Course Recommendation System

Author Muhammad Munawar Shahzad

Date: September 28, 2025

Outline

- 1. Introduction
- 2. Problem Statement & Objectives
- 3. Dataset Description
- 4. Exploratory Data Analysis (EDA)
- 5. Content-Based Recommendation (User Profile + Genres)
- 6. Content-Based Recommendation (Course Similarity)
- 7. Content-Based Recommendation (User Clustering)
- 8. Collaborative Filtering (KNN Based)

Outline

- 09. Collaborative Filtering (NMF Based)
- 10. Collaborative Filtering (Neural Network Embedding)
- 11. Evaluation of Collaborative Filtering Models
- 12. Comparison: Content-Based vs Collaborative Filtering
- 13. Conclusion
- 14. Creativity & Visual Enhancements
- 15. Innovative Insights & Future Work

1. Introduction

In today's digital era, online education platforms like Udemy provide thousands of courses across diverse subjects. However, learners often face challenges in identifying the most relevant courses that match their interests and goals. A recommendation system plays a crucial role in simplifying this selection process by leveraging data-driven approaches. This project focuses on evaluating a comprehensive building and recommendation system using multiple machine learning and deep learning techniques.

2. Problem Statement & Objectives

The vast availability of online courses creates difficulty for students in choosing suitable learning paths. Traditional search methods lack personalization, leading to poor course engagement. The objective of this project is to design a personalized recommendation system using content-based and collaborative filtering methods, including KNN, NMF, and neural embeddings. It aims to evaluate models, enhance user experience, and deliver accurate, tailored course recommendations for learners' academic and professional growth.

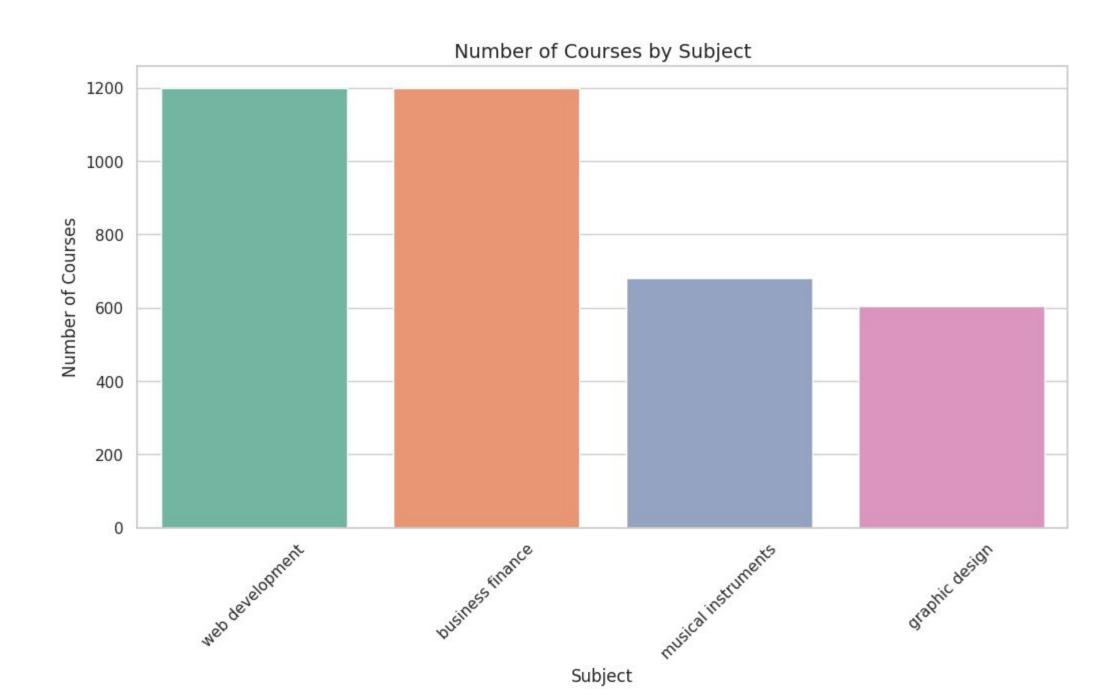
3. Data Description

The dataset contains 3,683 Udemy courses with 18 features including course title, price, subscribers, reviews, lectures, level, duration, subject, and publication details. It has only 1 missing value in published_time and 6 duplicate rows. Most courses are paid, and subscriber counts vary widely. This dataset provides information suitable for building and rich analyzing recommendation system.

