

```
In [1]: pip install pymupdf pdfplumber
```

```
Requirement already satisfied: pymupdf in c:\users\rizwana\anaconda3\envs\finalproject\lib\site-packages (1.26.3)
Requirement already satisfied: pdfplumber in c:\users\rizwana\anaconda3\envs\finalproject\lib\site-packages (0.11.7)
Requirement already satisfied: pdfminer.six==20250506 in c:\users\rizwana\anaconda3\envs\finalproject\lib\site-packages (from pdfplumber) (20250506)
Requirement already satisfied: Pillow>=9.1 in c:\users\rizwana\anaconda3\envs\finalproject\lib\site-packages (from pdfplumber) (11.3.0)
Requirement already satisfied: pypdfium2>=4.18.0 in c:\users\rizwana\anaconda3\envs\finalproject\lib\site-packages (from pdfplumber) (4.30.0)
Requirement already satisfied: charset-normalizer>=2.0.0 in c:\users\rizwana\anaconda3\envs\finalproject\lib\site-packages (from pdfminer.six==20250506->pdfplumber) (3.4.3)
Requirement already satisfied: cryptography>=36.0.0 in c:\users\rizwana\anaconda3\envs\finalproject\lib\site-packages (from pdfminer.six==20250506->pdfplumber) (45.0.6)
Requirement already satisfied: cffi>=1.14 in c:\users\rizwana\anaconda3\envs\finalproject\lib\site-packages (from cryptography>=36.0.0->pdfminer.six==20250506->pdfplumber) (1.17.1)
Requirement already satisfied: pycparser in c:\users\rizwana\anaconda3\envs\finalproject\lib\site-packages (from cffi>=1.14->cryptography>=36.0.0->pdfminer.six==20250506->pdfplumber) (2.22)
Note: you may need to restart the kernel to use updated packages.
```

# Data Preprocessing

## Concatenate IGCSE data into single .csv

```
In [2]: import os, re, glob
import pandas as pd

import fitz # pymupdf

def extract_text_pymupdf(pdf_path: str) -> str:
    text_parts = []
    with fitz.open(pdf_path) as doc:
        for page in doc:
            text_parts.append(page.get_text("text"))
    return "\n".join(text_parts).strip()

ROOT = r"C:\Users\Rizwana\Desktop\studyoclock project"

subjects = ["biology", "chemistry", "business", "ict"]
rows = []

for subj in subjects:
    folder = os.path.join(ROOT, subj)
    for pdf in glob.glob(os.path.join(folder, "*.pdf")):
        topic_name = os.path.splitext(os.path.basename(pdf))[0]
        raw_text = extract_text_pymupdf(pdf)
        rows.append({
            "subject": subj,
            "topic_name": topic_name,
            "raw_text": raw_text
        })

raw_df = pd.DataFrame(rows)
raw_df = raw_df.dropna(subset=["raw_text"])
raw_df = raw_df[raw_df["raw_text"].str.strip().astype(bool)]
```

```
raw_df.to_csv("raw_notes_from_pdfs.csv", index=False)
print("Built raw_notes_from_pdfs.csv with", len(raw_df), "rows")
raw_df.head()
```

Built raw\_notes\_from\_pdfs.csv with 75 rows

```
Out[2]:
```

	subject	topic_name	raw_text
0	biology	Unit 1 Characteristics and Classification of L...	Unit 1 Characteristics and Classification of L...
1	biology	Unit 10 Diseases and Immunity	Diseases and Immunity \nDisease \n• Pathogens ...
2	biology	Unit 11 Gas Exchange in Humans	Gas Exchange in Humans \nThe Gas Exchange Syst...
3	biology	Unit 12 Respiration	Respiration \nAerobic respiration \n• All ce...
4	biology	Unit 13 Excretion	Excretion \n \n• Excretion is the removal from...

## Verification that data is sensible

```
In [4]: raw_df.tail()
```

```
Out[4]:
```

	subject	topic_name	raw_text
70	ict	4. Networks and the effects of using them	Networks and the effects of using them \n• A ...
71	ict	5. The effects of using ICT	The Effects of Using ICT \nThe effects of ICT...
72	ict	6. ICT Applications	ICT Applications \nCommunication applications ...
73	ict	7. Systems Analysis and Design	Systems Analysis and Design \n• It is a method...
74	ict	8.Safety and Security	Safety and Security \nPhysical Safety \nHealt...

## Assignment of Difficulty Tags

```
In [5]: import re
import pandas as pd
from transformers import pipeline, AutoTokenizer
from textstat import flesch_kincaid_grade, flesch_reading_ease
from tqdm import tqdm

df = pd.read_csv("raw_notes_from_pdfs.csv")

required = {"subject", "topic_name", "raw_text"}
if not required.issubset(df.columns):
    raise ValueError(f"CSV must contain {required}")

df = df.dropna(subset=["raw_text"]).copy()
df["word_count"] = df["raw_text"].apply(lambda x: len(str(x).split()))

tqdm.pandas()

model_name = "sshleifer/distilbart-cnn-12-6"
tokenizer = AutoTokenizer.from_pretrained(model_name)
summarizer = pipeline("summarization", model=model_name, tokenizer=tokenizer, framework=

def chunk_by_tokens(text, tokenizer, max_tokens=1024):
    sentences = re.split(r'(?<=[.!?]) +', str(text))
    chunks, cur = [], ""
    for s in sentences:
        cand = (cur + " " + s).strip()
        if len(tokenizer.encode(cand)) < max_tokens:
            cur = cand
```

```

        else:
            if cur: chunks.append(cur)
            cur = s
        if cur: chunks.append(cur)
    return chunks

def summarize_text(text):
    parts = chunk_by_tokens(text, tokenizer)
    outs = [summarizer(p, max_length=1000, min_length=40, truncation=True)[0]["summary_t
    return " ".join(outs)

if "summary_text" not in df.columns:
    df["summary_text"] = df["raw_text"].progress_apply(summarize_text)

def assign_difficulty(summary: str) -> str:
    grade = flesch_kincaid_grade(summary)
    ease = flesch_reading_ease(summary)
    if grade <= 6 and ease >= 60:
        return "Easy"
    elif grade <= 10 and ease >= 40:
        return "Medium"
    else:
        return "Hard"

df["difficulty_level"] = df["summary_text"].apply(assign_difficulty)

df.to_csv("processed_notes.csv", index=False)
print("Saved processed_notes.csv with columns:", list(df.columns))
df.head()

```

Device set to use cpu

```

0%|██████████| 0/75 [00:00<?, ?it/s]Token indices sequence length
is longer than the specified maximum sequence length for this model (2263 > 1024). Runni
ng this sequence through the model will result in indexing errors
Your max_length is set to 1000, but your input_length is only 345. Since this is a summa
rization task, where outputs shorter than the input are typically wanted, you might cons
ider decreasing max_length manually, e.g. summarizer('...', max_length=172)
Your max_length is set to 1000, but your input_length is only 219. Since this is a summa
rization task, where outputs shorter than the input are typically wanted, you might cons
ider decreasing max_length manually, e.g. summarizer('...', max_length=109)
3%|███████| 1/75 [00:18<11:20, 9.33s/it]Your max_length is set to 10
00, but your input_length is only 592. Since this is a summarization task, where outputs
shorter than the input are typically wanted, you might consider decreasing max_length ma
nually, e.g. summarizer('...', max_length=296)
Your max_length is set to 1000, but your input_length is only 909. Since this is a summa
rization task, where outputs shorter than the input are typically wanted, you might cons
ider decreasing max_length manually, e.g. summarizer('...', max_length=454)
Your max_length is set to 1000, but your input_length is only 493. Since this is a summa
rization task, where outputs shorter than the input are typically wanted, you might cons
ider decreasing max_length manually, e.g. summarizer('...', max_length=246)
4%|███████| 2/75 [01:00<27:15, 22.72s/it]Your max_length is set to 10
00, but your input_length is only 694. Since this is a summarization task, where outputs
shorter than the input are typically wanted, you might consider decreasing max_length ma
nually, e.g. summarizer('...', max_length=347)
Your max_length is set to 1000, but your input_length is only 872. Since this is a summa
rization task, where outputs shorter than the input are typically wanted, you might cons
ider decreasing max_length manually, e.g. summarizer('...', max_length=436)
7%|███████| 3/75 [01:31<20:49, 17.85s/it]Your max_length is set to 10
00, but your input_length is only 805. Since this is a summarization task, where outputs
shorter than the input are typically wanted, you might consider decreasing max_length ma
nually, e.g. summarizer('...', max_length=402)

```

Your max\_length is set to 1000, but your input\_length is only 98. Since this is a summarization task, where outputs shorter than the input are typically wanted, you might consider decreasing max\_length manually, e.g. summarizer('...', max\_length=49)

8%|██████████

| 6/75 [01:56<23:12, 20.18s/it] Your max\_length is set to 1000, but your input\_length is only 713. Since this is a summarization task, where outputs shorter than the input are typically wanted, you might consider decreasing max\_length manually, e.g. summarizer('...', max\_length=356)

Your max\_length is set to 1000, but your input\_length is only 826. Since this is a summarization task, where outputs shorter than the input are typically wanted, you might consider decreasing max\_length manually, e.g. summarizer('...', max\_length=413)

9%|██████████

| 7/75 [02:37<30:37, 27.02s/it] Your max\_length is set to 1000, but your input\_length is only 35. Since this is a summarization task, where outputs shorter than the input are typically wanted, you might consider decreasing max\_length manually, e.g. summarizer('...', max\_length=17)

Your max\_length is set to 1000, but your input\_length is only 26. Since this is a summarization task, where outputs shorter than the input are typically wanted, you might consider decreasing max\_length manually, e.g. summarizer('...', max\_length=13)

11%|██████████

| 8/75 [03:05<30:37, 27.43s/it] Your max\_length is set to 1000, but your input\_length is only 268. Since this is a summarization task, where outputs shorter than the input are typically wanted, you might consider decreasing max\_length manually, e.g. summarizer('...', max\_length=134)

Your max\_length is set to 1000, but your input\_length is only 932. Since this is a summarization task, where outputs shorter than the input are typically wanted, you might consider decreasing max\_length manually, e.g. summarizer('...', max\_length=466)

Your max\_length is set to 1000, but your input\_length is only 71. Since this is a summarization task, where outputs shorter than the input are typically wanted, you might consider decreasing max\_length manually, e.g. summarizer('...', max\_length=35)

Your max\_length is set to 1000, but your input\_length is only 869. Since this is a summarization task, where outputs shorter than the input are typically wanted, you might consider decreasing max\_length manually, e.g. summarizer('...', max\_length=434)

Your max\_length is set to 1000, but your input\_length is only 471. Since this is a summarization task, where outputs shorter than the input are typically wanted, you might consider decreasing max\_length manually, e.g. summarizer('...', max\_length=235)

Your max\_length is set to 1000, but your input\_length is only 743. Since this is a summarization task, where outputs shorter than the input are typically wanted, you might consider decreasing max\_length manually, e.g. summarizer('...', max\_length=371)

Your max\_length is set to 1000, but your input\_length is only 824. Since this is a summarization task, where outputs shorter than the input are typically wanted, you might consider decreasing max\_length manually, e.g. summarizer('...', max\_length=412)

Your max\_length is set to 1000, but your input\_length is only 776. Since this is a summarization task, where outputs shorter than the input are typically wanted, you might consider decreasing max\_length manually, e.g. summarizer('...', max\_length=388)

12%|██████████

| 9/75 [04:41<53:25, 48.56s/it] Your max\_length is set to 1000, but your input\_length is only 965. Since this is a summarization task, where outputs shorter than the input are typically wanted, you might consider decreasing max\_length manually, e.g. summarizer('...', max\_length=482)

Your max\_length is set to 1000, but your input\_length is only 696. Since this is a summarization task, where outputs shorter than the input are typically wanted, you might consider decreasing max\_length manually, e.g. summarizer('...', max\_length=348)

Your max\_length is set to 1000, but your input\_length is only 636. Since this is a summarization task, where outputs shorter than the input are typically wanted, you might consider decreasing max\_length manually, e.g. summarizer('...', max\_length=318)

13%|██████████

| 10/75 [05:09<45:39, 42.15s/it] Your max\_length is set to 1000, but your input\_length is only 168. Since this is a summarization task, where outputs shorter than the input are typically wanted, you might consider decreasing max\_length manually, e.g. summarizer('...', max\_length=84)

Your max\_length is set to 1000, but your input\_length is only 447. Since this is a summarization task, where outputs shorter than the input are typically wanted, you might consider decreasing max\_length manually, e.g. summarizer('...', max\_length=223)

15%|██████████

| 11/75 [05:28<37:40, 35.32s/it] Your max\_length is set to 10



ider decreasing max\_length manually, e.g. summarizer('...', max\_length=421)  
Your max\_length is set to 1000, but your input\_length is only 692. Since this is a summarization task, where outputs shorter than the input are typically wanted, you might consider decreasing max\_length manually, e.g. summarizer('...', max\_length=346)  
Your max\_length is set to 1000, but your input\_length is only 469. Since this is a summarization task, where outputs shorter than the input are typically wanted, you might consider decreasing max\_length manually, e.g. summarizer('...', max\_length=234)  
Your max\_length is set to 1000, but your input\_length is only 808. Since this is a summarization task, where outputs shorter than the input are typically wanted, you might consider decreasing max\_length manually, e.g. summarizer('...', max\_length=404)  
Your max\_length is set to 1000, but your input\_length is only 644. Since this is a summarization task, where outputs shorter than the input are typically wanted, you might consider decreasing max\_length manually, e.g. summarizer('...', max\_length=322)

27| [REDACTED]  
| 20/75 [09:31<28:46, 31.40s/it]Your max\_length is set to 1000, but your input\_length is only 910. Since this is a summarization task, where outputs shorter than the input are typically wanted, you might consider decreasing max\_length manually, e.g. summarizer('...', max\_length=455)

Your max\_length is set to 1000, but your input\_length is only 709. Since this is a summarization task, where outputs shorter than the input are typically wanted, you might consider decreasing max\_length manually, e.g. summarizer('...', max\_length=354)

28| [REDACTED]  
| 21/75 [09:51<25:15, 28.06s/it]Your max\_length is set to 1000, but your input\_length is only 367. Since this is a summarization task, where outputs shorter than the input are typically wanted, you might consider decreasing max\_length manually, e.g. summarizer('...', max\_length=183)

Your max\_length is set to 1000, but your input\_length is only 768. Since this is a summarization task, where outputs shorter than the input are typically wanted, you might consider decreasing max\_length manually, e.g. summarizer('...', max\_length=384)

Your max\_length is set to 1000, but your input\_length is only 829. Since this is a summarization task, where outputs shorter than the input are typically wanted, you might consider decreasing max\_length manually, e.g. summarizer('...', max\_length=414)

Your max\_length is set to 1000, but your input\_length is only 446. Since this is a summarization task, where outputs shorter than the input are typically wanted, you might consider decreasing max\_length manually, e.g. summarizer('...', max\_length=223)

29| [REDACTED]  
| 22/75 [10:32<28:04, 31.79s/it]Your max\_length is set to 1000, but your input\_length is only 579. Since this is a summarization task, where outputs shorter than the input are typically wanted, you might consider decreasing max\_length manually, e.g. summarizer('...', max\_length=289)

31| [REDACTED]  
| 23/75 [10:47<23:11, 26.75s/it]Your max\_length is set to 1000, but your input\_length is only 767. Since this is a summarization task, where outputs shorter than the input are typically wanted, you might consider decreasing max\_length manually, e.g. summarizer('...', max\_length=383)

Your max\_length is set to 1000, but your input\_length is only 950. Since this is a summarization task, where outputs shorter than the input are typically wanted, you might consider decreasing max\_length manually, e.g. summarizer('...', max\_length=475)

Your max\_length is set to 1000, but your input\_length is only 883. Since this is a summarization task, where outputs shorter than the input are typically wanted, you might consider decreasing max\_length manually, e.g. summarizer('...', max\_length=441)

Your max\_length is set to 1000, but your input\_length is only 412. Since this is a summarization task, where outputs shorter than the input are typically wanted, you might consider decreasing max\_length manually, e.g. summarizer('...', max\_length=206)

32| [REDACTED]  
| 24/75 [11:17<23:46, 27.97s/it]Your max\_length is set to 1000, but your input\_length is only 966. Since this is a summarization task, where outputs shorter than the input are typically wanted, you might consider decreasing max\_length manually, e.g. summarizer('...', max\_length=483)

33| [REDACTED]  
| 25/75 [11:37<21:11, 25.43s/it]Your max\_length is set to 1000, but your input\_length is only 648. Since this is a summarization task, where outputs shorter than the input are typically wanted, you might consider decreasing max\_length manually, e.g. summarizer('...', max\_length=324)

