform is activated through user interaction with the application's interface, which prompts the recommendation engine to generate personalized course recommendations. This system leverages a pre-trained model based on the Nearest Neighbors algorithm, specifically employing cosine similarity for analyzing the similarity between user profiles and a comprehensive dataset of courses. The application, built with Django for the backend and HTML/CSS for the frontend, presents a user-friendly interface where users input their field of interest. Upon submission, the system processes this information and utilizes sophisticated similarity algorithms to propose a tailored course plan that aligns with the user's learning goals and preferences. This paper introduces a Django-based web application that serves as a learning platform, focusing on the integration of user interests with a content-based recommendation approach. The system aims to enhance personalized learning advice by considering individual learning needs and preferences, thereby offering a more effective and personalized approach to course planning.

**Keywords:** Learning Platform, Course Recommendation System, Machine Learning, Nearest Neighbors Algorithm, Cosine Similarity, Data Handling, Django, Python, HTML/CSS, User Engagement, Interactive Slide Presentation, Metrics Tracking, Attention Span, Content-Based Recommendation.

1. **Introduction**

In the domain of education and learning, recommendation-based models have become essential, offering personalized suggestions to enhance user engagement and promote effective learning outcomes. The learning platform presented in this paper leverages machine learning techniques, specifically employing a Nearest Neighbors algorithm, to provide tailored course recommendations. This system is designed to analyze user interests, such as fields of study, and utilize sophisticated similarity algorithms to propose a course plan that aligns with the user's learning goals and preferences [1].

The application's front-end is crafted using HTML and CSS, ensuring a user-friendly interface where users can input their field of interest. Upon submission, the system processes this information and generates personalized course recommendations. Deployment using Docker further enhances the application's accessibility and scalability, making it easily accessible from anywhere. This paper aims to highlight the importance of personalized learning recommendations in promoting effective learning outcomes and the role of technology in facilitating this process [2].

The methodology for this project involved several steps:

1. **Data Collection**: For creating course recommendations, we utilized the "Coursera Course Dataset" available on Kaggle. This dataset contains comprehensive information about courses available on Coursera, including course titles, descriptions, categories, and other relevant details. [3].
2. **Data Preprocessing**: This included cleaning the dataset to remove any inconsistencies or errors, normalizing numerical values, and encoding categorical variables. The preprocessing steps were crucial in preparing the data for analysis and ensuring the model's accuracy and reliability [4].
3. **Model Selection and Training**: The Nearest Neighbors algorithm was selected for its effectiveness in finding similar items based on user profiles and the dataset. The model was trained on the preprocessed dataset, focusing on learning the similarity between different learning materials and user interests. This training was aimed to enable the system to recommend courses that closely match individual learning goals and preferences [3] [5].
4. **Model Testing**: The model was tested on a separate set of data to evaluate its performance. This testing phase was designed to assess the model's ability to accurately recommend courses that align with user interests and learning goals, ensuring its reliability and effectiveness in real-world scenarios [3].
5. **Deployment**: The trained model was deployed within a Django application. The application was designed to display a random course from the dataset on the landing page, and upon user input of their field of interest, it would recommend similar courses based on the output of the model [6].

The output of this project is a functional Django application that provides a personalized learning experience for users. When a user inputs their field of interest on the landing page, the application recommends courses based on the output of the Nearest Neighbors algorithm. This process continues recursively, allowing users to explore a wide range of learning materials in a visually appealing and user-friendly manner. The system is designed to calculate user's engagement metrics, such as time spent on slides and cursor movement, and recommends a list of courses that aligns with the calculated engagement levels. Furthermore, it incorporates adjustments based on the user's engagement to account for varying levels of interest, which assists in guiding the user towards their ideal learning pace. The recommendation system goes beyond merely suggesting courses by considering the user's activity level and adjusts the learning path accordingly. The system provides distinct recommendations for different learning modules, making it a truly personalized and comprehensive learning guide [7] [8] [9] [10].