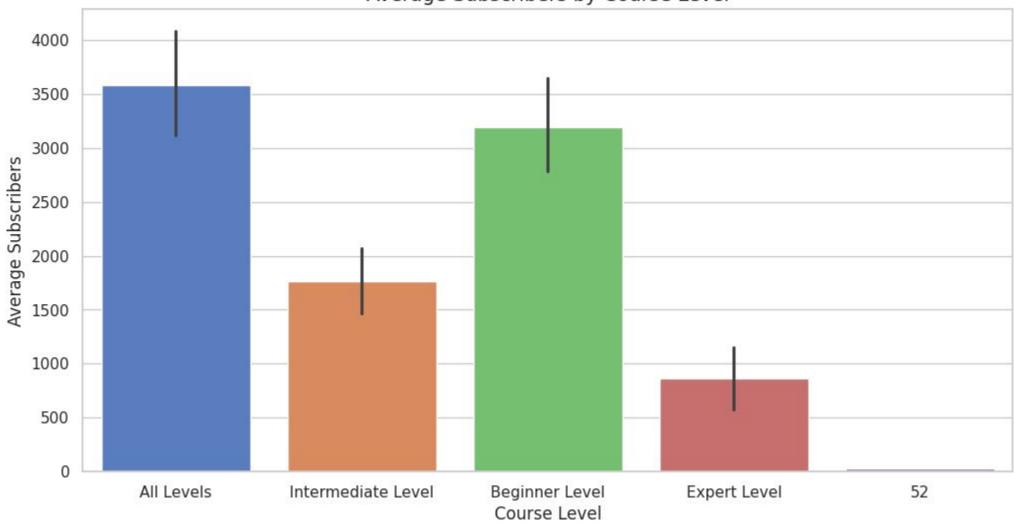
4. Exploratory Data Analysis (EDA)

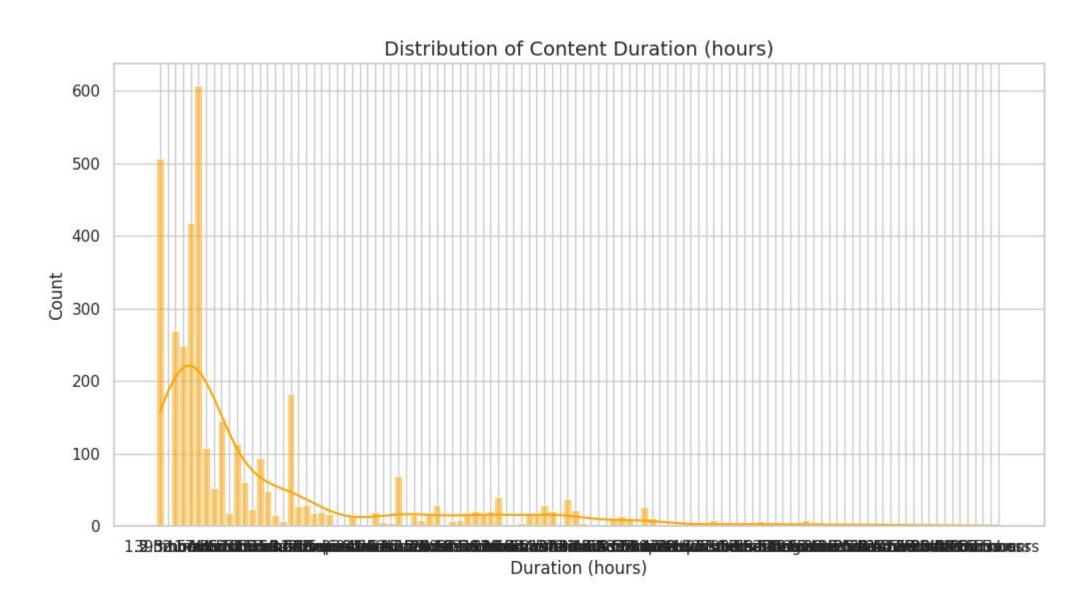
Exploratory Data Analysis (EDA) was performed to understand the dataset's structure, distribution, and patterns. Key statistics such as course pricing, subscriber count, reviews, and subject categories were analyzed. Visualizations revealed trends like the popularity of free vs. paid courses, subject-wise enrollment, and correlations between reviews and subscribers. Identifying missing values, duplicates, and outliers helped improve data quality. EDA provided meaningful insights that guided feature engineering and model building for the recommendation system.