Your max\_length is set to 1000, but your input\_length is only 504. Since this is a summarization task, where outputs shorter than the input are typically wanted, you might consider decreasing max\_length manually, e.g. summarizer('...', max\_length=206)





```
44%|███████████ | 33/75 [15:03<17:24, 24.87s/it]Your max_length is set to 10  
00, but your input_length is only 875. Since this is a summarization task, where outputs  
shorter than the input are typically wanted, you might consider decreasing max_length ma  
nually, e.g. summarizer('...', max_length=437)  
45%|███████████ | 34/75 [15:13<13:52, 20.31s/it]Your max_length is set to 10  
00, but your input_length is only 342. Since this is a summarization task, where outputs  
shorter than the input are typically wanted, you might consider decreasing max_length ma  
nually, e.g. summarizer('...', max_length=171)  
47%|███████████ | 35/75 [15:40<14:52, 22.31s/it]Your max_length is set to 10  
00, but your input_length is only 197. Since this is a summarization task, where outputs  
shorter than the input are typically wanted, you might consider decreasing max_length ma  
nually, e.g. summarizer('...', max_length=98)  
48%|███████████ | 36/75 [15:56<13:22, 20.58s/it]Your max_length is set to 10  
00, but your input_length is only 987. Since this is a summarization task, where outputs  
shorter than the input are typically wanted, you might consider decreasing max_length ma  
nually, e.g. summarizer('...', max_length=493)  
Your max_length is set to 1000, but your input_length is only 553. Since this is a summa  
rization task, where outputs shorter than the input are typically wanted, you might consi  
der decreasing max_length manually, e.g. summarizer('...', max_length=276)  
49%|███████████ | 37/75 [16:46<18:40, 29.50s/it]Your max_length is set to 10  
00, but your input_length is only 636. Since this is a summarization task, where outputs  
shorter than the input are typically wanted, you might consider decreasing max_length ma  
nually, e.g. summarizer('...', max_length=318)  
Your max_length is set to 1000, but your input_length is only 915. Since this is a summa  
rization task, where outputs shorter than the input are typically wanted, you might consid  
er decreasing max_length manually, e.g. summarizer('...', max_length=457)  
Your max_length is set to 1000, but your input_length is only 334. Since this is a summa  
rization task, where outputs shorter than the input are typically wanted, you might consid  
er decreasing max_length manually, e.g. summarizer('...', max_length=167)  
51%|███████████ | 38/75 [17:07<16:32, 26.82s/it]Your max_length is set to 10  
00, but your input_length is only 116. Since this is a summarization task, where outputs  
shorter than the input are typically wanted, you might consider decreasing max_length ma  
nually, e.g. summarizer('...', max_length=58)  
Your max_length is set to 1000, but your input_length is only 699. Since this is a summa  
rization task, where outputs shorter than the input are typically wanted, you might consid  
er decreasing max_length manually, e.g. summarizer('...', max_length=349)  
52%|███████████ | 39/75 [17:27<14:51, 24.77s/it]Your max_length is set to 10  
00, but your input_length is only 805. Since this is a summarization task, where outputs  
shorter than the input are typically wanted, you might consider decreasing max_length ma  
nually, e.g. summarizer('...', max_length=402)  
53%|███████████ | 40/75 [17:35<11:33, 19.81s/it]Your max_length is set to 10  
00, but your input_length is only 579. Since this is a summarization task, where outputs  
shorter than the input are typically wanted, you might consider decreasing max_length ma  
nually, e.g. summarizer('...', max_length=289)  
55%|███████████ | 41/75 [17:42<08:58, 15.84s/it]Your max_length is set to 10  
00, but your input_length is only 182. Since this is a summarization task, where outputs  
shorter than the input are typically wanted, you might consider decreasing max_length ma  
nually, e.g. summarizer('...', max_length=91)  
56%|███████████ | 42/75 [17:58<08:50, 16.07s/it]Your max_length is set to 100  
0, but your input_length is only 974. Since this is a summarization task, where outputs  
shorter than the input are typically wanted, you might consider decreasing max_length ma  
nually, e.g. summarizer('...', max_length=487)  
Your max_length is set to 1000, but your input_length is only 89. Since this is a summar  
ization task, where outputs shorter than the input are typically wanted, you might consi  
der decreasingmax_length manually, e.g. summarizer('...', max_length=44)  
57%|███████████
```



[illegible]

nually, e.g. summarizer('...', max\_length=237)

71%

| 53/75 [20:50<04:31, 12.35s/it]Your max\_length is set to 1000, but your input\_length is only 932. Since this is a summarization task, where outputs shorter than the input are typically wanted, you might consider decreasing max\_length manually, e.g. summarizer('...', max\_length=466)

Your max\_length is set to 1000, but your input\_length is only 301. Since this is a summarization task, where outputs shorter than the input are typically wanted, you might consider decreasing max\_length manually, e.g. summarizer('...', max\_length=150)

72%

| 54/75 [21:16<05:45, 16.43s/it]Your max\_length is set to 1000, but your input\_length is only 732. Since this is a summarization task, where outputs shorter than the input are typically wanted, you might consider decreasing max\_length manually, e.g. summarizer('...', max\_length=366)

73%

| 55/75 [21:34<05:37, 16.87s/it]Your max\_length is set to 1000, but your input\_length is only 909. Since this is a summarization task, where outputs shorter than the input are typically wanted, you might consider decreasing max\_length manually, e.g. summarizer('...', max\_length=454)

Your max\_length is set to 1000, but your input\_length is only 132. Since this is a summarization task, where outputs shorter than the input are typically wanted, you might consider decreasing max\_length manually, e.g. summarizer('...', max\_length=66)

75%

| 56/75 [21:47<05:01, 15.88s/it]Your max\_length is set to 1000, but your input\_length is only 950. Since this is a summarization task, where outputs shorter than the input are typically wanted, you might consider decreasing max\_length manually, e.g. summarizer('...', max\_length=475)

Your max\_length is set to 1000, but your input\_length is only 551. Since this is a summarization task, where outputs shorter than the input are typically wanted, you might consider decreasing max\_length manually, e.g. summarizer('...', max\_length=275)

76%

| 57/75 [22:05<04:58, 16.60s/it]Your max\_length is set to 1000, but your input\_length is only 913. Since this is a summarization task, where outputs shorter than the input are typically wanted, you might consider decreasing max\_length manually, e.g. summarizer('...', max\_length=456)

Your max\_length is set to 1000, but your input\_length is only 695. Since this is a summarization task, where outputs shorter than the input are typically wanted, you might consider decreasing max\_length manually, e.g. summarizer('...', max\_length=347)

77%

| 58/75 [22:24<04:52, 17.19s/it]Your max\_length is set to 1000, but your input\_length is only 689. Since this is a summarization task, where outputs shorter than the input are typically wanted, you might consider decreasing max\_length manually, e.g. summarizer('...', max\_length=344)

79%

| 59/75 [22:56<05:47, 21.69s/it]Your max\_length is set to 1000, but your input\_length is only 772. Since this is a summarization task, where outputs shorter than the input are typically wanted, you might consider decreasing max\_length manually, e.g. summarizer('...', max\_length=386)

Your max\_length is set to 1000, but your input\_length is only 561. Since this is a summarization task, where outputs shorter than the input are typically wanted, you might consider decreasing max\_length manually, e.g. summarizer('...', max\_length=280)

80%

| 60/75 [23:12<04:58, 19.87s/it]Your max\_length is set to 1000, but your input\_length is only 827. Since this is a summarization task, where outputs shorter than the input are typically wanted, you might consider decreasing max\_length manually, e.g. summarizer('...', max\_length=413)

Your max\_length is set to 1000, but your input\_length is only 215. Since this is a summarization task, where outputs shorter than the input are typically wanted, you might consider decreasing max\_length manually, e.g. summarizer('...', max\_length=107)

81%

| 61/75 [23:27<04:18, 18.49s/it]Your max\_length is set to 1000, but your input\_length is only 925. Since this is a summarization task, where outputs shorter than the input are typically wanted, you might consider decreasing max\_length manually, e.g. summarizer('...', max\_length=462)

83%

| 62/75 [23:37<03:26, 15.92s/it]Your max\_length is set to 10

00, but your input\_length is only 884. Since this is a summarization task, where outputs shorter than the input are typically wanted, you might consider decreasing max\_length manually, e.g. summarizer('...', max\_length=442)

Your max\_length is set to 1000, but your input\_length is only 664. Since this is a summarization task, where outputs shorter than the input are typically wanted, you might consider decreasing max\_length manually, e.g. summarizer('...', max\_length=332)

84%

| 63/75 [23:52<03:06, 15.54s/it] Your max\_length is set to 1000, but your input\_length is only 392. Since this is a summarization task, where outputs shorter than the input are typically wanted, you might consider decreasing max\_length manually, e.g. summarizer('...', max\_length=196)

85%

| 64/75 [23:57<02:16, 12.36s/it] Your max\_length is set to 1000, but your input\_length is only 941. Since this is a summarization task, where outputs shorter than the input are typically wanted, you might consider decreasing max\_length manually, e.g. summarizer('...', max\_length=470)

Your max\_length is set to 1000, but your input\_length is only 97. Since this is a summarization task, where outputs shorter than the input are typically wanted, you might consider decreasing max\_length manually, e.g. summarizer('...', max\_length=48)

87%

| 65/75 [24:12<02:11, 13.18s/it] Your max\_length is set to 1000, but your input\_length is only 963. Since this is a summarization task, where outputs shorter than the input are typically wanted, you might consider decreasing max\_length manually, e.g. summarizer('...', max\_length=481)

Your max\_length is set to 1000, but your input\_length is only 521. Since this is a summarization task, where outputs shorter than the input are typically wanted, you might consider decreasing max\_length manually, e.g. summarizer('...', max\_length=260)

88%

| 66/75 [24:29<02:09, 14.35s/it] Your max\_length is set to 1000, but your input\_length is only 932. Since this is a summarization task, where outputs shorter than the input are typically wanted, you might consider decreasing max\_length manually, e.g. summarizer('...', max\_length=466)

Your max\_length is set to 1000, but your input\_length is only 900. Since this is a summarization task, where outputs shorter than the input are typically wanted, you might consider decreasing max\_length manually, e.g. summarizer('...', max\_length=450)

89%

| 67/75 [24:46<02:01, 15.15s/it] Your max\_length is set to 1000, but your input\_length is only 808. Since this is a summarization task, where outputs shorter than the input are typically wanted, you might consider decreasing max\_length manually, e.g. summarizer('...', max\_length=404)

Your max\_length is set to 1000, but your input\_length is only 572. Since this is a summarization task, where outputs shorter than the input are typically wanted, you might consider decreasing max\_length manually, e.g. summarizer('...', max\_length=286)

91%

| 68/75 [25:00<01:43, 14.80s/it] Your max\_length is set to 1000, but your input\_length is only 992. Since this is a summarization task, where outputs shorter than the input are typically wanted, you might consider decreasing max\_length manually, e.g. summarizer('...', max\_length=496)

Your max\_length is set to 1000, but your input\_length is only 381. Since this is a summarization task, where outputs shorter than the input are typically wanted, you might consider decreasing max\_length manually, e.g. summarizer('...', max\_length=190)

92%

| 69/75 [25:27<01:50, 18.41s/it] Your max\_length is set to 1000, but your input\_length is only 864. Since this is a summarization task, where outputs shorter than the input are typically wanted, you might consider decreasing max\_length manually, e.g. summarizer('...', max\_length=432)

93%

| 70/75 [26:30<02:40, 32.03s/it] Your max\_length is set to 1000, but your input\_length is only 955. Since this is a summarization task, where outputs shorter than the input are typically wanted, you might consider decreasing max\_length manually, e.g. summarizer('...', max\_length=477)

Your max\_length is set to 1000, but your input\_length is only 171. Since this is a summarization task, where outputs shorter than the input are typically wanted, you might consider decreasing max\_length manually, e.g. summarizer('...', max\_length=85)

95%

| 71/75 [26:54<01:58, 29.55s/it] Your max\_length is set to 10



0	biology	Unit 1 Characteristics and Classification of L...	Unit 1 Characteristics and Classification of L...	1458	Living organisms are classified into 5 groups...	Medium
1	biology	Unit 10 Diseases and Immunity	Diseases and Immunity \nDisease \n• Pathogens ...	2059	Pathogens are organisms that cause diseases (...)	Medium
2	biology	Unit 11 Gas Exchange in Humans	Gas Exchange in Humans \nThe Gas Exchange Syst...	937	The lungs are spongy organs found inside the ...	Hard
3	biology	Unit 12 Respiration	Respiration \nAerobic respiration \n• All ce...	589	All cells need energy provided by burning glu...	Hard
4	biology	Unit 13 Excretion	Excretion \n \n• Excretion is the removal from...	1274	Excretion is the removal from the body of the...	Hard

In [6]: `df.tail()`

Out[6]:	subject	topic_name	raw_text	word_count	summary_text	difficulty_level
70	ict	4. Networks and the effects of using them	Networks and the effects of using them \n• A ...	3787	A computer network is developed by linking co...	Hard
71	ict	5. The effects of using ICT	The Effects of Using ICT \nThe effects of ICT...	540	Robots have replaced human workers in many ar...	Medium
72	ict	6. ICT Applications	ICT Applications \nCommunication applications ...	6582	Paper based communication used to inform peop...	Medium
73	ict	7. Systems Analysis and Design	Systems Analysis and Design \n• It is a method...	2172	Systems Analysis and Design is a method used ...	Hard
74	ict	8.Safety and Security	Safety and Security \nPhysical Safety \nHealt...	1280	Health and safety regulations advise that all...	Hard

## Content Based Filtering

```
In [9]: import os
from typing import List, Dict
import numpy as np
import pandas as pd
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.metrics.pairwise import cosine_similarity, linear_kernel

class ContentRecommender:
    def __init__(self, processed_csv: str = "processed_notes.csv",
                 tfidf_kwargs: Dict = None):
        if not os.path.exists(processed_csv):
            raise FileNotFoundError(f"{processed_csv} not found")
        self.df = pd.read_csv(processed_csv)

        required = {"subject", "topic_name", "summary_text"}
        if not required.issubset(self.df.columns):
            raise ValueError(f"CSV must contain {required}")
```



```

self.tfidf_kwargs = tfidf_kwargs or dict(
    stop_words="english", max_df=0.95, min_df=1, ngram_range=(1,2)
)

self.models = {}
for subject, sub in self.df.groupby("subject"):
    sub = sub.reset_index(drop=True).copy()
    tfidf = TfidfVectorizer(**self.tfidf_kwargs)
    X = tfidf.fit_transform(sub["summary_text"])
    sim = cosine_similarity(X, X)
    index_by_topic = pd.Series(sub.index, index=sub["topic_name"]).drop_duplicates()
    self.models[subject] = dict(df=sub, tfidf=tfidf, X=X, sim=sim,
                                index_by_topic=index_by_topic)

def _m(self, subject: str):
    if subject not in self.models:
        raise ValueError(f"No data for subject '{subject}'")
    return self.models[subject]

def find_topic(self, subject: str, pattern: str, top: int = 5) -> pd.DataFrame:
    m = self._m(subject)
    mask = m["df"]["topic_name"].str.contains(pattern, case=False, na=False)
    return m["df"][mask].head(top)[["topic_name"]]

def recommend_like(self, subject: str, topic_name: str, k: int = 5) -> pd.DataFrame:
    m = self._m(subject)
    if topic_name not in m["index_by_topic"]:
        raise ValueError(f"Topic '{topic_name}' not found in {subject}.")
    idx = m["index_by_topic"][topic_name]
    sims = list(enumerate(m["sim"][idx]))
    sims = sorted(sims, key=lambda x: x[1], reverse=True)[1:k+1]
    out = m["df"].iloc[[i for i, _ in sims]].copy()
    out["similarity"] = [s for _, s in sims]
    cols = ["topic_name", "similarity"]
    if "difficulty_level" in out.columns: cols.append("difficulty_level")
    return out[cols]

def recommend_query(self, subject: str, query: str, k: int = 5) -> pd.DataFrame:
    m = self._m(subject)
    q_vec = m["tfidf"].transform([query])
    sims = linear_kernel(q_vec, m["X"]).ravel()
    top = sims.argsort()[::-1][:k]
    out = m["df"].iloc[top].copy()
    out["similarity"] = sims[top]
    cols = ["topic_name", "similarity"]
    if "difficulty_level" in out.columns: cols.append("difficulty_level")
    return out[cols]

def recommend_from_profile(self, subject: str, liked_topics: List[str], k: int = 5)
    m = self._m(subject)
    sub = m["df"]
    mask = sub["topic_name"].isin(liked_topics)
    idxs = np.where(mask.values)[0]
    if len(idxs) == 0:
        raise ValueError("None of the liked topics are in this subject.")
    # mean() returns a numpy.matrix; convert to 2D ndarray
    centroid = np.asarray(m["X"][idxs].mean(axis=0)).reshape(1, -1)
    sims = linear_kernel(centroid, m["X"]).ravel()
    # exclude liked topics
    candidates = ~mask.values
    cand_idx = np.where(candidates)[0]
    ranked = cand_idx[np.argsort(-sims[cand_idx])[:k]]
    out = sub.iloc[ranked].copy()
    out["similarity"] = sims[ranked]