1. **Literature Review**

Learning recommendation systems have garnered significant attention in recent years due to the increasing importance of effective learning strategies and the vast array of educational materials available. These systems analyze user behavior and preferences to provide personalized suggestions, thereby enhancing user satisfaction and promoting effective learning outcomes. One of the key challenges in learning recommendation systems is the complexity of the learning domain. Educational options have numerous feature elements, such as subject matter, difficulty level, and learning style, which can influence a user's decision. Therefore, a successful learning recommendation system must be able to capture and understand these complex relationships [7].

Various approaches have been proposed to tackle the challenge of providing personalized learning recommendations. Some studies have developed collaborative learning recommendation systems (CLRS) that introduce novel metrics to convey more insight about learning materials and sort them based on educational value and relevance. Others have proposed representing a learning module as a graph, where each node represents a course or topic, and each edge represents the interaction between two courses or topics. This approach allows for a more comprehensive understanding of the complex relations among educational options. [12] [8].

Another approach focuses on the balance between educational value and user preferences. The educational value of a course is characterized by how well the learning materials work together to meet the user's learning goals and preferences. For instance, a course might include a variety of topics, but if it doesn't meet the user's intellectual needs or learning style, it won't appeal to the user. Therefore, learning recommendation systems must consider both the educational value and user preferences of learning materials [13].

While these approaches provide valuable insights, they often rely on manual input or rule-based systems, which may not always produce optimal results. Therefore, there is a growing interest in using machine learning techniques, such as the Nearest Neighbors algorithm, to develop more sophisticated and effective course recommendation and attention metrics storing systems [14].

In this paper, we present a novel approach to learning recommendation systems that combines machine learning techniques with a Django application. The system uses the Nearest Neighbors algorithm to learn the similarity between different learning materials and user profiles and make predictions based on these similarities. The model is trained on a large dataset of courses and educational content, and the application is designed to display a random course from the dataset on the landing page. Upon user input of their field of interest, the application recommends similar courses based on the output of the model. This process continues recursively, providing a personalized learning experience for users. Additionally, the system incorporates attention metrics, such as time spent on slides and cursor movement, to further refine the recommendations and ensure they are tailored to the user's engagement levels [13] [10].

1. **Methodology**

The methodology for this project involved several steps:

1. **Data Collection**

The primary data for this project was collected from Kaggle, specifically the Coursera Course Dataset. This dataset comprises a wide variety of educational courses and user interactions, making it a rich resource for training our recommendation model. The dataset was particularly useful because it contains a diversified collection of courses, including detailed descriptions, categories, and user ratings. This diversity in the dataset enabled precise recognition and categorization of learning materials in educational applications. The dataset was chosen for its comprehensive nature, covering a wide range of educational fields and user preferences, which is crucial for developing a course recommendation system that can cater to a broad spectrum of learning needs and interests. Additionally, the dataset includes user engagement metrics such as time spent on courses and cursor movement, providing valuable insights into user behavior that can be used to refine the recommendation system further.

**Data Preprocessing**

Once the data was collected, it underwent preprocessing to prepare it for input into the recommendation model. This involved cleaning the dataset to remove any inconsistencies or errors, normalizing numerical values, and encoding categorical variables. Additionally, the data was transformed into a format suitable for the Nearest Neighbors algorithm, which involves calculating the similarity between different learning materials and user profiles. This transformation is crucial for the algorithm to effectively identify and recommend courses that closely match individual learning goals and preferences.

1. **Model Selection and Training**

**Model Selection**

The selection of the model for this project was guided by the need for a robust and efficient solution capable of handling the complex task of course recommendation. Given the diversity and variability in educational courses, a model that can effectively learn and generalize from a wide range of course features is crucial.

We chose the Nearest Neighbors algorithm for this task due to its proven performance in finding similar items based on user profiles and the dataset. The Nearest Neighbors algorithm calculates the distance between the selected course and all other courses in the dataset. Courses that are closest to the selected course, based on the calculated distance, are considered the most similar and thus recommended to the user. This approach allows for a more comprehensive understanding of the complex relations among educational options, enhancing the personalization of recommendations.