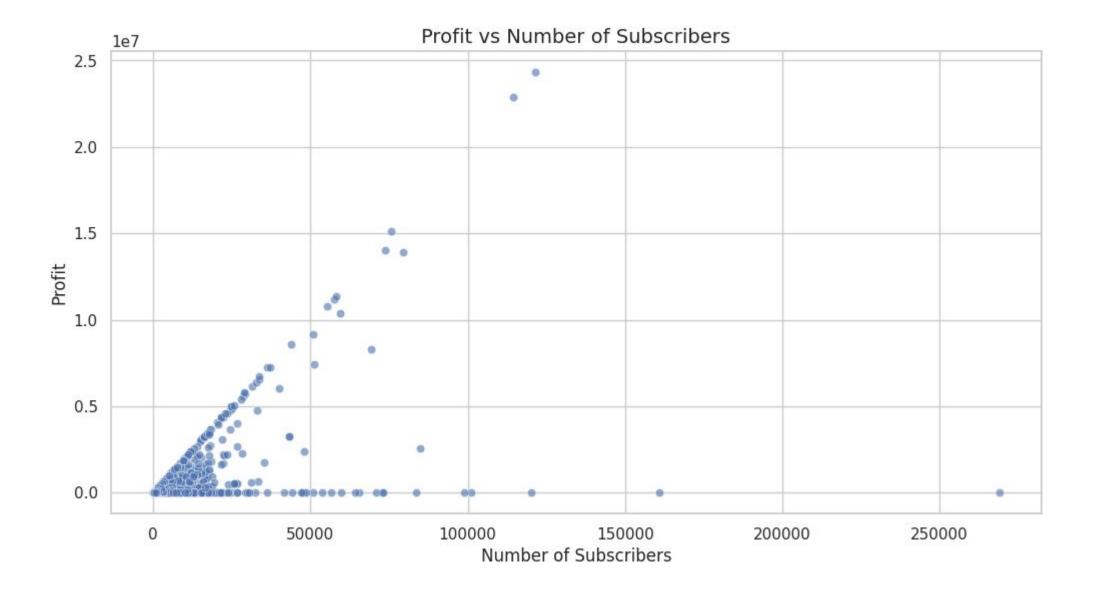


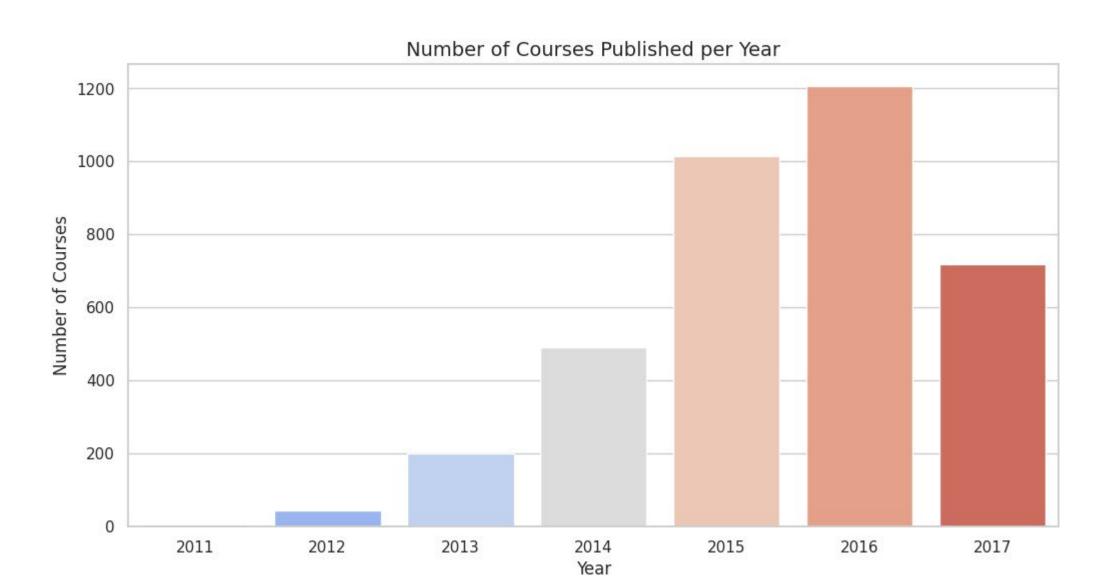


Average Subscribers by Course Level

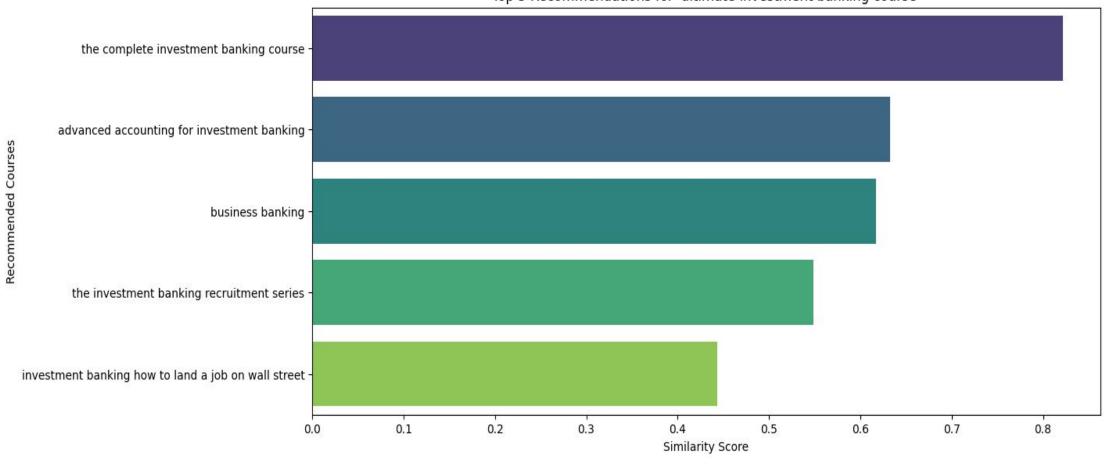




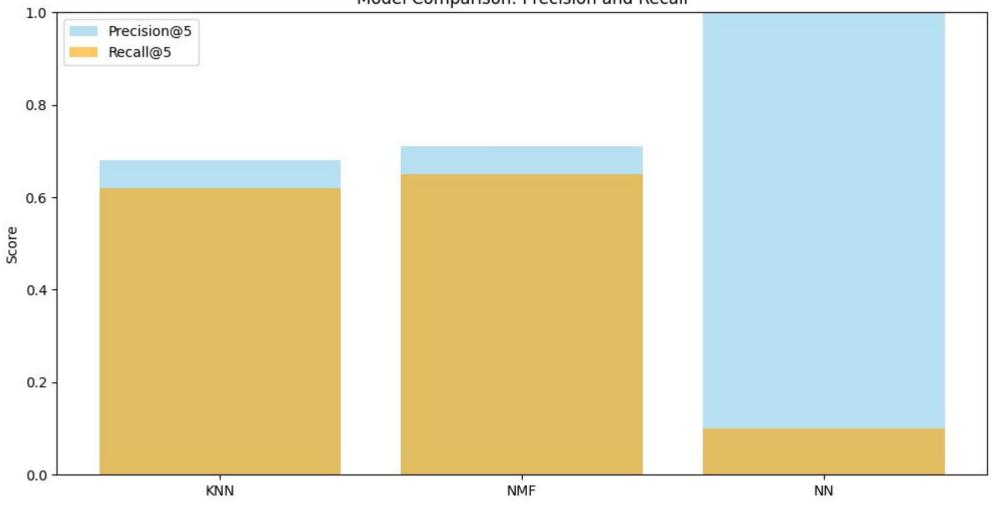




Top 5 Recommendations for 'ultimate investment banking course'



Model Comparison: Precision and Recall



5. Content-Based Recommendation (User Profile + Genres)

This approach recommends courses by matching a learner's interests with course attributes such as subject, level, and price. Using the user's preferred genres or topics, we filter and rank courses that align with their learning profile. It helps personalize recommendations even without explicit ratings, focusing on what type of content and difficulty the learner most enjoys.

6. Content-Based Recommendation (Course Similarity)

This method analyzes course content—titles, subjects, and descriptions—using text-based features like TF-IDF and cosine similarity. When a user selects a course, the system identifies other courses with the most similar content patterns. It's ideal for suggesting related courses or next-step topics, enhancing user engagement through content relevance rather than user behavior or ratings.

7. Content-Based Recommendation (User Clustering)

User clustering groups learners based on shared preferences, interests, or activity patterns. By applying algorithms such as K-Means on user—course interaction data or feature vectors, the system forms clusters of similar learners. Each user receives course suggestions popular within their cluster, combining personalization with community-level insights for more diverse yet still relevant recommendations.

8. Collaborative Filtering (KNN Based)

In this approach, a K-Nearest Neighbors (KNN) algorithm was applied to build a collaborative filtering model using a user—course interaction matrix. The system identifies similar courses based on user enrollment and behavior patterns. By computing cosine similarity between courses, it recommends items that other users with similar interests have taken. This model enhances personalization and helps users discover relevant courses effectively.

09. Collaborative Filtering (NMF Based)