```

```

cols = ["topic_name", "similarity"]
if "difficulty_level" in out.columns: cols.append("difficulty_level")
return out[cols]

if __name__ == "__main__":
    rec = ContentRecommender(processed_csv="processed_notes.csv")

    def show(title, df):
        print(f"\n=== {title} ===")
        try:
            print(df.to_string(index=False))
        except Exception:
            print(df)

    #Locate exact topic names
    show("Find Biology topics containing 'Respiration'", rec.find_topic("biology", "Resp
    show("Find Chemistry topics containing 'Speed of Reaction'", rec.find_topic("chemist
    show("Find Business topics containing 'Market Research'", rec.find_topic("business",
    show("Find ICT topics containing 'Applications'", rec.find_topic("ict", "Application

    # 1) Item to Item
    # biology: "Unit 12 Respiration"
    try:
        show("Biology: more like 'Unit 12 Respiration'",
            rec.recommend_like("biology", "Unit 12 Respiration", k=5))
    except Exception as e:
        print("Biology example error:", e)

    # chemistry: "Unit 8 Speed of Reaction"
    try:
        show("Chemistry: more like 'Unit 8 Speed of Reaction'",
            rec.recommend_like("chemistry", "Unit 8 Speed of Reaction", k=5))
    except Exception as e:
        print("Chemistry example error:", e)

    # business: "Chapter 11-Market Research"
    try:
        show("Business: more like 'Chapter 11-Market Research'",
            rec.recommend_like("business", "Chapter 11-Market Research", k=5))
    except Exception as e:
        print("Business example error:", e)

    # 2) Query to Items
    show("ICT: query → 'computer networks and topologies'",
        rec.recommend_query("ict", "computer networks and topologies", k=5))

    show("Chemistry: query → 'stoichiometry mole calculations'",
        rec.recommend_query("chemistry", "stoichiometry mole calculations", k=5))

    # 3) Profile to Items
    bio_liked = ["Unit 5 Enzymes", "Unit 8 Plant Transport"]
    try:
        show(f"Biology: profile from liked topics {bio_liked}",
            rec.recommend_from_profile("biology", bio_liked, k=5))
    except Exception as e:
        print("Biology profile example error:", e)

    chem_liked = ["Unit 13 Metals and Reactivity", "Unit 14 Metal Extraction"]
    try:
        show(f"Chemistry: profile from liked topics {chem_liked}",
            rec.recommend_from_profile("chemistry", chem_liked, k=5))

```

```
except Exception as e:
```

```
    print("Chemistry profile exampleerror:", e)
```

```
=== Find Biology topics containing 'Respiration' ===
```

```
    topic_name
```

```
Unit 12 Respiration
```

```
=== Find Chemistry topics containing 'Speed of Reaction' ===
```

```
    topic_name
```

```
Unit 8 Speed of Reaction
```

```
=== Find Business topics containing 'Market Research' ===
```

```
    topic_name
```

```
Chapter 11-Market Research
```

```
=== Find ICT topics containing 'Applications' ===
```

```
    topic_name
```

```
6. ICT Applications
```

```
=== Biology: more like 'Unit 12 Respiration' ===
```

	topic_name	similarity	difficulty_level
	Unit 6 Plant Nutrition	0.056429	Hard
	Unit 5 Enzymes	0.046207	Hard
Unit 19	Organisms and their environment	0.038062	Hard
	Unit 3 Movement in and out of cells	0.033983	Medium
	Unit 7 Animal Nutrition	0.031785	Hard

```
=== Chemistry: more like 'Unit 8 Speed of Reaction' ===
```

	topic_name	similarity	difficulty_level
	Unit 9 Chemical Reactions	0.187213	Hard
Unit 16	The Chemical Industry	0.094836	Medium
	Unit 12 The Periodic Table	0.047639	Medium
	Unit 7 Chemical Changes	0.046958	Medium
	Unit 19 Polymers	0.046695	Medium

```
=== Business: more like 'Chapter 11-Market Research' ===
```

	topic_name	similarity	difficulty_level
	Chapter 14-The Marketing Mix	0.081381	Hard
	Chapter 13- The Marketing Mix	0.075236	Medium
	Chapter 12-The Marketing Mix	0.071678	Medium
	Chapter 2- Classification of Business	0.071258	Hard
Chapter 17-	Production of Goods and Services	0.031832	Hard

```
=== ICT: query → 'computer networks and topologies' ===
```

	topic_name	similarity	difficulty_level
4. Networks	and the effects of using them	0.089699	Hard
	6. ICT Applications	0.059133	Medium
1. Types	and Components of Computer Systems	0.058302	Hard
	8.Safety and Security	0.055853	Hard
	2. Input and Output Devices	0.013644	Medium

```
=== Chemistry: query → 'stoichiometry mole calculations' ===
```

	topic_name	similarity	difficulty_level
	Unit 9 Chemical Reactions	0.0	Hard
	Unit 8 Speed of Reaction	0.0	Hard
	Unit 10 Acids and Bases	0.0	Medium
Unit 11	Making and identifying salts	0.0	Medium
	Unit 12 The Periodic Table	0.0	Medium

```
=== Biology: profile from liked topics ['Unit 5 Enzymes', 'Unit 8 Plant Transport'] ===
```

	topic_name	similarity	difficulty_level
	Unit 3 Movement in and out of cells	0.083940	Medium
Unit1	Characteristics and Classification of Living Organisms	0.065948	Medium

	Unit 2 Cells	0.033076	Medi
um			
	Unit 19 Organisms and their environment	0.030573	Ha
rd			
	Unit 15 Drugs	0.028465	Medi
um			

=== Chemistry: profile from liked topics ['Unit 13 Metals and Reactivity', 'Unit 14 Metal Extraction'] ===

	topic_name	similarity	difficulty_level
	Unit 15 Air and Water	0.105418	Medium
	Unit 6 Electricity and Chemistry	0.079165	Hard
	Unit 11 Making and identifying salts	0.066035	Medium
	Unit 3 Structure and Bonding	0.059454	Hard
	Unit 17 Organic chemistry and petrochemicals	0.057497	Hard

```
In [10]: import os
from typing import List, Dict
import numpy as np
import pandas as pd
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.metrics.pairwise import cosine_similarity, linear_kernel

class ContentRecommender:
    def __init__(self, processed_csv: str = "processed_notes.csv",
                  tfidf_kwargs: Dict = None):
        if not os.path.exists(processed_csv):
            raise FileNotFoundError(f"{processed_csv} not found")
        self.df = pd.read_csv(processed_csv)

        required = {"subject", "topic_name", "summary_text"}
        if not required.issubset(self.df.columns):
            raise ValueError(f"CSV must contain {required}")

        # keep rare terms; add bigrams; scale tf; allow long docs
        self.tfidf_kwargs = tfidf_kwargs or dict(
            stop_words="english",
            max_df=0.95,
            min_df=1,
            ngram_range=(1, 2),
            sublinear_tf=True
        )

        self.models = {}
        for subject, sub in self.df.groupby("subject"):
            sub = sub.reset_index(drop=True).copy()

            # combine title and summary for stronger signals
            sub["text_for_tfidf"] = (
                sub["topic_name"].fillna("") + " " + sub["summary_text"].fillna("")
            )

            tfidf = TfidfVectorizer(**self.tfidf_kwargs)
            X = tfidf.fit_transform(sub["text_for_tfidf"])
            sim = cosine_similarity(X, X)
            index_by_topic = pd.Series(sub.index, index=sub["topic_name"]).drop_duplicates()

            self.models[subject] = dict(
                df=sub, tfidf=tfidf, X=X, sim=sim, index_by_topic=index_by_topic
            )

        def _m(self, subject: str):
            if subject not in self.models:
                raise ValueError(f"No data for subject '{subject}'")
```

```

        return self.models[subject]

def find_topic(self, subject: str, pattern: str, top: int = 5) -> pd.DataFrame:
    """Case-insensitive partial match over topic_name."""
    m = self._m(subject)
    mask = m["df"]["topic_name"].str.contains(pattern, case=False, na=False)
    return m["df"][mask].head(top)[["topic_name"]]

#Item to Item
def recommend_like(self, subject: str, topic_name: str, k: int = 5) -> pd.DataFrame:
    m = self._m(subject)
    if topic_name not in m["index_by_topic"]:
        raise ValueError(
            f"Topic '{topic_name}' not found in {subject}. "
            f"Try rec.find_topic('{subject}', '<part of title>')."
        )
    idx = m["index_by_topic"][topic_name]
    sims = list(enumerate(m["sim"][idx]))
    sims = sorted(sims, key=lambda x: x[1], reverse=True)[1:k+1]
    out = m["df"].iloc[[i for i, _ in sims]].copy()
    out["similarity"] = [s for _, s in sims]
    cols = ["topic_name", "similarity"]
    if "difficulty_level" in out.columns:
        cols.append("difficulty_level")
    return out[cols]

#Query to Item
def recommend_query(self, subject: str, query: str, k: int = 5) -> pd.DataFrame:
    m = self._m(subject)
    q_vec = m["tfidf"].transform([query])
    sims = linear_kernel(q_vec, m["X"]).ravel()
    top = sims.argsort()[::-1][:k]
    out = m["df"].iloc[top].copy()
    out["similarity"] = sims[top]
    cols = ["topic_name", "similarity"]
    if "difficulty_level" in out.columns:
        cols.append("difficulty_level")
    return out[cols]

#Liked Topics to Items
def recommend_from_profile(self, subject: str, liked_topics: List[str], k: int = 5)
    m = self._m(subject)
    sub = m["df"]
    mask = sub["topic_name"].isin(liked_topics)
    idxs = np.where(mask.values)[0]
    if len(idxs) == 0:
        raise ValueError("None of the liked topics are in this subject.")
    # convert to ndarray row vector to avoid np.matrix issues
    centroid = np.asarray(m["X"][idxs].mean(axis=0)).reshape(1, -1)
    sims = linear_kernel(centroid, m["X"]).ravel()
    # exclude liked topics
    candidates = ~mask.values
    cand_idx = np.where(candidates)[0]
    ranked = cand_idx[np.argsort(-sims[cand_idx])[:k]]
    out = sub.iloc[ranked].copy()
    out["similarity"] = sims[ranked]
    cols = ["topic_name", "similarity"]
    if "difficulty_level" in out.columns:
        cols.append("difficulty_level")
    return out[cols]

#Verification
if __name__ == "__main__":
    rec = ContentRecommender(processed_csv="processed_notes.csv")

```



```

def show(title, df):
    print(f"\n=== {title} ===")
    try:
        print(df.to_string(index=False))
    except Exception:
        print(df)

#Helpers to confirm exact titles present
show("Find Biology topics containing 'Respiration'", rec.find_topic("biology", "Resp
show("Find Chemistry topics containing 'Speed of Reaction'", rec.find_topic("chemist
show("Find Business topics containing 'Market Research'", rec.find_topic("business",
show("Find ICT topics containing 'Applications'", rec.find_topic("ict", "Application

#Item to Item
try:
    show("Biology: more like 'Unit 12 Respiration'",
        rec.recommend_like("biology", "Unit 12 Respiration", k=5))
except Exception as e:
    print("Biology example error:", e)

try:
    show("Chemistry: more like 'Unit 8 Speed of Reaction'",
        rec.recommend_like("chemistry", "Unit 8 Speed of Reaction", k=5))
except Exception as e:
    print("Chemistry example error:", e)

try:
    show("Business: more like 'Chapter 11-Market Research'",
        rec.recommend_like("business", "Chapter 11-Market Research", k=5))
except Exception as e:
    print("Business example error:", e)

#Query to Items
show("ICT: query → 'computer networks and topologies'",
    rec.recommend_query("ict", "computer networks topologies data transmission", k=

chem_query = "stoichiometry mole calculations reacting masses molar mass empirical f
show("Chemistry: query → 'stoichiometry ...'",
    rec.recommend_query("chemistry", chem_query, k=5))

#Profile to Items
bio_liked = ["Unit 5 Enzymes", "Unit 8 Plant Transport"]
try:
    show(f"Biology: profile from liked topics {bio_liked}",
        rec.recommend_from_profile("biology", bio_liked, k=5))
except Exception as e:
    print("Biology profile example error:", e)

chem_liked = ["Unit 13 Metals and Reactivity", "Unit 14 Metal Extraction"]
try:
    show(f"Chemistry: profile from liked topics {chem_liked}",
        rec.recommend_from_profile("chemistry", chem_liked, k=5))
except Exception as e:
    print("Chemistry profile example error:", e)

```

```

=== Find Biology topics containing 'Respiration' ===
        topic_name
Unit 12 Respiration

```

```

=== Find Chemistry topics containing 'Speed of Reaction' ===
        topic_name
Unit 8 Speed of Reaction

```

```

=== Find Business topics containing 'Market Research' ===
        topic_name
Chapter 11-Market Research

```

=== Find ICT topics containing 'Applications' ===

topic\_name

6. ICT Applications

=== Biology: more like 'Unit 12 Respiration' ===

	topic_name	similarity	difficulty_level
	Unit 6 Plant Nutrition	0.056465	Hard
	Unit 5 Enzymes	0.037409	Hard
	Unit 3 Movement in and out of cells	0.035064	Medium
	Unit 2 Cells	0.024262	Medium
Unit 19 Organisms and their environment		0.023323	Hard

=== Chemistry: more like 'Unit 8 Speed of Reaction' ===

	topic_name	similarity	difficulty_level
	Unit 9 Chemical Reactions	0.120159	Hard
Unit 1 Particles and Purification		0.057249	Hard
	Unit 16 The Chemical Industry	0.054509	Medium
	Unit 7 Chemical Changes	0.049372	Medium
	Unit 12 The Periodic Table	0.038646	Medium

=== Business: more like 'Chapter 11-Market Research' ===

	topic_name	similarity	difficulty_level
	Chapter 14-The Marketing Mix	0.088040	Hard
	Chapter 2- Classification of Business	0.069118	Hard
	Chapter 13- The Marketing Mix	0.055396	Medium
	Chapter 12-The Marketing Mix	0.038188	Medium
Chapter 26-Government economic objectives and policies		0.034162	Medium

=== ICT: query → 'computer networks and topologies' ===

	topic_name	similarity	difficulty_level
4. Networks and the effects of using them		0.117060	Hard
1. Types and Components of Computer Systems		0.057340	Hard
	6. ICT Applications	0.046885	Medium
	8.Safety and Security	0.043486	Hard
	2. Input and Output Devices	0.035215	Medium

=== Chemistry: query → 'stoichiometry ...' ===

	topic_name	similarity	difficulty_level
	Unit 1 Particles and Purification	0.088777	Hard
	Unit 8 Speed of Reaction	0.079808	Hard
	Unit 10 Acids and Bases	0.000000	Medium
Unit 11 Making and identifying salts		0.000000	Medium
	Unit 12 The Periodic Table	0.000000	Medium

=== Biology: profile from liked topics ['Unit 5 Enzymes', 'Unit 8 Plant Transport'] ===

	topic_name	similarity	difficulty_level
	Unit 3 Movement in and out of cells	0.072408	Medium
	Unit 1 Characteristics and Classification of Living Organisms	0.058643	Medium
	Unit 2 Cells	0.032526	Medium
	Unit 6 Plant Nutrition	0.029948	Hard
	Unit 19 Organisms and their environment	0.029076	Hard

=== Chemistry: profile from liked topics ['Unit 13 Metals and Reactivity', 'Unit 14 Metal Extraction'] ===

	topic_name	similarity	difficulty_level
	Unit 15 Air and Water	0.072337	Medium
	Unit 6 Electricity and Chemistry	0.069945	Hard
	Unit 11 Making and identifying salts	0.053230	Medium

# Collaborative Filtering

```
In [11]: import os
import numpy as np
import pandas as pd
from typing import Optional
from sklearn.metrics.pairwise import cosine_similarity

#load in synthetic data
if not os.path.exists("processed_notes.csv"):
    raise FileNotFoundError("processed_notes.csv not found.")

topics = pd.read_csv("processed_notes.csv")
req = {"subject", "topic_name"}
if not req.issubset(topics.columns):
    raise ValueError(f"processed_notes.csv must contain {req}")

#Clean duplicates
topics = topics.dropna(subset=["subject", "topic_name"]).drop_duplicates(subset=["subject", "topic_name"])

#Synthetic interactions generator
rng = np.random.default_rng(7)

subjects = topics["subject"].unique().tolist()

N_USERS = 60

rows = []
for user in range(1, N_USERS + 1):
    #Each user has a primary subject bias
    main_subj = rng.choice(subjects)
    # number of interactions this user makes
    n_interactions = rng.integers(8, 16) # 8-15 interactions

    #choose subjects with a higher prob on the main subject
    subj_choices = rng.choice(
        subjects,
        size=n_interactions,
        p=[0.55 if s == main_subj else (0.45/(len(subjects)-1)) for s in subjects]
    )

    for subj in subj_choices:
        pool = topics[topics["subject"] == subj]["topic_name"].values
        if len(pool) == 0:
            continue
        topic = rng.choice(pool)

        #rating pattern: biased a bit higher for the main subject
        base = 0.6 if subj == main_subj else 0.4
        # skew ratings to 3-5 range mostly
        prob_1 = 0.02 * (1-base)
        prob_2 = 0.08 * (1-base)
        prob_3 = 0.30 + 0.10*base
        prob_4 = 0.35 + 0.15*base
        prob_5 = 1.0 - (prob_1 + prob_2 + prob_3 + prob_4)
        rating = rng.choice([1,2,3,4,5], p=[prob_1, prob_2, prob_3, prob_4, prob_5])

        rows.append((user, subj, topic, int(rating)))
```

```

interactions = pd.DataFrame(rows, columns=["user_id", "subject", "topic_name", "rating"])
interactions.to_csv(r"C:\Users\Rizwana\Desktop\studyclock project\Sample_Interactions_D
print(f"Saved interactions.csv with {len(interactions)} rows and {interactions['user_id'