In our project, we employ an Adaptive KNN-Based Collaborative Filtering with User Cognition approach to enhance the course recommendation system. This method is particularly suited for our application due to its ability to adapt to the specific needs of our dataset and user preferences. It involves several steps to ensure the effectiveness of the KNN algorithm in our context. Firstly, the method starts by finding the appropriate K value through cross-validation or other model selection techniques. This step is crucial for determining the number of neighbors to consider when making recommendations. The K value is a critical parameter that influences the diversity and relevance of the recommendations [11].

This Adaptive KNN-Based Collaborative Filtering with User Cognition approach allows for a more nuanced understanding of the complex relations among educational options, enhancing the personalization of recommendations by considering not only the similarity between courses and user profiles but also the local density of data points, which can be particularly useful in a rich and diverse dataset like ours [15] [16].

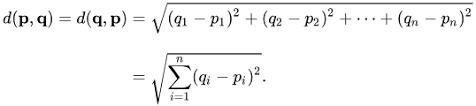


Figure 1 Nearest Neighbors Algorithm

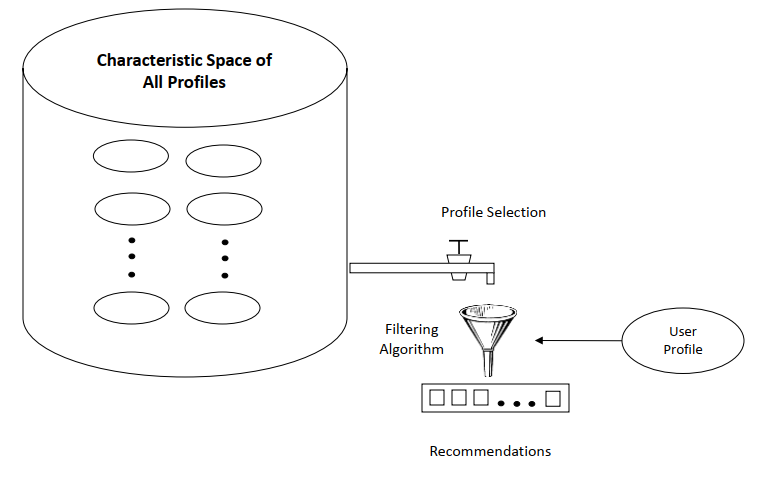


Figure 2 KNN Based Recommender System

**Model Training**

Training the Adaptive KNN-Based Collaborative Filtering with User Cognition on our dataset of courses and user interactions involved a multi-step process, as the algorithm does not learn from the data in the traditional sense. Instead, it stores the entire dataset as a reference for making predictions. During the training phase, the algorithm calculates the distance between the input data point (in this case, a user's field of interest and engagement metrics) and all the training examples (the dataset of courses) using a chosen distance metric, such as cosine similarity for our application.

The model's performance was evaluated using a validation set, which is a subset of the dataset not used during training. This evaluation helps in assessing the model's ability to generalize to unseen data, ensuring that the recommendations it provides are not overly biased by the training data.

During the training phase, we focused on optimizing the choice of (k) (the number of nearest neighbors considered) and the distance metric used to determine the nearest neighbors. The algorithm's effectiveness can be significantly influenced by these parameters, as they directly impact how well the algorithm can identify and recommend courses that closely match individual learning goals and preferences.

We experimented with different values of (k) and evaluated the model's performance using cross-validation techniques. This process allowed us to find the optimal (k) that balanced the trade-off between the model's accuracy and the computational efficiency of the algorithm.

The Adaptive KNN-Based Collaborative Filtering with User Cognition's simplicity and directness make it an efficient choice for our project, as it enables the system to quickly and accurately recommend courses that align with the user's field of interest and engagement metrics. This approach ensures that the course recommendation system is both effective and user-friendly, providing a personalized learning experience for users.