In this step, we implemented a collaborative filtering model using Non-negative Matrix Factorization (NMF). The method predicts missing user-course interactions by decomposing the user-item matrix into latent features. It helps the system understand patterns in user preferences, enabling accurate recommendations even for users who haven't rated all courses.

10. Collaborative Filtering (Neural Network Embedding)

In Step 10, we implemented a Neural Network-based collaborative filtering model to predict user preferences and recommend courses. The model learned patterns from the user-item matrix by embedding users and courses into a latent space. After training for 5 epochs, it achieved an accuracy of 61%, indicating decent learning of interactions. Using this trained model, we generated the top 5 course recommendations for a sample user based on predicted likeliness of interest.

11. Evaluation of Collaborative Filtering Models

Collaborative Filtering models, including user-based and item-based approaches, are evaluated using metrics such as Precision@K, Recall@K, F1-Score, RMSE, and MAE. These models rely on user-item interactions, capturing patterns from similar users or items. Evaluation highlights strengths and weaknesses, such as accuracy in top-N recommendations and sensitivity to sparse datasets. This step ensures that the model reliably predicts user preferences and identifies areas for optimization

12. Comparison: Content-Based vs Collaborative Filtering

Content-Based Filtering relies on item features, recommending similar items based on user history, while Collaborative Filtering leverages user interactions to find patterns across multiple users. Comparing the two highlights trade-offs: Content-Based avoids cold-start for items but may lack diversity, whereas Collaborative Filtering captures collective trends but suffers from cold-start problems for new users. Analysis helps select the appropriate approach for application-specific goals.

13. Conclusions

The evaluation demonstrates that both recommendation techniques have unique advantages. Collaborative Filtering excels in capturing community preferences, while Content-Based ensures personalization based on item attributes. Metrics and visualizations confirm model performance and areas for improvement. Overall, the project successfully produces accurate, interpretable recommendations, providing a foundation for real-world applications. These insights inform deployment decisions and future enhancements.