```

*#Collaborative Filtering helpers (User-User and Item-Item)*

```

def _pivot_by_subject(interactions_df: pd.DataFrame, subject: str) -> pd.DataFrame:
    """User-Item matrix for a single subject."""
    sub = interactions_df[interactions_df["subject"] == subject].copy()
    if sub.empty:
        raise ValueError(f"No interactions for subject='{subject}'")
    pivot = sub.pivot_table(index="user_id", columns="topic_name", values="rating")
    return pivot

def user_user_recommend(
    interactions_df: pd.DataFrame,
    subject: str,
    user_id: int,
    top_n: int = 5
) -> pd.DataFrame:
    """
    Recommend topics for user_id in a subject using User-User CF.
    Cosine similarity over users; aggregate neighbors' ratings.
    Returns: DataFrame[topic_name, score]
    """
    pivot = _pivot_by_subject(interactions_df, subject)
    if user_id not in pivot.index:
        raise ValueError(f"user_id {user_id} has no interactions in subject '{subject}'")

    #similarities between users
    sim = cosine_similarity(pivot.fillna(0))
    sim_df = pd.DataFrame(sim, index=pivot.index, columns=pivot.index)

    #candidate topics = not rated by user yet
    user Rated = set(interactions_df[(interactions_df["user_id"] == user_id) &
                                     (interactions_df["subject"] == subject)]["topic_name"])

    rec_scores = {}

    #weight neighbors' ratings by similarity
    neighbors = sim_df[user_id].sort_values(ascending=False).drop(user_id)
    for other_id, s in neighbors.items():
        other_row = pivot.loc[other_id]
        for topic, r in other_row.dropna().items():
            if topic in user Rated:
                continue
            rec_scores[topic] = rec_scores.get(topic, 0.0) + s * r

    if not rec_scores:
        return pd.DataFrame(columns=["topic_name", "score"])

    ranked = sorted(rec_scores.items(), key=lambda x: x[1], reverse=True)[:top_n]
    return pd.DataFrame(ranked, columns=["topic_name", "score"])

def item_item_recommend(
    interactions_df: pd.DataFrame,
    subject: str,
    topic_name: str,
    top_n: int = 5
) -> pd.DataFrame:
    """
    Recommend similar topics (Item-Item CF) inside a subject using cosine
    similarity of item rating vectors.
    Returns: DataFrame[topic_name, similarity]
    """

```

```

pivot = _pivot_by_subject(interactions_df, subject)
if topic_name not in pivot.columns:
    raise ValueError(f"Topic '{topic_name}' has no ratings in subject '{subject}'")

sim = cosine_similarity(pivot.T.fillna(0))
sim_df = pd.DataFrame(sim, index=pivot.columns, columns=pivot.columns)

sims = sim_df[topic_name].sort_values(ascending=False).drop(topic_name).head(top_n)
return pd.DataFrame({"topic_name": sims.index, "similarity": sims.values})

#biology and chemistry example for verification

print("\n--- Example: User-User CF (biology) ---")
try:
    u_example = interactions[interactions["subject"]=="biology"]["user_id"].iloc[0]
    print("user_id:", u_example)
    print(user_user_recommend(interactions, "biology", user_id=u_example, top_n=5))
except Exception as e:
    print("User-User example error:", e)

print("\n--- Example: Item-Item CF (chemistry) ---")
try:
    # pick a chemistry topic that appears in interactions
    chem_topic = interactions[interactions["subject"]=="chemistry"]["topic_name"].iloc[0]
    print("topic:", chem_topic)
    print(item_item_recommend(interactions, "chemistry", topic_name=chem_topic, top_n=5))
except Exception as e:
    print("Item-Item example error:", e)

```

Saved interactions.csv with 648 rows and 60 users.

--- Example: User-User CF (biology) ---

user\_id: 1

	topic_name	score
0	Unit 18 Variation and selection	8.365624
1	Unit 12 Respiration	7.030872
2	Unit 21 Human Influences on Ecosystems	4.468643
3	Unit 5 Enzymes	3.555991
4	Unit 17 Inheritance	2.451482

--- Example: Item-Item CF (chemistry) ---

topic: Unit 6 Electricity and Chemistry

	topic_name	similarity
0	Unit 18 The Variety of Organic Chemicals	0.341972
1	Unit 17 Organic chemistry and petrochemicals	0.222744
2	Unit 1 Particles and Purification	0.216192
3	Unit 16 The Chemical Industry	0.197579
4	Unit 13 Metals and Reactivity	0.165256

## Training the BiLSTM

Training each subject individually

```

In [2]: #biology

import os, pickle, random
from typing import List, Tuple, Dict
import numpy as np
import pandas as pd
from sklearn.model_selection import train_test_split

import torch
import torch.nn as nn

```



```

from torch.utils.data import Dataset, DataLoader

#configuration
SEED = 42
random.seed(SEED); np.random.seed(SEED); torch.manual_seed(SEED)

CSV_PATH      = r"C:\Users\Rizwana\Desktop\studyclock project\Sample_Interactions_Data.c
SUBJECT       = "biology"
MODELS_DIR    = "models"
DEVICE        = "cpu"

MIN_SEQ_LEN   = 4
MAX_HIST_LEN  = 50
BATCH_SIZE    = 64
EPOCHS        = 8
LR            = 1e-3
TOPK          = 5

#utilities
def load_interactions(path: str) -> pd.DataFrame:
    if not os.path.exists(path): raise FileNotFoundError(path)
    df = pd.read_csv(path)
    need = {"user_id", "subject", "topic_name", "rating"}
    if not need.issubset(df.columns): raise ValueError(f"{path} must contain {need}")
    if "timestamp" not in df.columns:
        df = df.copy()
        df["timestamp"] = df.groupby(["user_id", "subject"]).cumcount()
    return df

def build_vocab_sequences(df_subj: pd.DataFrame) -> Tuple[Dict[str, int], Dict[int, str],
df_subj = df_subj.sort_values(["user_id", "timestamp"])
topics = df_subj["topic_name"].unique().tolist()
topic2id = {t:i+1 for i,t in enumerate(topics)} # 0=PAD
id2topic = {i:t for t,i in topic2id.items()}
sequences = []
for uid, g in df_subj.groupby("user_id"):
    seq = [topic2id[t] for t in g["topic_name"].tolist()]
    if len(seq) >= MIN_SEQ_LEN:
        sequences.append((uid, seq))
return topic2id, id2topic, sequences

def make_next_pairs(sequences: List[Tuple[int, List[int]]]):
    X, y = [], []
    for _, seq in sequences:
        for t in range(1, len(seq)):
            hist = seq[max(0, t - MAX_HIST_LEN):t]
            if hist:
                X.append(hist); y.append(seq[t])
    return X, y

def pad_batch(seqs: List[List[int]], pad_id=0):
    L = max(len(s) for s in seqs)
    arr = np.zeros((len(seqs), L), dtype=np.int64)
    lens = np.array([len(s) for s in seqs], dtype=np.int64)
    for i,s in enumerate(seqs): arr[i,:len(s)] = s
    x = torch.tensor(arr); lengths = torch.tensor(lens)
    mask = (x != pad_id).float()
    return x, lengths, mask

class NextDataset(Dataset):
    def __init__(self, X, y): self.X, self.y = X, y
    def __len__(self): return len(self.X)
    def __getitem__(self, i): return self.X[i], self.y[i]

def collate_fn(batch, pad_id=0):
    seqs, targets = zip(*batch)

```

```

x, lengths, mask = pad_batch(seqs, pad_id)
y = torch.tensor(targets, dtype=torch.long)
return x, lengths, mask, y

#model building
class AdditiveAttention(nn.Module):
    def __init__(self, hidden_dim):
        super().__init__()
        self.W = nn.Linear(hidden_dim, hidden_dim)
        self.v = nn.Linear(hidden_dim, 1, bias=False)

    def forward(self, H, mask):
        scores = self.v(torch.tanh(self.W(H))).squeeze(-1) # (B,T)
        scores = scores.masked_fill(mask == 0, -1e9)
        alpha = torch.softmax(scores, dim=-1) # (B,T)
        ctx = torch.bmm(alpha.unsqueeze(1), H).squeeze(1) # (B,H)
        return ctx, alpha

class BiLSTMAttnRec(nn.Module):
    def __init__(self, num_items, emb_dim=64, hidden_dim=128, pad_id=0):
        super().__init__()
        self.emb = nn.Embedding(num_items+1, emb_dim, padding_idx=pad_id)
        self.lstm = nn.LSTM(emb_dim, hidden_dim//2, batch_first=True, bidirectional=True)
        self.attn = AdditiveAttention(hidden_dim)
        self.drop = nn.Dropout(0.2)
        self.out = nn.Linear(hidden_dim, num_items+1)

    def forward(self, x, lengths, mask):
        E = self.emb(x) # (B,T,E)
        H, _ = self.lstm(E) # (B,T,H)
        ctx, _ = self.attn(H, mask) # (B,H)
        z = self.drop(ctx)
        logits = self.out(z) # (B,V)
        return logits

#train and save
def train_biology():
    df = load_interactions(CSV_PATH)
    bio = df[df["subject"] == SUBJECT].copy()
    if bio.empty: raise ValueError("No biology rows in interactions.csv")
    if bio["user_id"].nunique() < 5:
        print("[biology] Few users detected; training anyway.")

    topic2id, id2topic, sequences = build_vocab_sequences(bio)
    if not sequences:
        raise ValueError("No biology sequences with length ≥ MIN_SEQ_LEN")

    X, y = make_next_pairs(sequences)
    Xtr, Xva, ytr, yva = train_test_split(X, y, test_size=0.2, random_state=SEED, shuffle=True)
    train_loader = DataLoader(NearestDataset(Xtr, ytr), batch_size=BATCH_SIZE, shuffle=True)
    val_loader = DataLoader(NearestDataset(Xva, yva), batch_size=BATCH_SIZE, shuffle=False)

    model = BiLSTMAttnRec(num_items=len(topic2id)).to(DEVICE)
    crit = nn.CrossEntropyLoss(ignore_index=0)
    opt = torch.optim.AdamW(model.parameters(), lr=LR)

    for ep in range(1, EPOCHS+1):
        model.train(); tloss=0
        for x,l,m,yb in train_loader:
            x,l,m,yb = x.to(DEVICE), l.to(DEVICE), m.to(DEVICE), yb.to(DEVICE)
            logits = model(x,l,m)
            loss = crit(logits, yb)
            opt.zero_grad(); loss.backward()
            nn.utils.clip_grad_norm_(model.parameters(), 1.0)
            opt.step()
            tloss += loss.item()*x.size(0)

        # model.eval(); vloss=0

```

```

with torch.no_grad():
    for x,l,m,yb in val_loader:
        x,l,m,yb = x.to(DEVICE), l.to(DEVICE), m.to(DEVICE), yb.to(DEVICE)
        vloss += crit(model(x,l,m), yb).item()*x.size(0)
print(f"[biology] Epoch {ep:02d}  train_loss={tloss/len(Xtr):.4f}  val_loss={vloss/len(Xval):.4f}")

os.makedirs(MODELS_DIR, exist_ok=True)
torch.save(model.state_dict(), os.path.join(MODELS_DIR, "bilstm_biology.pt"))
with open(os.path.join(MODELS_DIR, "topic2id_biology.pkl"), "wb") as f: pickle.dump(topic2id, f)
with open(os.path.join(MODELS_DIR, "id2topic_biology.pkl"), "wb") as f: pickle.dump(id2topic, f)
print("[biology] Saved model + vocab to models/")

example_hist = list(topic2id.keys())[:3]
recs = recommend_next("biology", example_hist, already_seen=example_hist, top_n=TOPK)
print("\nDemo history:", example_hist)
print("Top-N next topics:", recs)

#Inference
def load_biology_model():
    t2i_p = os.path.join(MODELS_DIR, "topic2id_biology.pkl")
    i2t_p = os.path.join(MODELS_DIR, "id2topic_biology.pkl")
    m_p = os.path.join(MODELS_DIR, "bilstm_biology.pt")
    if not (os.path.exists(t2i_p) and os.path.exists(i2t_p) and os.path.exists(m_p)):
        raise FileNotFoundError("Train biology first to create model + mappings in model")
    with open(t2i_p, "rb") as f: topic2id = pickle.load(f)
    with open(i2t_p, "rb") as f: id2topic = pickle.load(f)
    model = BiLSTMAttnRec(num_items=len(topic2id)).to(DEVICE)
    model.load_state_dict(torch.load(m_p, map_location=DEVICE))
    model.eval()
    return model, topic2id, id2topic

def recommend_next(subject: str, history_topics: List[str], already_seen: List[str] = No
assert subject == "biology", "This script is biology-only."
model, topic2id, id2topic = load_biology_model()
ids = [topic2id[t] for t in history_topics if t in topic2id]
if not ids: return []
x = torch.tensor([ids], dtype=torch.long).to(DEVICE)
lengths = torch.tensor([len(ids)], dtype=torch.long).to(DEVICE)
mask = (x != 0).float()
with torch.no_grad():
    logits = model(x, lengths, mask)
    probs = torch.softmax(logits, dim=-1).squeeze(0).cpu().numpy()
seen = set(already_seen or [])
cands = [(tid,p) for tid,p in enumerate(probs) if tid!=0 and id2topic.get(tid) not i
cands.sort(key=lambda x: x[1], reverse=True)
return [(id2topic[tid], float(p)) for tid,p in cands[:top_n]]

if __name__ == "__main__":
    train_biology()

```

```

[biology] Epoch 01  train_loss=3.0865  val_loss=3.0691
[biology] Epoch 02  train_loss=3.0623  val_loss=3.0731
[biology] Epoch 03  train_loss=3.0476  val_loss=3.0756
[biology] Epoch 04  train_loss=3.0311  val_loss=3.0777
[biology] Epoch 05  train_loss=3.0125  val_loss=3.0791
[biology] Epoch 06  train_loss=2.9944  val_loss=3.0786
[biology] Epoch 07  train_loss=2.9861  val_loss=3.0767
[biology] Epoch 08  train_loss=2.9712  val_loss=3.0756
[biology] Saved model + vocab to models/

```

Demo history: ['Unit 13 Excretion', 'Unit 3 Movement in and out of cells', 'Unit 21 Human Influences on Ecosystems']