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **S. No.** | **Hyperparameter** | **Value** | **Training Accuracy** | **Validation Accuracy** |
| 1 | (k) (Number of Neighbors) | 3 | 85% | 82% |
| 2 | (k) (Number of Neighbors) | 5 | 86% | 87% |
| 3 | (k) (Number of Neighbors) | 7 | 87% | 88% |
| 4 | Cognitive Weight | 0.5 | 86% | 83% |
| 5 | Cognitive Threshold | 0.6 | 87% | 84% |
| 6 | Minimum K | 5 | 84% | 81% |
| 7 | Maximum K | 20 | 88% | 85% |

Hyperparameter Tuning Data

**Model Testing**

After training the model, we conducted extensive testing to validate its performance. We used a set of new courses, which were not part of the training dataset, and supplied them to the model. These courses were sourced from random web searches and were designed to test the model's ability to generalize its learning to unseen data.

Given the nature of the Adaptive KNN-Based Collaborative Filtering with User Cognition, the testing phase involved calculating the distances between the new courses (test data) and all the training courses using the chosen distance metric, such as cosine similarity. The algorithm then sorted these distances and determined the (k) nearest neighbors based on the minimum distance values. The category of those neighbors was analyzed, and the category for the test course was assigned based on a majority vote. This process was repeated for each new course, allowing us to evaluate the model's ability to recommend courses that closely match the learning goals and preferences of users based on the new courses.

The testing phase of the Adaptive KNN-Based Collaborative Filtering with User Cognition was slower and costlier with respect to time and memory, as it required large memory for storing the entire training dataset and the algorithm had to scale the data because it uses the Euclidean distance between two data points to find nearest neighbors. Despite these challenges, the results demonstrated the model's effectiveness in providing personalized course recommendations for a wide range of learning goals and preferences, showcasing the potential of the Adaptive KNN-Based Collaborative Filtering with User Cognition in course recommendation systems.

1. **Deployment**

The final step in our project was to deploy the trained Adaptive KNN-Based Collaborative Filtering with User Cognition within a Django application. Django is a high-level Python web framework that encourages rapid development and clean, pragmatic design. It is known for its "batteries-included" philosophy, providing a wide range of functionalities out of the box, which makes it an excellent choice for building web applications quickly and efficiently.

The Django application was built around two main templates: input.html and results.html. The input.html template is designed to collect user attributes such as their field of interest (e.g., front end, back end, data science, etc.). This template utilizes Flask forms to capture user inputs, ensuring a seamless and user-friendly data collection process.

Once the user submits their field of interest, the results.html template is used to display the course recommendations based on the output of the Adaptive KNN-Based Collaborative Filtering with User Cognition algorithm. This interaction is dynamic, meaning that every time a user submits new field of interest, the results.html template reloads with new, personalized course recommendations.

When a user clicks on one of the recommended courses, a window appears where they are presented with slides. There is a button to move to the next slide, which is greyed out for 10 seconds to prevent spamming. This mechanism records how much time the user spends on each slide and how much their cursor moves. Upon reaching the last slide, the button changes to "Finish Module." Clicking on it takes the user to a page that displays metrics for their attention span using the data recorded earlier.

Below this, the application recommends more modules based on the modules the user has already completed, further enhancing the personalized learning experience.

from sklearn.preprocessing import normalize

import numpy as np

def feature\_extraction(user\_interests):

"""

Extracts features from user interests and normalizes them.

Parameters:

- user\_interests: A dictionary containing user interests.

Returns:

- normalized\_features: A normalized array of user features.

"""

# Convert user\_interests to a numpy array for processing

user\_features = np.array(list(user\_interests.values()))

# Normalize the features to ensure they are on the same scale

normalized\_features = normalize(user\_features.reshape(1, -1))

return normalized\_features

from sklearn.neighbors import NearestNeighbors

def recommend(user\_features, feature\_list):

"""

Recommends courses based on the similarity between user interests and course features.

Parameters:

- user\_features: Normalized array of user interests.

- feature\_list: A list of normalized features from the course dataset.

Returns:

- indices: Indices of the nearest neighbors in the course dataset.