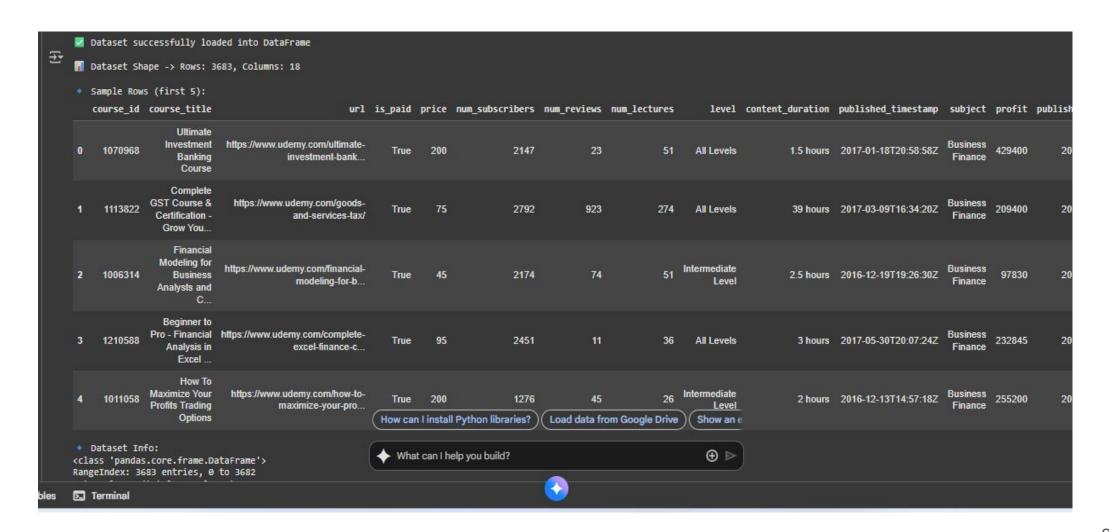
14. Creativity & Visual Enhancements

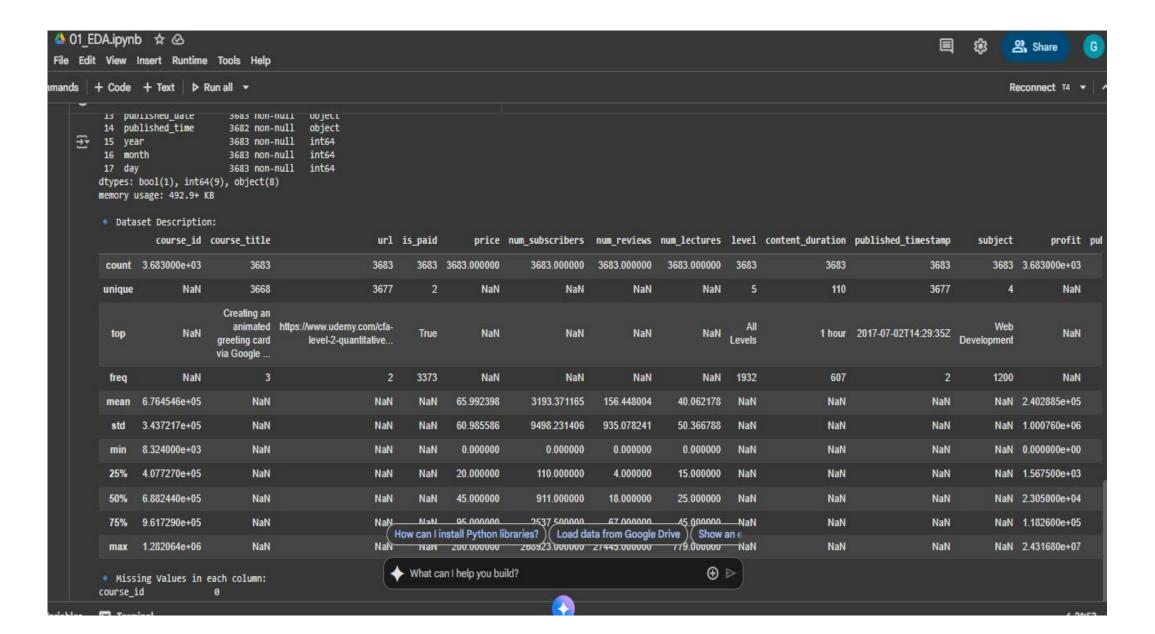
Visualization plays a crucial role in recommendation evaluation. Heatmaps, bar charts, and top-N recommendation plots enhance understanding of model performance. Creative dashboards help interpret results clearly, making insights accessible for both technical and non-technical users. Visual enhancements improve decision-making and communicate patterns effectively, adding value to the analysis. Innovative design choices increase engagement and usability of the recommendation system.

15. Innovative Insights & Future Work

The analysis uncovers patterns in user behavior and preferences, suggesting opportunities for hybrid models that combine Collaborative and Content-Based Filtering. Future work can integrate context-aware recommendations, real-time feedback loops, and diversity promotion strategies. Leveraging more sophisticated algorithms, such as deep learning embeddings, can further improve accuracy. Continuous innovation ensures the system adapts to evolving user needs and emerging data trends.