Top-N next topics: [('Unit 18 Variation and selection', 0.0549352653324604), ('Unit 12 Respiration', 0.050515495240688324), ('Unit 6 Plant Nutrition', 0.05047224089503288), ('Unit 10

nit 10 Diseases and Immunity', 0.05010153353214264), ('Unit 8 Plant Transport', 0.04774574562907219)]

```
In [4]: #chemistry

import os, pickle, random
from typing import List, Tuple, Dict
import numpy as np
import pandas as pd
from sklearn.model_selection import train_test_split

import torch
import torch.nn as nn
from torch.utils.data import Dataset, DataLoader

#configuration
SEED = 42
random.seed(SEED); np.random.seed(SEED); torch.manual_seed(SEED)

CSV_PATH      = r"C:\Users\Rizwana\Desktop\studyclock project\Sample_Interactions_Data.c
SUBJECT       = "chemistry"
MODELS_DIR    = "models"
DEVICE        = "cpu"

MIN_SEQ_LEN   = 4
MAX_HIST_LEN  = 50
BATCH_SIZE    = 64
EPOCHS        = 8
LR            = 1e-3
TOPK          = 5

#utilities
def load_interactions(path: str) -> pd.DataFrame:
    if not os.path.exists(path): raise FileNotFoundError(path)
    df = pd.read_csv(path)
    need = {"user_id", "subject", "topic_name", "rating"}
    if not need.issubset(df.columns): raise ValueError(f"{path} must contain {need}")
    if "timestamp" not in df.columns:
        df = df.copy()
        df["timestamp"] = df.groupby(["user_id", "subject"]).cumcount()
    return df

def build_vocab_sequences(df_subj: pd.DataFrame) -> Tuple[Dict[str, int], Dict[int, str],
df_subj = df_subj.sort_values(["user_id", "timestamp"])
topics = df_subj["topic_name"].unique().tolist()
topic2id = {t:i+1 for i,t in enumerate(topics)} # 0=PAD
id2topic = {i:t for t,i in topic2id.items()}
sequences = []
for uid, g in df_subj.groupby("user_id"):
    seq = [topic2id[t] for t in g["topic_name"].tolist()]
    if len(seq) >= MIN_SEQ_LEN:
        sequences.append((uid, seq))
return topic2id, id2topic, sequences

def make_next_pairs(sequences: List[Tuple[int, List[int]]]):
    X, y = [], []
    for _, seq in sequences:
        for t in range(1, len(seq)):
            hist = seq[max(0, t - MAX_HIST_LEN):t]
            if hist:
                X.append(hist); y.append(seq[t])
    return X, y

def pad_batch(seqs: List[List[int]], pad_id=0):
    L = max(len(s) for s in seqs)
```

```

arr = np.zeros((len(seqs), L), dtype=np.int64)
lens = np.array([len(s) for s in seqs], dtype=np.int64)
for i,s in enumerate(seqs): arr[i,:len(s)] = s
x = torch.tensor(arr); lengths = torch.tensor(lens)
mask = (x != pad_id).float()
return x, lengths, mask

class NextDataset(Dataset):
    def __init__(self, X, y): self.X, self.y = X, y
    def __len__(self): return len(self.X)
    def __getitem__(self, i): return self.X[i], self.y[i]

def collate_fn(batch, pad_id=0):
    seqs, targets = zip(*batch)
    x, lengths, mask = pad_batch(seqs, pad_id)
    y = torch.tensor(targets, dtype=torch.long)
    return x, lengths, mask, y

#model building
class AdditiveAttention(nn.Module):
    def __init__(self, hidden_dim):
        super().__init__()
        self.W = nn.Linear(hidden_dim, hidden_dim)
        self.v = nn.Linear(hidden_dim, 1, bias=False)
    def forward(self, H, mask):
        scores = self.v(torch.tanh(self.W(H))).squeeze(-1) # (B,T)
        scores = scores.masked_fill(mask == 0, -1e9)
        alpha = torch.softmax(scores, dim=-1) # (B,T)
        ctx = torch.bmm(alpha.unsqueeze(1), H).squeeze(1) # (B,H)
        return ctx, alpha

class BiLSTMAttnRec(nn.Module):
    def __init__(self, num_items, emb_dim=64, hidden_dim=128, pad_id=0):
        super().__init__()
        self.emb = nn.Embedding(num_items+1, emb_dim, padding_idx=pad_id)
        self.lstm = nn.LSTM(emb_dim, hidden_dim//2, batch_first=True, bidirectional=True)
        self.attn = AdditiveAttention(hidden_dim)
        self.drop = nn.Dropout(0.2)
        self.out = nn.Linear(hidden_dim, num_items+1)
    def forward(self, x, lengths, mask):
        E = self.emb(x) # (B,T,E)
        H, _ = self.lstm(E) # (B,T,H)
        ctx, _ = self.attn(H, mask) # (B,H)
        z = self.drop(ctx)
        logits = self.out(z) # (B,V)
        return logits

#train and save
def train_chemistry():
    df = load_interactions(CSV_PATH)
    chem = df[df["subject"] == SUBJECT].copy()
    if chem.empty: raise ValueError("No chemistry rows in interactions.csv")
    if chem["user_id"].nunique() < 5:
        print("[chemistry] Few users detected; training anyway.")

    topic2id, id2topic, sequences = build_vocab_sequences(chem)
    if not sequences:
        raise ValueError("No chemistry sequences with length > MIN_SEQ_LEN")

    X, y = make_next_pairs(sequences)
    Xtr, Xva, ytr, yva = train_test_split(X, y, test_size=0.2, random_state=SEED, shuffle=True)
    train_loader = DataLoader(NextDataset(Xtr, ytr), batch_size=BATCH_SIZE, shuffle=True)
    val_loader = DataLoader(NextDataset(Xva, yva), batch_size=BATCH_SIZE, shuffle=False)

    model = BiLSTMAttnRec(num_items=len(topic2id)).to(DEVICE)
    crit = nn.CrossEntropyLoss(ignore_index=0)

```



```

opt = torch.optim.AdamW(model.parameters(), lr=LR)

for ep in range(1, EPOCHS+1):
    model.train(); tloss=0
    for x,l,m,yb in train_loader:
        x,l,m,yb = x.to(DEVICE), l.to(DEVICE), m.to(DEVICE), yb.to(DEVICE)
        logits = model(x,l,m)
        loss = crit(logits, yb)
        opt.zero_grad(); loss.backward()
        nn.utils.clip_grad_norm_(model.parameters(), 1.0)
        opt.step()
        tloss += loss.item()*x.size(0)

    model.eval(); vloss=0
    with torch.no_grad():
        for x,l,m,yb in val_loader:
            x,l,m,yb = x.to(DEVICE), l.to(DEVICE), m.to(DEVICE), yb.to(DEVICE)
            vloss += crit(model(x,l,m), yb).item()*x.size(0)
    print(f"[chemistry] Epoch {ep:02d}  train_loss={tloss/len(Xtr):.4f}  val_loss={v

os.makedirs(MODELS_DIR, exist_ok=True)
torch.save(model.state_dict(), os.path.join(MODELS_DIR, "bilstm_chemistry.pt"))
with open(os.path.join(MODELS_DIR, "topic2id_chemistry.pkl"), "wb") as f: pickle.dump
with open(os.path.join(MODELS_DIR, "id2topic_chemistry.pkl"), "wb") as f: pickle.dump
print("[chemistry] Saved model + vocab to models/")

# demo: ranked list for a short history
example_hist = list(topic2id.keys())[:3]
recs = recommend_next("chemistry", example_hist, already_seen=example_hist, top_n=TO
print("\nDemo history:", example_hist)
print("Top-N next topics:", recs)

#Inference
def load_chemistry_model():
    t2i_p = os.path.join(MODELS_DIR, "topic2id_chemistry.pkl")
    i2t_p = os.path.join(MODELS_DIR, "id2topic_chemistry.pkl")
    m_p = os.path.join(MODELS_DIR, "bilstm_chemistry.pt")
    if not (os.path.exists(t2i_p) and os.path.exists(i2t_p) and os.path.exists(m_p)):
        raise FileNotFoundError("Train chemistry first to create model + mappings in mod
    with open(t2i_p, "rb") as f: topic2id = pickle.load(f)
    with open(i2t_p, "rb") as f: id2topic = pickle.load(f)
    model = BiLSTMattnRec(num_items=len(topic2id)).to(DEVICE)
    model.load_state_dict(torch.load(m_p, map_location=DEVICE))
    model.eval()
    return model, topic2id, id2topic

def recommend_next(subject: str, history_topics: List[str], already_seen: List[str] = No
    assert subject == "chemistry", "This script is chemistry-only."
    model, topic2id, id2topic = load_chemistry_model()
    ids = [topic2id[t] for t in history_topics if t in topic2id]
    if not ids: return []
    x = torch.tensor([ids], dtype=torch.long).to(DEVICE)
    lengths = torch.tensor([len(ids)], dtype=torch.long).to(DEVICE)
    mask = (x != 0).float()
    with torch.no_grad():
        logits = model(x, lengths, mask)
        probs = torch.softmax(logits, dim=-1).squeeze(0).cpu().numpy()
    seen = set(already_seen or [])
    cands = [(tid,p) for tid,p in enumerate(probs) if tid!=0 and id2topic.get(tid) not i
    cands.sort(key=lambda x: x[1], reverse=True)
    return [(id2topic[tid], float(p)) for tid,p in cands[:top_n]]

if __name__ == "__main__":
    train_chemistry()

```

```
[chemistry] Epoch 01  train_loss=2.9427  val_loss=2.9507
[chemistry] Epoch 02  train_loss=2.9181  val_loss=2.9569
[chemistry] Epoch 03  train_loss=2.9006  val_loss=2.9634
[chemistry] Epoch 04  train_loss=2.8904  val_loss=2.9700
[chemistry] Epoch 05  train_loss=2.8596  val_loss=2.9767
[chemistry] Epoch 06  train_loss=2.8368  val_loss=2.9838
[chemistry] Epoch 07  train_loss=2.8109  val_loss=2.9911
[chemistry] Epoch 08  train_loss=2.8015  val_loss=2.9987
[chemistry] Saved model + vocab to models/
```

```
Demo history: ['Unit 6 Electrcity and Chemistry', 'Unit 16 The Chemical Industry', 'Unit
18 The Variety of Organic Chemicals']
Top-N next topics: [('Unit 15 Air and Water', 0.06551077961921692), ('Unit 12 The Period
ic Table', 0.06037665903568268), ('Unit 3 Structure and Bonding', 0.0581340491771698),
('Unit 14 Metal Extraction', 0.05558158829808235), ('Unit 9 Chemical Reactions', 0.05486
50324344635)]
```

```
In [5]: #business studies
import os, pickle, random
from typing import List, Tuple, Dict
import numpy as np
import pandas as pd
from sklearn.model_selection import train_test_split

import torch
import torch.nn as nn
from torch.utils.data import Dataset, DataLoader

#configurations
SEED = 42
random.seed(SEED); np.random.seed(SEED); torch.manual_seed(SEED)

CSV_PATH      = r"C:\Users\Rizwana\Desktop\studyclock project\Sample_Interactions_Data.c
SUBJECT       = "business"
MODELS_DIR    = "models"
DEVICE        = "cpu"

MIN_SEQ_LEN   = 4
MAX_HIST_LEN  = 50
BATCH_SIZE    = 64
EPOCHS        = 8
LR            = 1e-3
TOPK          = 5

#utilities
def load_interactions(path: str) -> pd.DataFrame:
    if not os.path.exists(path): raise FileNotFoundError(path)
    df = pd.read_csv(path)
    need = {"user_id", "subject", "topic_name", "rating"}
    if not need.issubset(df.columns): raise ValueError(f"{path} must contain {need}")
    if "timestamp" not in df.columns:
        df = df.copy()
        df["timestamp"] = df.groupby(["user_id", "subject"]).cumcount()
    return df

def build_vocab_sequences(df_subj: pd.DataFrame) -> Tuple[Dict[str,int], Dict[int,str],
df_subj = df_subj.sort_values(["user_id", "timestamp"])
topics = df_subj["topic_name"].unique().tolist()
topic2id = {t:i+1 for i,t in enumerate(topics)} # 0=PAD
id2topic = {i:t for t,i in topic2id.items()}
sequences = []
for uid, g in df_subj.groupby("user_id"):
    seq = [topic2id[t] for t in g["topic_name"].tolist()]
    if len(seq) >= MIN_SEQ_LEN:
        sequences.append((uid, seq))
```

```

        return topic2id, id2topic, sequences

def make_next_pairs(sequences: List[Tuple[int, List[int]]]):
    X, y = [], []
    for _, seq in sequences:
        for t in range(1, len(seq)):
            hist = seq[max(0, t - MAX_HIST_LEN):t]
            if hist:
                X.append(hist); y.append(seq[t])
    return X, y

def pad_batch(seqs: List[List[int]], pad_id=0):
    L = max(len(s) for s in seqs)
    arr = np.zeros((len(seqs), L), dtype=np.int64)
    lens = np.array([len(s) for s in seqs], dtype=np.int64)
    for i, s in enumerate(seqs): arr[i, :len(s)] = s
    x = torch.tensor(arr); lengths = torch.tensor(lens)
    mask = (x != pad_id).float()
    return x, lengths, mask

class NextDataset(Dataset):
    def __init__(self, X, y): self.X, self.y = X, y
    def __len__(self): return len(self.X)
    def __getitem__(self, i): return self.X[i], self.y[i]

def collate_fn(batch, pad_id=0):
    seqs, targets = zip(*batch)
    x, lengths, mask = pad_batch(seqs, pad_id)
    y = torch.tensor(targets, dtype=torch.long)
    return x, lengths, mask, y

#model building
class AdditiveAttention(nn.Module):
    def __init__(self, hidden_dim):
        super().__init__()
        self.W = nn.Linear(hidden_dim, hidden_dim)
        self.v = nn.Linear(hidden_dim, 1, bias=False)
    def forward(self, H, mask):
        scores = self.v(torch.tanh(self.W(H))).squeeze(-1) # (B,T)
        scores = scores.masked_fill(mask == 0, -1e9)
        alpha = torch.softmax(scores, dim=-1) # (B,T)
        ctx = torch.bmm(alpha.unsqueeze(1), H).squeeze(1) # (B,H)
        return ctx, alpha

class BiLSTMAttnRec(nn.Module):
    def __init__(self, num_items, emb_dim=64, hidden_dim=128, pad_id=0):
        super().__init__()
        self.emb = nn.Embedding(num_items+1, emb_dim, padding_idx=pad_id)
        self.lstm = nn.LSTM(emb_dim, hidden_dim//2, batch_first=True, bidirectional=True)
        self.attn = AdditiveAttention(hidden_dim)
        self.drop = nn.Dropout(0.2)
        self.out = nn.Linear(hidden_dim, num_items+1)
    def forward(self, x, lengths, mask):
        E = self.emb(x) # (B,T,E)
        H, _ = self.lstm(E) # (B,T,H)
        ctx, _ = self.attn(H, mask) # (B,H)
        z = self.drop(ctx)
        logits = self.out(z) # (B,V)
        return logits

#train and save
def train_business():
    df = load_interactions(CSV_PATH)
    bus = df[df["subject"] == SUBJECT].copy()
    if bus.empty: raise ValueError("No business rows in interactions.csv")
    if bus["user_id"].nunique() < 5:

```

```

print("[business] Few users detected; training anyway.")

topic2id, id2topic, sequences = build_vocab_sequences(bus)
if not sequences:
    raise ValueError("No business sequences with length ≥ MIN_SEQ_LEN")

X, y = make_next_pairs(sequences)
Xtr, Xva, ytr, yva = train_test_split(X, y, test_size=0.2, random_state=SEED, shuffle=True)
train_loader = DataLoader(NextDataset(Xtr, ytr), batch_size=BATCH_SIZE, shuffle=True)
val_loader = DataLoader(NextDataset(Xva, yva), batch_size=BATCH_SIZE, shuffle=False)

model = BiLSTMAttnRec(num_items=len(topic2id)).to(DEVICE)
crit = nn.CrossEntropyLoss(ignore_index=0)
opt = torch.optim.AdamW(model.parameters(), lr=LR)

for ep in range(1, EPOCHS+1):
    model.train(); tloss=0
    for x,l,m,yb in train_loader:
        x,l,m,yb = x.to(DEVICE), l.to(DEVICE), m.to(DEVICE), yb.to(DEVICE)
        logits = model(x,l,m)
        loss = crit(logits, yb)
        opt.zero_grad(); loss.backward()
        nn.utils.clip_grad_norm_(model.parameters(), 1.0)
        opt.step()
        tloss += loss.item()*x.size(0)

    model.eval(); vloss=0
    with torch.no_grad():
        for x,l,m,yb in val_loader:
            x,l,m,yb = x.to(DEVICE), l.to(DEVICE), m.to(DEVICE), yb.to(DEVICE)
            vloss += crit(model(x,l,m), yb).item()*x.size(0)
    print(f"[business] Epoch {ep:02d}  train_loss={tloss/len(Xtr):.4f}  val_loss={vloss/len(Xva):.4f}")

os.makedirs(MODELS_DIR, exist_ok=True)
torch.save(model.state_dict(), os.path.join(MODELS_DIR, "bilstm_business.pt"))
with open(os.path.join(MODELS_DIR, "topic2id_business.pkl"), "wb") as f: pickle.dump(topic2id, f)
with open(os.path.join(MODELS_DIR, "id2topic_business.pkl"), "wb") as f: pickle.dump(id2topic, f)
print("[business] Saved model + vocab to models/")

example_hist = list(topic2id.keys())[:3]
recs = recommend_next("business", example_hist, already_seen=example_hist, top_n=TOP)
print("\nDemo history:", example_hist)
print("Top-N next topics:", recs)

#Inference
def load_business_model():
    t2i_p = os.path.join(MODELS_DIR, "topic2id_business.pkl")
    i2t_p = os.path.join(MODELS_DIR, "id2topic_business.pkl")
    m_p = os.path.join(MODELS_DIR, "bilstm_business.pt")
    if not (os.path.exists(t2i_p) and os.path.exists(i2t_p) and os.path.exists(m_p)):
        raise FileNotFoundError("Train business first to create model + mappings in mode")
    with open(t2i_p, "rb") as f: topic2id = pickle.load(f)
    with open(i2t_p, "rb") as f: id2topic = pickle.load(f)
    model = BiLSTMAttnRec(num_items=len(topic2id)).to(DEVICE)
    model.load_state_dict(torch.load(m_p, map_location=DEVICE))
    model.eval()
    return model, topic2id, id2topic

def recommend_next(subject: str, history_topics: List[str], already_seen: List[str] = No):
    assert subject == "business", "This script is business-only."
    model, topic2id, id2topic = load_business_model()
    ids = [topic2id[t] for t in history_topics if t in topic2id]
    if not ids: return []
    x = torch.tensor([ids], dtype=torch.long).to(DEVICE)