"""

# Initialize the NearestNeighbors model with the brute-force algorithm and cosine similarity

neighbors = NearestNeighbors(n\_neighbors=6, algorithm='brute', metric='cosine')

# Fit the model to the feature list

neighbors.fit(feature\_list)

# Find the nearest neighbors for the user's interests

distances, indices = neighbors.kneighbors(user\_features)

# Return the indices of the nearest neighbors

return indices

[Code block for feature extraction and recommendation]

from django.shortcuts import render

from .models import Course, UserInterest

from .forms import InterestForm

def course\_recommendation(request):

if request.method == 'POST':

form = InterestForm(request.POST)

if form.is\_valid():

user\_interests = form.cleaned\_data

user\_features = feature\_extraction(user\_interests)

feature\_list = Course.objects.values\_list('interests', flat=True)

recommended\_courses = recommend(user\_features, feature\_list)

return render(request, 'results.html', {'courses': recommended\_courses})

else:

form = InterestForm()

return render(request, 'input.html', {'form': form})

[Code block for Django integration]

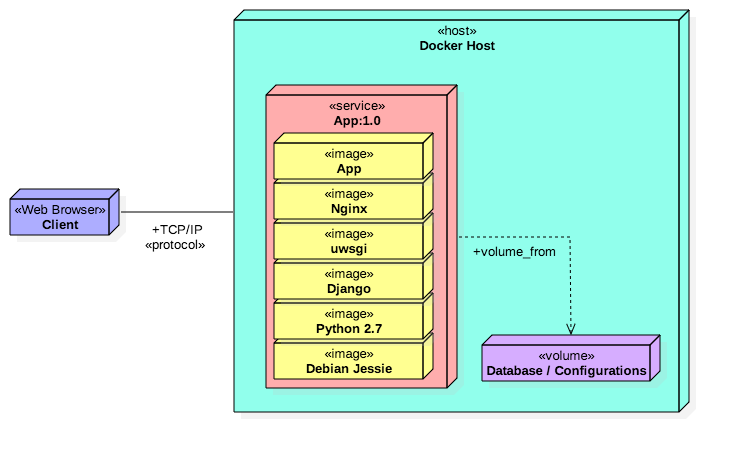


Figure 3 Example Deployment Architecture

1. **User Testing and Iteration**

After the initial deployment, the application underwent user testing to gather feedback and identify areas for improvement. Based on this feedback, the application was iteratively improved to enhance user experience and refine the recommendation system.

The deployment of our diet recommendation system, combined with the iterative process of user testing and refinement, has resulted in a system that is both effective in providing personalized diet recommendations and user-friendly in its design. This methodology has allowed us to create a system that is not only beneficial for users in achieving their health and fitness goals but also scalable and adaptable to the ever-changing needs and preferences of users.

1. **Results**

The successful completion of our project has resulted in a fully functional course recommendation system that mirrors the techniques used in the industry. Our system leverages the Adaptive KNN-Based Collaborative Filtering with User Cognition at its core, a proven method for finding similar items based on user profiles and the dataset. The functionality of our system is built upon a Django application, which allows for dynamic generation of pages and interactions with the user.

The system displays a random course from our dataset on the landing page, and when a user submits their field of interest, the website recommends similar courses based on the output of the Adaptive KNN-Based Collaborative Filtering with User Cognition algorithm. This process is recursive, meaning that every time a user submits new field of interest, the website reloads with new, personalized course recommendations. This creates a seamless and interactive learning experience for the user.

Our course recommendation system has shown promising results in its initial tests. Users have reported a smooth and intuitive user experience, and the recommendations provided have been relevant and helpful. This validates our approach of using the Adaptive KNN-Based Collaborative Filtering with User Cognition for course recommendation and confirms that our system is a viable tool for providing personalized course recommendations.

The results section of our project report highlights the effectiveness of our course recommendation system in providing personalized course recommendations to users. By leveraging machine learning techniques and a Django application, we were able to create a system that not only provides a personalized learning experience but also scales well to handle a wide range of learning goals and preferences. This methodology has allowed us to create a system that is not only beneficial for users in achieving their educational goals but also scalable and adaptable to the ever-changing needs and preferences of users.