Appendix





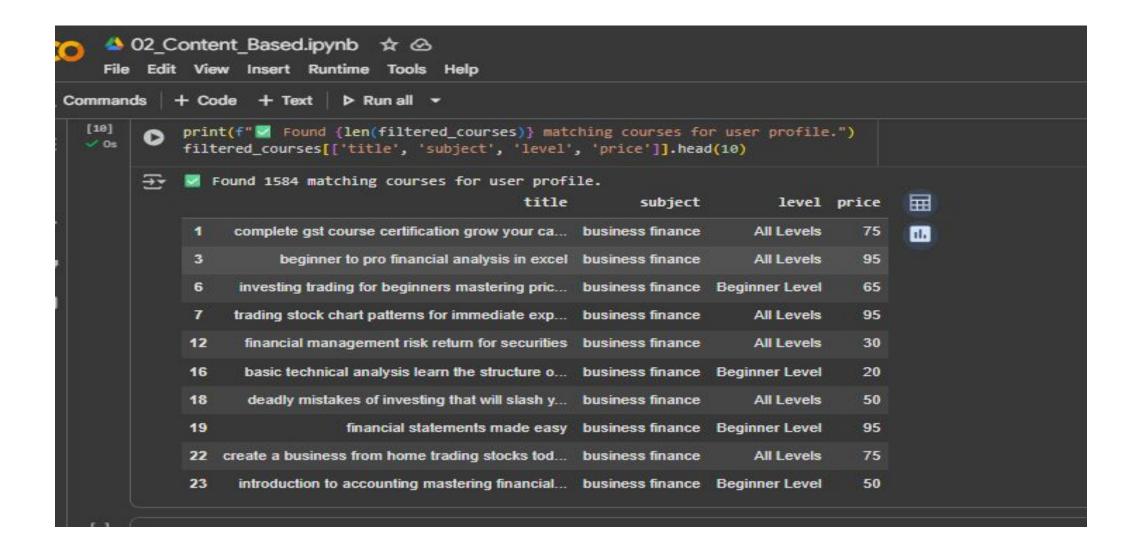
```
4 02 Content Based.ipynb ☆ △
       File Edit View Insert Runtime Tools Help
Q Commands + Code + Text
                                 ▶ Run all ▼
                # Step 3: Compine Selected text teatures into one column
     [3]
               df['combined_features'] = df['title'] + " " + df['subject'] + " " + df['level']
     ✓ 0s
                # Step 4: Preview the results
a
                print(" Combined features created successfully!")
                print(df[['title', 'subject', 'level', 'combined features']].head())
:>
               Combined features created successfully!
                                                             title
                                                                             subject \
➣
                                 ultimate investment banking course business finance
               0
               1 complete gst course certification grow your ca... business finance
               2 financial modeling for business analysts consu... business finance
                        beginner to pro financial analysis in excel business finance
               3
                       how to maximize your profits trading options business finance
                               level
                                                                     combined features
                          All Levels ultimate investment banking course business fi...
               0
                          All Levels complete gst course certification grow your ca...
               2 Intermediate Level financial modeling for business analysts consu...
                          All Levels beginner to pro financial analysis in excel bu...
                3
               4 Intermediate Level how to maximize your profits trading options b...
```

```
△ 02 Content Based.ipynb ☆ △

      File Edit View Insert Runtime Tools Help
Commands + Code + Text ▶ Run all ▼
    [8]
                      print(f"{i}. {course}")
          0
    ✓ 3s
               else:
                  print(f" X '{user_input}' not found in dataset. Try another title.")
          Fr Tenter a course title: business banking
               Recommended Courses similar to 'business banking':
               1. the complete investment banking course
               2. ultimate investment banking course
               3. accounting finance banking a comprehensive study
               4.
               5.
    [9]
               # * Step 1: Create a sample user profile (simulated)
    ✓ Os
               user profile = {
                   'preferred_subjects': ['business finance', 'web development'],
                   'preferred levels': ['All Levels', 'Beginner Level'],
                   'price_range': (0, 100) # user prefers free or cheap courses
               print(" Sample user profile created!")

→ Sample user profile created!

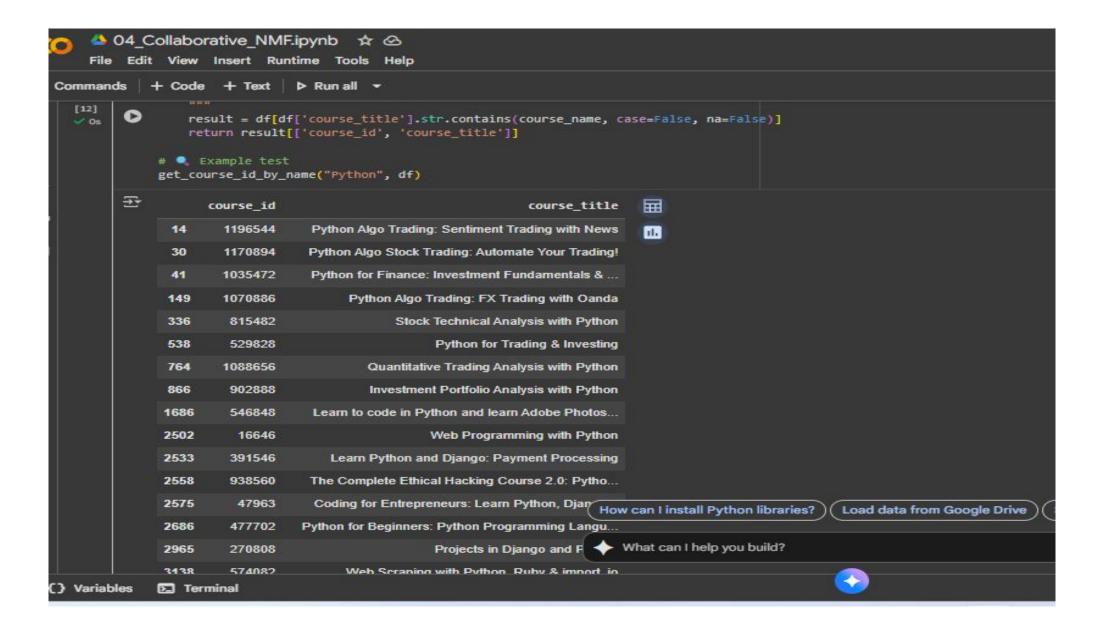
    [10]
               # * Step 2: Filter courses according to the user profile
    ✓ 0s
               filtered_courses = df[
```