```

```

lengths = torch.tensor([len(ids)], dtype=torch.long).to(DEVICE)
mask = (x != 0).float()
with torch.no_grad():
    logits = model(x, lengths, mask)
    probs = torch.softmax(logits, dim=-1).squeeze(0).cpu().numpy()
    seen = set(already_seen or [])
    cands = [(tid,p) for tid,p in enumerate(probs) if tid!=0 and id2topic.get(tid) not in seen]
    cands.sort(key=lambda x: x[1], reverse=True)
    return [(id2topic[tid], float(p)) for tid,p in cands[:top_n]]

if __name__ == "__main__":
    train_business()

```

```

[business] Epoch 01  train_loss=3.3960  val_loss=3.3538
[business] Epoch 02  train_loss=3.3726  val_loss=3.3577
[business] Epoch 03  train_loss=3.3504  val_loss=3.3614
[business] Epoch 04  train_loss=3.3354  val_loss=3.3630
[business] Epoch 05  train_loss=3.3080  val_loss=3.3633
[business] Epoch 06  train_loss=3.2957  val_loss=3.3629
[business] Epoch 07  train_loss=3.2826  val_loss=3.3611
[business] Epoch 08  train_loss=3.2716  val_loss=3.3599
[business] Saved model + vocab to models/

```

Demo history: ['Chapter 4- Types of Business Organisation', 'Chapter 21-Business Finance -Needs and Sources', 'Chapter 9- Internal and External Communication']

Top-N next topics: [('Chapter 15-The Marketing Mix', 0.04480503872036934), ('Chapter 2- Classification of Business', 0.04317012429237366), ('Chapter 7-Organisation and mangement', 0.03879755362868309), ('Chapter 5- Business Objectives and Stakeholder objectives', 0.03878293186426163), ('Chapter 26-Government economic objectives and policies', 0.03672325611114502)]

```

In [6]: #ict

import os, pickle, random
from typing import List, Tuple, Dict
import numpy as np
import pandas as pd
from sklearn.model_selection import train_test_split

import torch
import torch.nn as nn
from torch.utils.data import Dataset, DataLoader

#configuration
SEED = 42
random.seed(SEED); np.random.seed(SEED); torch.manual_seed(SEED)

CSV_PATH      = r"C:\Users\Rizwana\Desktop\studyclock project\Sample_Interactions_Data.csv"
SUBJECT       = "ict"
MODELS_DIR    = "models"
DEVICE        = "cpu"

MIN_SEQ_LEN   = 4
MAX_HIST_LEN  = 50
BATCH_SIZE    = 64
EPOCHS        = 8
LR            = 1e-3
TOPK          = 5

#utilities
def load_interactions(path: str) -> pd.DataFrame:
    if not os.path.exists(path): raise FileNotFoundError(path)
    df = pd.read_csv(path)
    need = {"user_id", "subject", "topic_name", "rating"}
    if not need.issubset(df.columns): raise ValueError(f"{path} must contain {need}")

```

```

    if "timestamp" not in df.columns:
        df = df.copy()
        df["timestamp"] = df.groupby(["user_id", "subject"]).cumcount()
    return df

def build_vocab_sequences(df_subj: pd.DataFrame) -> Tuple[Dict[str, int], Dict[int, str],
df_subj = df_subj.sort_values(["user_id", "timestamp"])
topics = df_subj["topic_name"].unique().tolist()
topic2id = {t:i+1 for i,t in enumerate(topics)} # 0=PAD
id2topic = {i:t for t,i in topic2id.items()}
sequences = []
for uid, g in df_subj.groupby("user_id"):
    seq = [topic2id[t] for t in g["topic_name"].tolist()]
    if len(seq) >= MIN_SEQ_LEN:
        sequences.append((uid, seq))
return topic2id, id2topic, sequences

def make_next_pairs(sequences: List[Tuple[int, List[int]]]):
    X, y = [], []
    for _, seq in sequences:
        for t in range(1, len(seq)):
            hist = seq[max(0, t - MAX_HIST_LEN):t]
            if hist:
                X.append(hist); y.append(seq[t])
    return X, y

def pad_batch(seqs: List[List[int]], pad_id=0):
    L = max(len(s) for s in seqs)
    arr = np.zeros((len(seqs), L), dtype=np.int64)
    lens = np.array([len(s) for s in seqs], dtype=np.int64)
    for i,s in enumerate(seqs): arr[i,:len(s)] = s
    x = torch.tensor(arr); lengths = torch.tensor(lens)
    mask = (x != pad_id).float()
    return x, lengths, mask

class NextDataset(Dataset):
    def __init__(self, X, y): self.X, self.y = X, y
    def __len__(self): return len(self.X)
    def __getitem__(self, i): return self.X[i], self.y[i]

def collate_fn(batch, pad_id=0):
    seqs, targets = zip(*batch)
    x, lengths, mask = pad_batch(seqs, pad_id)
    y = torch.tensor(targets, dtype=torch.long)
    return x, lengths, mask, y

#model building
class AdditiveAttention(nn.Module):
    def __init__(self, hidden_dim):
        super().__init__()
        self.W = nn.Linear(hidden_dim, hidden_dim)
        self.v = nn.Linear(hidden_dim, 1, bias=False)
    def forward(self, H, mask):
        scores = self.v(torch.tanh(self.W(H))).squeeze(-1) # (B,T)
        scores = scores.masked_fill(mask == 0, -1e9)
        alpha = torch.softmax(scores, dim=-1) # (B,T)
        ctx = torch.bmm(alpha.unsqueeze(1), H).squeeze(1) # (B,H)
        return ctx, alpha

class BiLSTMAtnRec(nn.Module):
    def __init__(self, num_items, emb_dim=64, hidden_dim=128, pad_id=0):
        super().__init__()
        self.emb = nn.Embedding(num_items+1, emb_dim, padding_idx=pad_id)
        self.lstm = nn.LSTM(emb_dim, hidden_dim//2, batch_first=True, bidirectional=True)
        self.attn = AdditiveAttention(hidden_dim)
        self.drop = nn.Dropout(0.2)

```

```

self.out = nn.Linear(hidden_dim, num_items+1)

def forward(self, x, lengths, mask):
    E = self.emb(x) # (B,T,E)
    H, _ = self.lstm(E) # (B,T,H)
    ctx, _ = self.attn(H, mask) # (B,H)
    z = self.drop(ctx)
    logits = self.out(z) # (B,V)
    return logits

#train and save
def train_ict():
    df = load_interactions(CSV_PATH)
    ict = df[df["subject"] == SUBJECT].copy()
    if ict.empty: raise ValueError("No ICT rows in interactions.csv")
    if ict["user_id"].nunique() < 5:
        print("[ict] Few users detected; training anyway.")

    topic2id, id2topic, sequences = build_vocab_sequences(ict)
    if not sequences:
        raise ValueError("No ICT sequences with length ≥ MIN_SEQ_LEN")

    X, y = make_next_pairs(sequences)
    Xtr, Xva, ytr, yva = train_test_split(X, y, test_size=0.2, random_state=SEED, shuffle=True)
    train_loader = DataLoader(NnextDataset(Xtr, ytr), batch_size=BATCH_SIZE, shuffle=True)
    val_loader = DataLoader(NnextDataset(Xva, yva), batch_size=BATCH_SIZE, shuffle=False)

    model = BiLSTMAttnRec(num_items=len(topic2id)).to(DEVICE)
    crit = nn.CrossEntropyLoss(ignore_index=0)
    opt = torch.optim.AdamW(model.parameters(), lr=LR)

    for ep in range(1, EPOCHS+1):
        model.train(); tloss=0
        for x,l,m,yb in train_loader:
            x,l,m,yb = x.to(DEVICE), l.to(DEVICE), m.to(DEVICE), yb.to(DEVICE)
            logits = model(x,l,m)
            loss = crit(logits, yb)
            opt.zero_grad(); loss.backward()
            nn.utils.clip_grad_norm_(model.parameters(), 1.0)
            opt.step()
            tloss += loss.item()*x.size(0)

        model.eval(); vloss=0
        with torch.no_grad():
            for x,l,m,yb in val_loader:
                x,l,m,yb = x.to(DEVICE), l.to(DEVICE), m.to(DEVICE), yb.to(DEVICE)
                vloss += crit(model(x,l,m), yb).item()*x.size(0)
        print(f"[ict] Epoch {ep:02d}  train_loss={tloss/len(Xtr):.4f}  val_loss={vloss/len(Xva):.4f}")

    os.makedirs(MODELS_DIR, exist_ok=True)
    torch.save(model.state_dict(), os.path.join(MODELS_DIR, "bilstm_ict.pt"))
    with open(os.path.join(MODELS_DIR, "topic2id_ict.pkl"), "wb") as f: pickle.dump(topic2id, f)
    with open(os.path.join(MODELS_DIR, "id2topic_ict.pkl"), "wb") as f: pickle.dump(id2topic, f)
    print("[ict] Saved model + vocab to models/")

    example_hist = list(topic2id.keys())[:3]
    recs = recommend_next("ict", example_hist, already_seen=example_hist, top_n=TOPK)
    print("\nDemo history:", example_hist)
    print("Top-N next topics:", recs)

#Inference
def load_ict_model():
    t2i_p = os.path.join(MODELS_DIR, "topic2id_ict.pkl")
    i2t_p = os.path.join(MODELS_DIR, "id2topic_ict.pkl")
    m_p = os.path.join(MODELS_DIR, "bilstm_ict.pt")

```



```

if not (os.path.exists(t2i_p) and os.path.exists(i2t_p) and os.path.exists(m_p)):
    raise FileNotFoundError("Train ICT first to create model + mappings in models/")
with open(t2i_p, "rb") as f: topic2id = pickle.load(f)
with open(i2t_p, "rb") as f: id2topic = pickle.load(f)
model = BiLSTMAttnRec(num_items=len(topic2id)).to(DEVICE)
model.load_state_dict(torch.load(m_p, map_location=DEVICE))
model.eval()
return model, topic2id, id2topic

def recommend_next(subject: str, history_topics: List[str], already_seen: List[str] = No
assert subject == "ict", "This script is ICT-only."
model, topic2id, id2topic = load_ict_model()
ids = [topic2id[t] for t in history_topics if t in topic2id]
if not ids: return []
x = torch.tensor([ids], dtype=torch.long).to(DEVICE)
lengths = torch.tensor([len(ids)], dtype=torch.long).to(DEVICE)
mask = (x != 0).float()
with torch.no_grad():
    logits = model(x, lengths, mask)
    probs = torch.softmax(logits, dim=-1).squeeze(0).cpu().numpy()
seen = set(already_seen or [])
cands = [(tid,p) for tid,p in enumerate(probs) if tid!=0 and id2topic.get(tid) not i
cands.sort(key=lambda x: x[1], reverse=True)
return [(id2topic[tid], float(p)) for tid,p in cands[:top_n]]

if __name__ == "__main__":
    train_ict()

```

```

[ict] Epoch 01  train_loss=2.1836  val_loss=2.1953
[ict] Epoch 02  train_loss=2.1590  val_loss=2.1948
[ict] Epoch 03  train_loss=2.1363  val_loss=2.1947
[ict] Epoch 04  train_loss=2.1200  val_loss=2.1927
[ict] Epoch 05  train_loss=2.1047  val_loss=2.1904
[ict] Epoch 06  train_loss=2.0796  val_loss=2.1885
[ict] Epoch 07  train_loss=2.0659  val_loss=2.1870
[ict] Epoch 08  train_loss=2.0447  val_loss=2.1867
[ict] Saved model + vocab to models/

```

Demo history: ['4. Networks and the effects of using them', '5. The effects of using IC  
T', '1. Types and Components of Computer Systems']  
Top-N next topics: [('8.Safety and Security', 0.12913718819618225), ('3. Storage Devices  
and Media', 0.1258760243654251), ('7. Systems Analysis and Design', 0.1099312976002693  
2), ('2. Input and Output Devices', 0.10689781606197357), ('6. ICT Applications', 0.1059  
8456859588623)]

```

In [5]: import pandas as pd
import numpy as np
from sklearn.metrics.pairwise import cosine_similarity

PATH = r"C:\Users\Rizwana\Desktop\studyclock project\interactions_real.csv"

df = pd.read_csv(PATH)

#verification of data
for subj in ["biology", "chemistry", "business", "ict"]:
    sub = df[df.subject==subj]
    users = sub["user_id"].nunique()
    avg_per_user = sub.groupby("user_id").size().mean()
    print(f"{subj:10s} users={users:3d}  avg_interactions/user={avg_per_user:.1f}")

#per-user holdout
def per_user_holdout(df_subj: pd.DataFrame):
    train_rows = []
    test_truth = {}
    for uid, g in df_subj.groupby("user_id"):

```

```

        if len(g) < 2:
            continue
        g = g.sort_values("timestamp")
        n_test = max(1, int(0.3*len(g)))
        test_part = g.tail(n_test)
        train_part = g.iloc[:-n_test]
        if train_part.empty:
            continue
        train_rows.append(train_part)
        test_truth[uid] = set(test_part["topic_name"].tolist())
    train_df = pd.concat(train_rows, ignore_index=True) if train_rows else pd.DataFrame()
    return train_df, test_truth

#self-contained user-user CF (evaluation)
def user_user_recommend_eval(train_df: pd.DataFrame, subject: str, user_id, top_n=5):
    sub = train_df[train_df["subject"]==subject].copy()
    if sub.empty:
        return []
    #user-item matrix
    users = sub["user_id"].unique().tolist()
    items = sub["topic_name"].unique().tolist()
    ui = pd.pivot_table(sub, index="user_id", columns="topic_name", values="rating")
    ui = ui.reindex(index=users, columns=items)
    if user_id not in ui.index:
        return []
    sim = cosine_similarity(ui.fillna(0))
    sim = pd.DataFrame(sim, index=ui.index, columns=ui.index)

    # weighted scores
    scores = sim.loc[user_id].values @ ui.fillna(0).values
    scores = pd.Series(scores, index=ui.columns)

    # remove already-seen
    seen = set(sub[sub["user_id"]==user_id]["topic_name"])
    scores.loc[list(seen)] = -np.inf

    ranked = scores.sort_values(ascending=False)
    return ranked.index[:top_n].tolist()

def precision_recall_at_k(pred_items, true_items, k):
    if not pred_items:
        return 0.0, 0.0
    pred_k = pred_items[:k]
    hits = len(set(pred_k) & true_items)
    return hits/float(k), hits/float(len(true_items))

#evaluate with the fallback recommender
def evaluate_cf_fallback(df: pd.DataFrame, subjects, k=5):
    rows = []
    for subj in subjects:
        sub = df[df["subject"]==subj].copy()
        if sub.empty:
            print(f"[{subj}] no rows; skip")
            continue
        train_df, test_truth = per_user_holdout(sub)
        if train_df.empty or not test_truth:
            print(f"[{subj}] holdout produced 0 users; skip")
            continue
        p_list, r_list = [], []
        for uid, truth in test_truth.items():
            recs = user_user_recommend_eval(train_df, subj, uid, top_n=k)
            p, r = precision_recall_at_k(recs, truth, k)
            p_list.append(p); r_list.append(r)
        if p_list:
            rows.append({
                "subject": subj,

```

```

        f"precision@{k}": float(np.mean(p_list)),
        f"recall@{k}": float(np.mean(r_list)),
        "users_eval": int(len(p_list))
    })
    else:
        print(f"[{subj}] recommender returned empty for all users.")
    return pd.DataFrame(rows)

report = evaluate_cf_fallback(df, ["biology", "chemistry", "business", "ict"], k=5)
print("\nCF fallback evaluation:")
print(report if not report.empty else "No evaluable users (unexpected).")

```

```

biology    users= 0  avg_interactions/user=nan
chemistry  users= 0  avg_interactions/user=nan
business   users= 0  avg_interactions/user=nan
ict        users= 0  avg_interactions/user=nan
[biology] no rows; skip
[chemistry] no rows; skip
[business] no rows; skip
[ict] no rows; skip

```

```

CF fallback evaluation:
No evaluable users (unexpected).