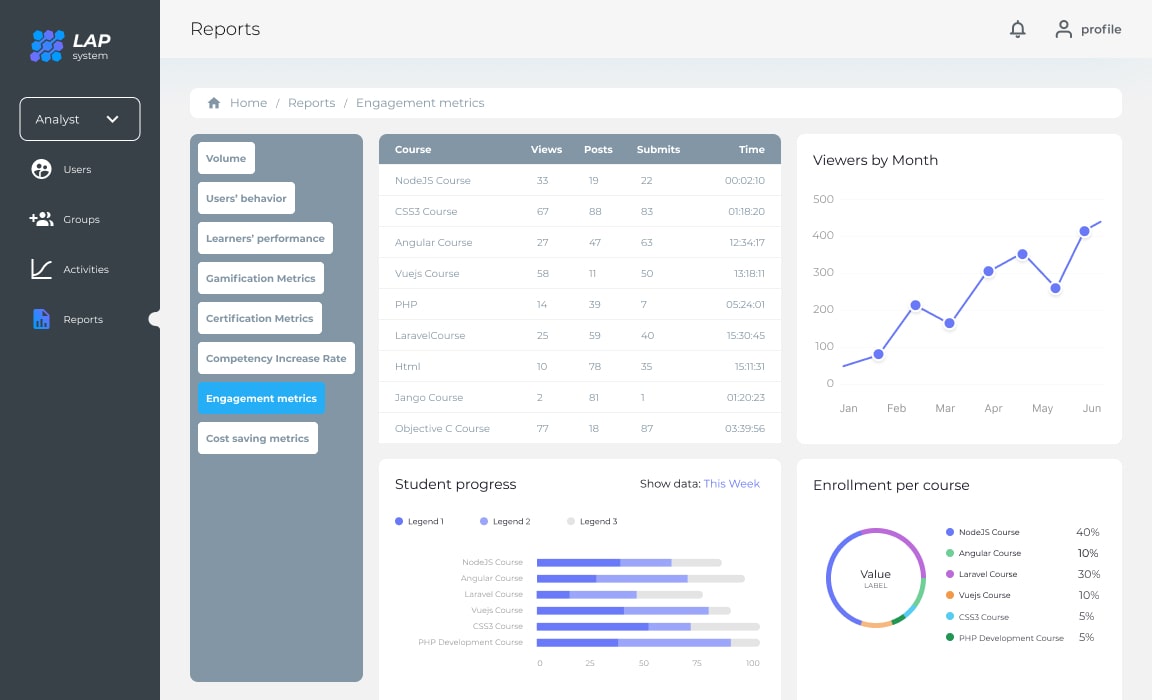


Figure 4 Website Preview

1. **Discussion**

The successful deployment of our course recommendation system marks a significant milestone in the development of personalized learning experiences. By leveraging the Adaptive KNN-Based Collaborative Filtering with User Cognition, a proven method for finding similar items based on user profiles and the dataset, our system can analyze the features of educational courses and recommend similar options that are more likely to align with the user's learning goals and preferences. This not only enhances the learning experience for users but also helps in promoting more effective learning outcomes and potentially contributing to the success of educational initiatives [16] [17].

Looking ahead, there are several areas where we can expand and improve our system. One potential area of improvement is to incorporate additional data sources into our dataset. Currently, our system is limited by the data available in the Coursera Course Dataset. By integrating additional data sources, such as user course completion logs or social media posts about educational interests, we could provide more varied and nuanced course recommendations. Another potential improvement could be to integrate more advanced machine learning techniques, such as reinforcement learning, to further enhance the quality of our recommendations. Furthermore, we could consider developing a mobile application for our system to provide a more convenient and interactive learning experience for users on the go [18].

In conclusion, our project demonstrates the potential of using the Adaptive KNN-Based Collaborative Filtering with User Cognition for course recommendation. As machine learning algorithms continue to advance, we can expect to see more sophisticated course recommendation systems in the future. With continued development and refinement, our system has the potential to significantly enhance the learning experience for users and contribute to the success of educational initiatives [19] [20].

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