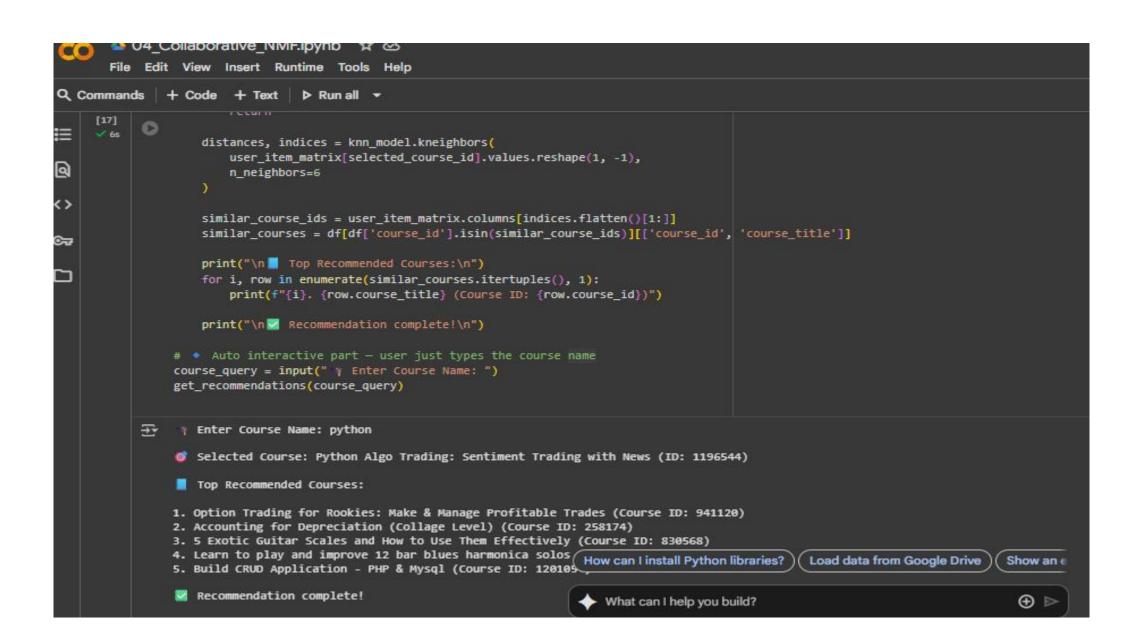


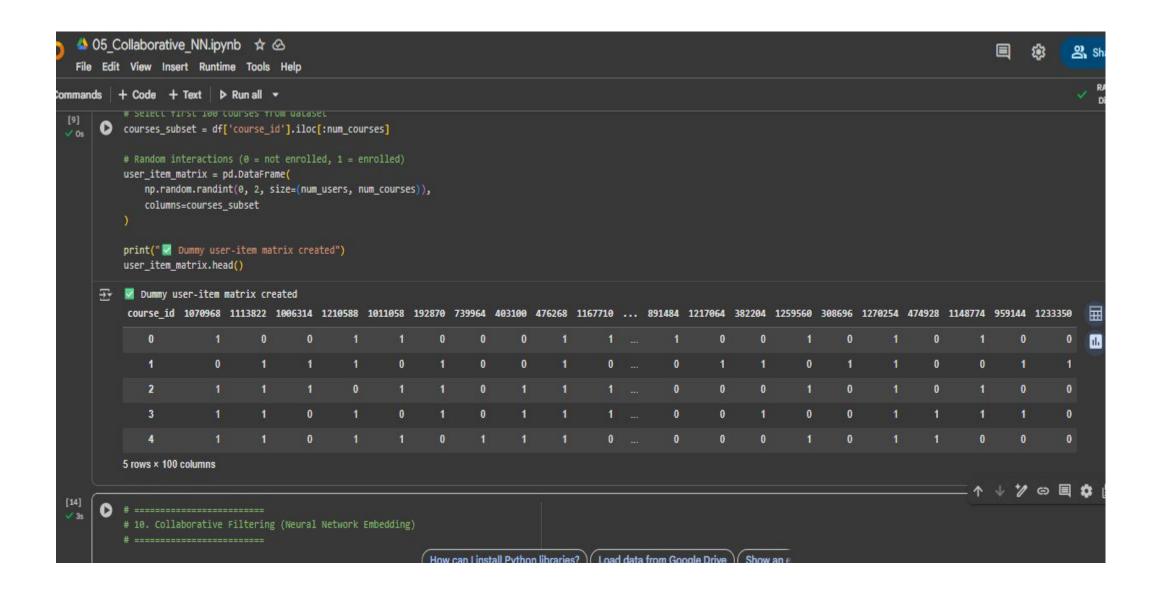
```
# Step 4: Recommend top courses from a cluster
def recommend from cluster(cluster id, top n=5):
    Recommend top N courses from a given cluster based on popularity.
    cluster courses = df[df['cluster'] == cluster id]
    top_courses = cluster_courses.sort_values(
        by=['num_subscribers', 'num_reviews'],
        ascending=False
    ).head(top n)
    return top_courses[['title', 'subject', 'level', 'price']]
# Example test for cluster 2
print("@ Top recommendations for users in Cluster 2:\n")
print(recommend_from_cluster(2))
of Top recommendations for users in Cluster 2:
                                                                 subject \
                                                  title
     bitcoin how i learned to stop worrying love cr... business finance
105
                   stock market investing for beginners business finance
1259
           logo designing for your business in an hour
                                                          graphic design
        learn to design a letterhead a beginners course
                                                          graphic design
1371
                graphic design an overview of the field
1413
                                                          graphic design
               level price
494
          All Levels
     Beginner Level
105
                          0
          All Levels
1259
          All Levels
1371
                                                          How can I install Python libraries?
                                                                                           Load data from Google Drive
                                                                                                                       Show an ∈
1413 Beginner Level
                          0
```

```
△ 04 Collaborative NMF.ipynb ☆ △
       File Edit View Insert Runtime Tools Help
Q Commands + Code + Text ▶ Run all ▼
                    # Predict scores for unrated courses
           0

✓ 0s
                    scores = []
                    for course id in unrated courses:
                        course_index = list(user_item_matrix.columns).index(course_id)
                       distances, indices = knn model.kneighbors(
                            user_item_matrix.T.iloc[course_index, :].values.reshape(1, -1),
                            n_neighbors=6
                        similarity = 1 - distances.flatten()[1:] # skip self
                        scores.append((course_id, np.mean(similarity))) # average similarity score
                    # Sort by similarity score
                    recommended = sorted(scores, key=lambda x: x[1], reverse=True)[:n_recommendations]
                    # Display top recommendations