```

## Hybrid Recommender (BiLSTM)

```

In [6]: import os
import pickle
from typing import List, Optional, Dict, Tuple
import numpy as np
import pandas as pd

#Content
class ContentEmbedRecommender:
    """
    Semantic content recommender using sentence-transformer embeddings.
    Falls back to TF-IDF if sentence-transformers isn't available.
    """
    def __init__(self, processed_csv: str, model_name: str = "sentence-transformers/all-
self.df = pd.read_csv(processed_csv)
need = {"subject", "topic_name", "summary_text"}
if not need.issubset(self.df.columns):
    raise ValueError(f"{processed_csv} must contain {need}")
self.df["text_for_embed"] = (
    self.df["topic_name"].fillna("") + " | " + self.df["summary_text"].fillna("")
)
self.model_name = model_name
self._fit()

    def _fit(self):
        try:
            from sentence_transformers import SentenceTransformer
            from sklearn.preprocessing import normalize
            self.encoder = SentenceTransformer(self.model_name)
            embs = self.encoder.encode(self.df["text_for_embed"].tolist(), normalize_emb
            self.embs = embs.astype(np.float32)  # (N, d), already L2-normalized
            self.backend = "sbert"
        except Exception:
            #Fallback: TF-IDF
            from sklearn.feature_extraction.text import TfidfVectorizer
            from sklearn.preprocessing import normalize
            self.vectorizer = TfidfVectorizer(min_df=2, max_df=0.9, ngram_range=(1,2))
            X = self.vectorizer.fit_transform(self.df["text_for_embed"].tolist())
            self.embs = normalize(X).astype(np.float32)

```

```

        self.backend = "tfidf"

def _cosine_topk(self, vec, mask_idx, k):

    if hasattr(self.embs, "dot"):
        sims = self.embs.dot(vec.T).toarray().ravel()
    else:
        sims = self.embs @ vec.ravel()
    if mask_idx is not None:
        sims[mask_idx] = -np.inf
    order = np.argsort(-sims, range(min(k, len(sims))))[:k]
    order = order[np.argsort(-sims[order])]
    return order, sims

def _encode_text(self, text: str):
    if self.backend == "sbert":
        v = self.encoder.encode([text], normalize_embeddings=True)
        return v.astype(np.float32)
    else:
        v = self.vectorizer.transform([text])
        from sklearn.preprocessing import normalize
        return normalize(v).astype(np.float32)

def _mask_subject(self, subject: str):
    return np.where(self.df["subject"].values != subject)[0]

def recommend_like(self, subject: str, topic_name: str, top_n=5) -> pd.DataFrame:
    if topic_name not in set(self.df.loc[self.df["subject"]==subject, "topic_name"]):
        raise ValueError(f"'{topic_name}' not found in subject='{subject}'")
    idx = self.df.index[(self.df["subject"]==subject) & (self.df["topic_name"]==topic_name)]
    vec = self.embs[idx:idx+1] if self.backend=="sbert" else self.embs[idx:idx+1]
    mask_idx = np.where(self.df.index.values == idx)[0]
    order, sims = self._cosine_topk(vec, mask_idx, top_n+1)
    order = [i for i in order if i != idx][:top_n]
    out = self.df.loc[order, ["subject", "topic_name", "difficulty_level"]].copy()
    out["score_content"] = sims[order]
    return out.reset_index(drop=True)

def recommend_query(self, subject: str, query: str, top_n=5) -> pd.DataFrame:
    vec = self._encode_text(query)
    mask = self._mask_subject(subject)
    order, sims = self._cosine_topk(vec, mask, top_n)
    out = self.df.loc[order, ["subject", "topic_name", "difficulty_level"]].copy()
    out["score_content"] = sims[order]
    return out.reset_index(drop=True)

def recommend_from_profile(self, subject: str, liked_topics: List[str], top_n=5) -> pd.DataFrame:
    #Average embeddings of liked topics
    rows = self.df[(self.df["subject"]==subject) & (self.df["topic_name"].isin(liked_topics))]
    if rows.empty:
        raise ValueError("None of the liked topics found in this subject.")
    idxs = rows.index.values
    if hasattr(self.embs, "mean"):
        vec = np.mean(self.embs[idxs], axis=0, keepdims=True)
        vec = vec / (np.linalg.norm(vec) + 1e-8)
    else:
        vec = self.embs[idxs].mean(axis=0)
        from sklearn.preprocessing import normalize
        vec = normalize(vec)
    mask_idx = self._mask_subject(subject)

    mask_idx = np.unique(np.concatenate([mask_idx, np.array([np.where(self.df.index.values == idxs)[0]])]))
    order, sims = self._cosine_topk(vec, mask_idx, top_n)
    out = self.df.loc[order, ["subject", "topic_name", "difficulty_level"]].copy()
    out["score_content"] = sims[order]
    return out.reset_index(drop=True)

```

```
#Collaborative Filtering (User-User)
```

```
class UserUserCF:
```

```
    """
```

```
    Simple cosine User-User CF. Designed to run on a per-subject train slice.
```

```
    """
```

```
    def __init__(self, interactions_csv: str):
```

```
        self.full = pd.read_csv(interactions_csv)
```

```
        need = {"user_id", "subject", "topic_name", "rating"}
```

```
        if not need.issubset(self.full.columns):
```

```
            raise ValueError(f"{interactions_csv} must contain {need}")
```

```
    def _pivot(self, df_subj: pd.DataFrame):
```

```
        users = df_subj["user_id"].unique().tolist()
```

```
        items = df_subj["topic_name"].unique().tolist()
```

```
        ui = pd.pivot_table(df_subj, index="user_id", columns="topic_name", values="rating")
```

```
        ui = ui.reindex(index=users, columns=items)
```

```
        return ui
```

```
    def recommend(self, subject: str, user_id, top_n=5) -> pd.DataFrame:
```

```
        from sklearn.metrics.pairwise import cosine_similarity
```

```
        df_subj = self.full[self.full["subject"]==subject].copy()
```

```
        if df_subj.empty:
```

```
            return pd.DataFrame(columns=["topic_name", "score_cf"])
```

```
        ui = self._pivot(df_subj)
```

```
        if user_id not in ui.index:
```

```
            return pd.DataFrame(columns=["topic_name", "score_cf"])
```

```
        sim = cosine_similarity(ui.fillna(0))
```

```
        sim = pd.DataFrame(sim, index=ui.index, columns=ui.index)
```

```
        scores = sim.loc[user_id].values @ ui.fillna(0).values
```

```
        scores = pd.Series(scores, index=ui.columns)
```

```
        seen = set(df_subj[df_subj["user_id"]==user_id]["topic_name"])
```

```
        if seen:
```

```
            scores.loc[list(seen)] = -np.inf
```

```
        ranked = scores.sort_values(ascending=False)
```

```
        top_items = ranked.head(top_n)
```

```
        return pd.DataFrame({"topic_name": top_items.index, "score_cf": top_items.values})
```

```
#BiLSTM loader
```

```
class BiLSTMNextTopic:
```

```
    """
```

```
    Thin loader/inferencer for your saved BiLSTM models (optional).
```

```
    If assets aren't found, calls return empty DataFrames.
```

```
    """
```

```
    def __init__(self, models_dir="models", device="cpu"):
```

```
        self.models_dir = models_dir
```

```
        self.device = device
```

```
        self._cache = {}
```

```
    def _paths(self, subject):
```

```
        return (
```

```
            os.path.join(self.models_dir, f"bilstm_{subject}.pt"),
```

```
            os.path.join(self.models_dir, f"topic2id_{subject}.pkl"),
```

```
            os.path.join(self.models_dir, f"id2topic_{subject}.pkl"),
```

```
        )
```

```
    def _load(self, subject):
```

```
        if subject in self._cache:
```

```
            return self._cache[subject]
```

```
        m_p, t2i_p, i2t_p = self._paths(subject)
```

```
        if not (os.path.exists(m_p) and os.path.exists(t2i_p) and os.path.exists(i2t_p)):
```

```
            self._cache[subject] = None
```

```
            return None
```

```

import torch
import torch.nn as nn

class AdditiveAttention(nn.Module):
    def __init__(self, hidden_dim):
        super().__init__()
        self.W = nn.Linear(hidden_dim, hidden_dim)
        self.v = nn.Linear(hidden_dim, 1, bias=False)
    def forward(self, H, mask):
        scores = self.v(torch.tanh(self.W(H))).squeeze(-1)
        scores = scores.masked_fill(mask==0, -1e9)
        alpha = torch.softmax(scores, dim=-1)
        ctx = torch.bmm(alpha.unsqueeze(1), H).squeeze(1)
        return ctx

class BiLSTMAttnRec(nn.Module):
    def __init__(self, num_items, emb_dim=64, hidden_dim=128, pad_id=0):
        super().__init__()
        self.emb = nn.Embedding(num_items+1, emb_dim, padding_idx=pad_id)
        self.lstm = nn.LSTM(emb_dim, hidden_dim//2, batch_first=True, bidirectional=True)
        self.attn = AdditiveAttention(hidden_dim)
        self.out = nn.Linear(hidden_dim, num_items+1)
    def forward(self, x, mask):
        E = self.emb(x)
        H, _ = self.lstm(E)
        ctx = self.attn(H, mask)
        logits = self.out(ctx)
        return logits

with open(t2i_p, "rb") as f: topic2id = pickle.load(f)
with open(i2t_p, "rb") as f: id2topic = pickle.load(f)
num_items = len(topic2id)

model = BiLSTMAttnRec(num_items=num_items)
import torch
model.load_state_dict(torch.load(m_p, map_location=self.device))
model.eval()
self._cache[subject] = (model, topic2id, id2topic)
return self._cache[subject]

def recommend(self, subject: str, history: List[str], already_seen: Optional[List[str]] = None):
    pack = self._load(subject)
    if pack is None:
        return pd.DataFrame(columns=["topic_name", "score_seq"])
    import torch
    model, topic2id, id2topic = pack
    ids = [topic2id[t] for t in history if t in topic2id]
    if not ids:
        return pd.DataFrame(columns=["topic_name", "score_seq"])
    x = torch.tensor([ids], dtype=torch.long)
    mask = (x != 0).float()
    with torch.no_grad():
        logits = model(x, mask)
        probs = torch.softmax(logits, dim=-1).squeeze(0).numpy()
    seen = set(already_seen or [])
    items = []
    for tid, p in enumerate(probs):
        if tid == 0: # pad
            continue
        name = id2topic.get(tid)
        if name and name not in seen:
            items.append((name, float(p)))
    items.sort(key=lambda z: z[1], reverse=True)
    items = items[:top_n]
    if not items:
        return pd.DataFrame(columns=["topic_name", "score_seq"])
    return pd.DataFrame(columns=["topic_name", "score_seq"])

```



```

        return pd.DataFrame(items, columns=["topic_name", "score_seq"])

#Hybrid ranker
class HybridRecommender:
    """
    Blend Content, CF, and Sequence scores (min-max normalized per list) and rank.
    Weights default to a recall-friendly profile: content 0.4, CF 0.3, seq 0.3.
    """
    def __init__(self, processed_csv: str, interactions_csv: str, models_dir="models"):
        self.content = ContentEmbedRecommender(processed_csv)
        self.cf = UserUserCF(interactions_csv)
        self.seq = BiLSTMNextTopic(models_dir=models_dir)

    @staticmethod
    def _normalize(series: pd.Series) -> pd.Series:
        if series.empty:
            return series
        vmin, vmax = float(series.min()), float(series.max())
        if not np.isfinite(vmin) or not np.isfinite(vmax) or vmax <= vmin:
            return pd.Series(np.zeros(len(series)), index=series.index)
        return (series - vmin) / (vmax - vmin)

    def _blend(self, frames: List[pd.DataFrame], weights: Dict[str, float], k=10) -> pd.D
        # Outer-join on topic_name and fill NaNs with 0
        if not frames:
            return pd.DataFrame(columns=["topic_name", "score"])
        df = frames[0]
        for f in frames[1:]:
            df = df.merge(f, on=["topic_name"], how="outer")
        # normalize individual score columns
        for col in ["score_content", "score_cf", "score_seq"]:
            if col in df.columns:
                df[col] = df[col].fillna(0.0)
                df[col] = self._normalize(df[col])
            else:
                df[col] = 0.0
        score = (
            weights.get("content", 0.0) * df["score_content"]
            + weights.get("cf", 0.0) * df["score_cf"]
            + weights.get("seq", 0.0) * df["score_seq"]
        )
        df["score"] = score
        df = df.sort_values("score", ascending=False)
        return df[["topic_name", "score", "score_content", "score_cf", "score_seq"]].head(k)

    # Public APIs
    def recommend_like(self, subject: str, topic_name: str, user_id=None, history: Optional[
        weights={"content": 0.4, "cf": 0.3, "seq": 0.3}, k=10) -> pd.DataFrame
        frames = []
        frames.append(self.content.recommend_like(subject, topic_name, top_n=k)[["topic_name", "score"]])
        if user_id is not None:
            frames.append(self.cf.recommend(subject, user_id, top_n=k)[["topic_name", "score"]])
        if history:
            frames.append(self.seq.recommend(subject, history, already_seen=[topic_name])
        return self._blend([f for f in frames if not f.empty], weights, k)

    def recommend_query(self, subject: str, query: str, user_id=None, history: Optional[
        weights={"content": 0.5, "cf": 0.25, "seq": 0.25}, k=10) -> pd.DataFrame
        frames = []
        frames.append(self.content.recommend_query(subject, query, top_n=k)[["topic_name", "score"]])
        if user_id is not None:
            frames.append(self.cf.recommend(subject, user_id, top_n=k)[["topic_name", "score"]])
        if history:
            frames.append(self.seq.recommend(subject, history, already_seen=history, top_n=k)
        return self._blend([f for f in frames if not f.empty], weights, k)

```

```

def recommend_from_profile(self, subject: str, liked_topics: List[str], user_id=None,
                           weights={"content":0.4,"cf":0.3,"seq":0.3}, k=10) -> pd.D
    frames = []
    frames.append(self.content.recommend_from_profile(subject, liked_topics, top_n=k))
    if user_id is not None:
        frames.append(self.cf.recommend(subject, user_id, top_n=k)[["topic_name","score_cf"]]
    if history:
        frames.append(self.seq.recommend(subject, history, already_seen=liked_topics))
    return self._blend([f for f in frames if not f.empty], weights, k)

#Evaluation
if __name__ == "__main__":
    PROCESSED = "processed_notes.csv"
    INTERACTIONS = r"C:\Users\Rizwana\Downloads\interactions2.csv"

    if not (os.path.exists(PROCESSED) and os.path.exists(INTERACTIONS)):
        raise SystemExit("Place processed_notes.csv and interactions*.csv next to this s

    rec = HybridRecommender(PROCESSED, INTERACTIONS)

    #Example 1: Biology
    print("\n=== Hybrid: 'like' a Biology topic (user_3) ===")
    out1 = rec.recommend_like(
        subject="biology",
        topic_name="Unit 5 Enzymes",
        user_id="user_3",
        history=["Unit 2 Cells", "Unit 12 Respiration"],
        k=8
    )
    print(out1)

    # Example 2:Chemistry
    print("\n=== Hybrid: query 'rates of reaction' (Chemistry, user_10) ===")
    out2 = rec.recommend_query(
        subject="chemistry",
        query="rates of reaction, collision theory, catalysts",
        user_id="user_10",
        history=["Unit 12 Periodic Table", "Unit 3 Structure and Bonding"],
        k=8
    )
    print(out2)

```

```

=== Hybrid: 'like' a Biology topic (user_3) ===

```

	topic_name	score	score_content	score_cf	score_seq
0	Unit 9 Chemical Reactions	0.400000	1.000000	0.0	0.000000
1	Unit 8 Speed of Reaction	0.346783	0.866958	0.0	0.000000
2	Unit 10 Diseases and Immunity	0.300000	0.000000	0.0	1.000000
3	Unit 13 Excretion	0.290038	0.000000	0.0	0.966793
4	Unit 6 Plant Nutrition	0.287960	0.000000	0.0	0.959865
5	Unit 8 Plant Transport	0.285170	0.000000	0.0	0.950566
6	Unit 17 Inheritance	0.281574	0.000000	0.0	0.938581
7	Unit 4 Biological Molecules	0.281152	0.000000	0.0	0.937174

```

=== Hybrid: query 'rates of reaction' (Chemistry, user_10) ===

```

	topic_name	score	score_content	score_cf	\
0	Unit 8 Speed of Reaction	0.500000	1.000000	0.0	
1	Unit 16 The Chemical Industry	0.372615	0.245230	0.0	
2	Unit 9 Chemical Reactions	0.336670	0.284830	0.0	
3	Unit 12 The Periodic Table	0.226644	0.082268	0.0	
4	Unit 14 Metal Extraction	0.212034	0.000000	0.0	
5	Unit 15 Air and Water	0.208325	0.000000	0.0	
6	Unit 1 Particles and Purification	0.205907	0.000000	0.0	

```

score_seq
0    0.000000
1    1.000000
2    0.777022
3    0.742041
4    0.848135
5    0.833299
6    0.823626
7    0.811252

```

## Establishing the Baseline

```

In [1]: import numpy as np
import pandas as pd
from difflib import get_close_matches

def _closest_topic(df: pd.DataFrame, subject: str, topic_name: str, cutoff: float = 0.55) -> str:
    pool = df.loc[df["subject"] == subject, "topic_name"].astype(str).unique().tolist()
    match = get_close_matches(str(topic_name), pool, n=1, cutoff=cutoff)
    return match[0] if match else None

def _normalize_vec(vec):
    try:
        v = np.asarray(vec).astype(np.float32)
        if v.ndim == 1:
            v = v[None, :]
        norm = np.linalg.norm(v) + 1e-8
        return (v / norm).astype(np.float32)
    except Exception:
        return vec

def patched_recommend_from_profile(self, subject: str, liked_topics, top_n: int = 8) -> str:
    """
    Robust version:
    - Accepts messy liked_topics (exact or fuzzy).
    - Works with SBERT (dense) and TF-IDF (sparse) embeddings.
    - Falls back to query if nothing matches.
    """
    liked_topics = list(liked_topics or [])
    subdf = self.df[self.df["subject"] == subject]

    #Build a valid list of liked topics (exact or fuzzy)
    valid = []
    for t in liked_topics:
        if (subdf["topic_name"] == t).any():
            valid.append(t)
        else:
            m = _closest_topic(self.df, subject, t, cutoff=0.55)
            if m:
                print(f"[content] liked '{t}' -> matched '{m}'")
                valid.append(m)

    #Unique while preserving order
    seen = set()
    valid = [x for x in valid if not (x in seen or seen.add(x))]

    if not valid:
        print("[content] No liked topics matched; using query fallback.")
        return self.recommend_query(subject, " ".join(liked_topics), top_n=top_n)

```

```

#Indices of the valid liked topics
idxs = subdf.index[subdf["topic_name"].isin(valid)].values
if len(idxs) == 0:
    print("[content] Matched liked topics not found in embeddings; using query fallback")
    return self.recommend_query(subject, " ".join(liked_topics), top_n=top_n)

#Dense vs Sparse average embedding (safe)
if getattr(self, "backend", "") == "sbert":
    # Dense numpy array: (N,d) → mean (1,d)
    vec = np.mean(self.embs[idxs], axis=0, keepdims=True).astype(np.float32)
    vec = _normalize_vec(vec)
else:
    #Sparse matrix: use scipy sparse .mean(axis=0), then convert to dense row
    from sklearn.preprocessing import normalize
    vec = self.embs[idxs].mean(axis=0) # 1 x V (sparse)
    vec = normalize(vec) # L2 normalize sparse
    vec = np.asarray(vec.todense(), dtype=np.float32) # (1,V) as dense row

#Ban liked items themselves
banned_idx = self.df.index[self.df["topic_name"].isin(valid)].values

#Retrieve top-k by cosine similarity
order, sims = self._cosine_topk(vec, banned_idx, top_n + len(valid))

#Filter out liked items (in case any slipped through) and take top_n
order = [i for i in order if self.df.iloc[i]["topic_name"] not in valid][:top_n]

out = self.df.loc[order, ["subject", "topic_name", "difficulty_level"]].copy()
out["score_content"] = sims[order]
return out.reset_index(drop=True)

try:
    ContentEmbedRecommender.recommend_from_profile = patched_recommend_from_profile
    print("Patched ContentEmbedRecommender.recommend_from_profile successfully.")
except NameError:
    print("ContentEmbedRecommender class not found in this kernel. "
          "Run the cell that defines the class first, then re-run this patch.")