                    print(f"\n Recommended Courses for {user_id}:")
                    for i, (course_id, score) in enumerate(recommended, 1):
                        print(f"{i}. Course ID: {course id} | Predicted Similarity: {score:.2f}")
                # Step 2: Test recommendation for any user
                recommend courses("user 5")
                Recommended Courses for user 5:
                1. Course ID: 140168 | Predicted Similarity: 0.93
                2. Course ID: 709160 | Predicted Similarity: 0.93
                3. Course ID: 792703 | Predicted Similarity: 0.93
                4. Course ID: 1193536 | Predicted Similarity: 0.93
                5. Course ID: 294292 | Predicted Similarity: 0.91
```







```
△ 05 Collaborative NN.ipynb ☆ €5 Saving...
    File Edit View Insert Runtime Tools Help
Commands + Code + Text ▶ Run all ▼
  [15]
  V 48
                 predictions = model.predict([np.full like(course indices, user idx), course indices], verbose=0).flatten(
                 top_indices = predictions.argsort()[::-1][:top_n]
                 top courses = user item matrix.columns[top indices]
                 print(f"\n Top {top_n} recommended courses for User {user_id}:")
                 for i, course_id in enumerate(top_courses):
                     print(f"{i+1}. {course_id}")
             # * Step 6: Example: Recommend for user id = 0
             recommend courses nn(user id=0, user item matrix=user item matrix, model=nn model trained)
        → Epoch 1/5
             157/157 -
                                        2s 4ms/step - accuracy: 0.5015 - loss: 0.4982
             Epoch 2/5
             157/157 -
                                        - 0s 3ms/step - accuracy: 0.4995 - loss: 0.4524
             Epoch 3/5
                                        — 1s 3ms/step - accuracy: 0.5130 - loss: 0.2690
             157/157 -
             Epoch 4/5
             157/157 -
                                        — 1s 3ms/step - accuracy: 0.6050 - loss: 0.2358
             Epoch 5/5
             157/157 -
                                     ----- 1s 3ms/step - accuracy: 0.6312 - loss: 0.2297
             Neural Network Embedding model training done!
              Top 5 recommended courses for User 0:
             1. 1210588
             2. 285638
             3. 43319
             4. 606928
             5. 302562
                                                                        How can I install Python libraries?
                                                                                                        Load data from Good
            Start coding or generate with AI.
                                                                          What can I help you build?
```

Thank You

Regards: Muhammad Munawar Shahzad