```

ContentEmbedRecommender class not found in this kernel. Run the cell that defines the class first, then re-run this patch.

```

In [7]: import os
import math
import random
import argparse
import pickle
from typing import List, Dict, Tuple

import numpy as np
import pandas as pd

import torch
import torch.nn as nn
from torch.utils.data import Dataset, DataLoader

SEED = 42
random.seed(SEED); np.random.seed(SEED); torch.manual_seed(SEED)
if torch.cuda.is_available():
    torch.cuda.manual_seed_all(SEED)
    torch.backends.cudnn.deterministic = True
    torch.backends.cudnn.benchmark = False

DEVICE = "cuda" if torch.cuda.is_available() else "cpu"

```

```
#utilities
```

```
def load_subject_sequences(interactions_csv: str, subject: str) -> Dict[str, List[str]]:
    """Load user → ordered topic sequences for a subject from interactions CSV."""
    df = pd.read_csv(interactions_csv)
    need = {"user_id", "subject", "topic_name", "timestamp"}
    if not need.issubset(df.columns):
        raise ValueError(f"{interactions_csv} must contain columns: {need}")
    sub = df[df["subject"].str.lower() == subject.lower()].copy()
    if sub.empty:
        raise ValueError(f"No rows for subject='{subject}' in {interactions_csv}")
    sub = sub.sort_values(["user_id", "timestamp"])
    sessions: Dict[str, List[str]] = {}
    for uid, g in sub.groupby("user_id"):
        seq = g["topic_name"].tolist()
        if len(seq) >= 3:  # need at least 3 to learn transitions robustly
            sessions[uid] = seq
    if not sessions:
        raise ValueError(f"No users with >=3 interactions for subject='{subject}'.")
    return sessions

def build_vocab(sessions: Dict[str, List[str]]) -> Tuple[Dict[str, int], Dict[int, str]]:
    """Create topic ↔ id mapping (0 reserved for PAD)."""
    topics = sorted({t for seq in sessions.values() for t in seq})
    topic2id = {t:i+1 for i,t in enumerate(topics)}  # 1..V
    id2topic = {i+1:t for i,t in enumerate(topics)}
    return topic2id, id2topic

def make_examples(sessions: Dict[str, List[str]], topic2id: Dict[str, int], seq_len: int):
    """Sliding-window next-item examples: history → next_topic."""
    X, y = [], []
    for seq in sessions.values():
        ids = [topic2id[t] for t in seq if t in topic2id]
        for i in range(1, len(ids)):
            hist = ids[max(0, i - seq_len):i]
            target = ids[i]
            if len(hist) == 0:  # require at least 1 item in history
                continue
            X.append(hist); y.append(target)
    return X, y

def pad_left(seqs: List[List[int]], pad_id=0, max_len=None):
    """Left-pad sequences to max_len; mask=1 for real tokens, 0 for pad."""
    if max_len is None:
        max_len = max(len(s) for s in seqs)
    X = np.zeros((len(seqs), max_len), dtype=np.int64)
    M = np.zeros((len(seqs), max_len), dtype=np.float32)
    for i, s in enumerate(seqs):
        s = s[-max_len:]  # truncate long histories
        X[i, -len(s):] = np.array(s, dtype=np.int64)
        M[i, -len(s):] = 1.0
    return torch.from_numpy(X), torch.from_numpy(M)

class NextTopicDataset(Dataset):
    def __init__(self, X_hist: List[List[int]], y_next: List[int], seq_len: int, pad_id: int):
        self.X, self.mask = pad_left(X_hist, pad_id=pad_id, max_len=seq_len)
        self.y = torch.tensor(y_next, dtype=torch.long)
    def __len__(self): return len(self.y)
    def __getitem__(self, idx): return self.X[idx], self.mask[idx], self.y[idx]

def split_users(sessions: Dict[str, List[str]], val_frac=0.2):
    """User-level split to avoid leakage; returns two dicts like sessions."""
    users = list(sessions.keys())
    random.shuffle(users)
    n_val = max(1, int(len(users) * val_frac))
    val_users = set(users[:n_val])
```

```

train = {u:s for u,s in sessions.items() if u not in val_users}
val = {u:s for u,s in sessions.items() if u in val_users}
return train, val

#Model
class AdditiveAttention(nn.Module):
    def __init__(self, hidden_dim):
        super().__init__()
        self.W = nn.Linear(hidden_dim, hidden_dim)
        self.v = nn.Linear(hidden_dim, 1, bias=False)

    def forward(self, H, mask):
        # H: (B,T,H), mask: (B,T)
        scores = self.v(torch.tanh(self.W(H))).squeeze(-1) # (B,T)
        scores = scores.masked_fill(mask == 0, -1e9)
        alpha = torch.softmax(scores, dim=-1) # (B,T)
        ctx = torch.bmm(alpha.unsqueeze(1), H).squeeze(1) # (B,H)
        return ctx

class BiLSTMAttnRec(nn.Module):
    def __init__(self, num_items, emb_dim=64, hidden_dim=128, pad_id=0, dropout=0.2):
        super().__init__()
        self.emb = nn.Embedding(num_items+1, emb_dim, padding_idx=pad_id)
        self.lstm = nn.LSTM(emb_dim, hidden_dim//2, batch_first=True, bidirectional=True)
        self.drop = nn.Dropout(dropout)
        self.attn = AdditiveAttention(hidden_dim)
        self.out = nn.Linear(hidden_dim, num_items+1)

    def forward(self, x, mask):
        E = self.emb(x) # (B,T,E)
        H, _ = self.lstm(E) # (B,T,H)
        H = self.drop(H)
        ctx = self.attn(H, mask) # (B,H)
        logits = self.out(ctx) # (B, V+1)
        return logits

#Train/Eval
@torch.no_grad()
def evaluate(model, loader, device, topk=(5,10)):
    model.eval()
    total = 0
    hits = {k:0 for k in topk}
    for X, M, y in loader:
        X, M, y = X.to(device), M.to(device), y.to(device)
        logits = model(X, M) # (B,V)
        probs = torch.softmax(logits, dim=-1)
        for k in topk:
            topk_ids = torch.topk(probs, k=k, dim=-1).indices # (B,k)
            hits[k] += (topk_ids == y.view(-1,1)).any(dim=1).sum().item()
        total += y.size(0)
    return {f"recall@{k}": (hits[k] / max(total,1)) for k in topk}

def train_subject(
    interactions: str,
    subject: str,
    save_dir: str = "models",
    seq_len: int = 10,
    batch_size: int = 128,
    epochs: int = 12,
    lr: float = 1e-3,
    weight_decay: float = 0.0,
    dropout: float = 0.2,
    hidden_dim: int = 128,
    emb_dim: int = 64,
    val_frac: float = 0.2,
    patience: int = 4,
    clip_norm: float = 1.0,
):

```

```

os.makedirs(save_dir, exist_ok=True)

# 1)Build sequences
sessions = load_subject_sequences(interactions, subject)
topic2id, id2topic = build_vocab(sessions)
num_items = len(topic2id)
print(f"[{subject}] users={len(sessions)} vocab_size={num_items}")

# 2)Split by user to avoid leakage
train_sess, val_sess = split_users(sessions, val_frac=val_frac)

# 3)Create sliding-window examples
Xtr, ytr = make_examples(train_sess, topic2id, seq_len)
Xva, yva = make_examples(val_sess, topic2id, seq_len)
if len(Xtr) == 0 or len(Xva) == 0:
    raise RuntimeError("Not enough examples after split; increase data density or re

# 4)Datasets/DataLoaders
train_ds = NextTopicDataset(Xtr, ytr, seq_len)
val_ds = NextTopicDataset(Xva, yva, seq_len)
train_loader = DataLoader(train_ds, batch_size=batch_size, shuffle=True, drop_last=
val_loader = DataLoader(val_ds, batch_size=batch_size, shuffle=False, drop_last=

# 5)Model/optim/loss
model = BiLSTMATtnRec(num_items=num_items, emb_dim=emb_dim, hidden_dim=hidden_dim, d
opt = torch.optim.AdamW(model.parameters(), lr=lr, weight_decay=weight_decay)
crit = nn.CrossEntropyLoss()

# 6)Training loop with early stopping on recall@5
best_val = -1.0
bad = 0
save_path = os.path.join(save_dir, f"bilstm_{subject}.pt")
t2i_path = os.path.join(save_dir, f"topic2id_{subject}.pkl")
i2t_path = os.path.join(save_dir, f"id2topic_{subject}.pkl")

print(f"[{subject}] Training on {DEVICE} ...")
for epoch in range(1, epochs+1):
    model.train()
    total_loss = 0.0
    for X, M, y in train_loader:
        X, M, y = X.to(DEVICE), M.to(DEVICE), y.to(DEVICE)
        opt.zero_grad()
        logits = model(X, M)
        loss = crit(logits, y)
        loss.backward()
        nn.utils.clip_grad_norm_(model.parameters(), clip_norm)
        opt.step()
        total_loss += loss.item() * y.size(0)

    train_loss = total_loss / len(train_ds)
    val_metrics = evaluate(model, val_loader, DEVICE, topk=(5,10))
    score = val_metrics["recall@5"]

    print(f"[{subject}] Epoch {epoch:02d} loss={train_loss:.4f} "
          f"val@5={val_metrics['recall@5']:.3f} val@10={val_metrics['recall@10']:.3

    if score > best_val:
        best_val, bad = score, 0
        torch.save(model.state_dict(), save_path)
        with open(t2i_path, "wb") as f: pickle.dump(topic2id, f)
        with open(i2t_path, "wb") as f: pickle.dump(id2topic, f)
    else:
        bad += 1
        if bad >= patience:
            print(f"[{subject}] Early stopping.")
            break

```



```

print(f"[{subject}] Best val recall@5 = {best_val:.3f}")
print(f"[{subject}] Saved model/vocabs to: {save_dir}")

# 7) demo on a random val history
if len(val_sess) > 0:
    any_user = next(iter(val_sess))
    hist = val_sess[any_user][-seq_len:]
    print(f"[{subject}] Demo history ({any_user}): {hist}")

    #Reload best
    model.load_state_dict(torch.load(save_path, map_location=DEVICE))
    model.eval()
    ids = [topic2id[t] for t in hist if t in topic2id]
    X = torch.tensor([([0]*(seq_len-len(ids)) + ids[-seq_len:]), dtype=torch.long).
    M = (X != 0).float()
    with torch.no_grad():
        probs = torch.softmax(model(X, M), dim=-1).squeeze(0).cpu().numpy()
        top_idx = np.argsort(probs)[::-1][:8]
        top_names = [id2topic[i] for i in top_idx if i in id2topic][:8]
        print(f"[{subject}] Top-8 next topics: {top_names}")

#CLI
def parse_args():
    ap = argparse.ArgumentParser(description="Train BiLSTM+Attention next-topic model pe
    ap.add_argument("--interactions", type=str, required=True,
                    help="Path to interactions CSV (requires columns: user_id, subject,
    ap.add_argument("--subject", type=str, required=True, choices=["biology", "chemistry"
    ap.add_argument("--save_dir", type=str, default="models")
    ap.add_argument("--seq_len", type=int, default=10)
    ap.add_argument("--batch_size", type=int, default=128)
    ap.add_argument("--epochs", type=int, default=12)
    ap.add_argument("--lr", type=float, default=1e-3)
    ap.add_argument("--weight_decay", type=float, default=0.0)
    ap.add_argument("--dropout", type=float, default=0.2)
    ap.add_argument("--hidden_dim", type=int, default=128)
    ap.add_argument("--emb_dim", type=int, default=64)
    ap.add_argument("--val_frac", type=float, default=0.2)
    ap.add_argument("--patience", type=int, default=4)
    return ap.parse_args()

if __name__ == "__main__":
    args = parse_args()
    train_subject(
        interactions=args.interactions,
        subject=args.subject,
        save_dir=args.save_dir,
        seq_len=args.seq_len,
        batch_size=args.batch_size,
        epochs=args.epochs,
        lr=args.lr,
        weight_decay=args.weight_decay,
        dropout=args.dropout,
        hidden_dim=args.hidden_dim,
        emb_dim=args.emb_dim,
        val_frac=args.val_frac,
        patience=args.patience,
    )

```

```

usage: ipykernel_launcher.py [-h] --interactions INTERACTIONS --subject {biology,chemist
ry,business,ict} [--save_dir SAVE_DIR] [--seq_len SEQ_LEN]
                        [--batch_size BATCH_SIZE] [--epochs EPOCHS] [--lr LR] [--we
ight_decay WEIGHT_DECAY] [--dropout DROPOUT]
                        [--hidden_dim HIDDEN_DIM] [--emb_dim EMB_DIM] [--val_frac V
AL_FRAC] [--patience PATIENCE]

```

```
ipykernel_launcher.py: error: the following arguments are required: --interactions, --subject
```

An exception has occurred, use %tb to see the full traceback.

**SystemExit: 2**

C:\Users\Rizwana\anaconda3\envs\finalproject\lib\site-packages\IPython\core\interactiveshell.py:3587: UserWarning: To exit: use 'exit', 'quit', or Ctrl-D.

warn("To exit: use 'exit', 'quit', or Ctrl-D.", stacklevel=1)

In [10]: *# Baseline embedding model per subject (fixed)*

```
import os
import numpy as np
import pandas as pd
from sklearn.model_selection import train_test_split
import torch
import torch.nn as nn
import torch.optim as optim

INTERACTIONS = r"C:\Users\Rizwana\Downloads\interactions2.csv"
SAVE_DIR = "trained_models"
os.makedirs(SAVE_DIR, exist_ok=True)

#Load & sanity
df = pd.read_csv(INTERACTIONS)
required = {"user_id", "subject", "topic_name"}
missing = required - set(df.columns)
if missing:
    raise ValueError(f"CSV is missing columns: {missing}")

#Optional rating; if absent, assume implicit positive = 1
if "rating" not in df.columns:
    df["rating"] = 1.0

# Normalize subject labels
df["subject"] = df["subject"].str.lower().str.strip()

#Make indices (NO item_id column in csv; we derive from topic_name -----
df["user_idx"] = df["user_id"].astype("category").cat.codes
df["item_key"] = df["topic_name"].astype(str).str.strip() #
df["item_idx"] = df["item_key"].astype("category").cat.codes

num_users_total = int(df["user_idx"].nunique())
num_items_total = int(df["item_idx"].nunique())
print(f"Users (global): {num_users_total} | Items (global): {num_items_total}")
print("Subjects:", sorted(df["subject"].unique()))

# Label (binary for BCE)
# If rating is numeric, treat >0 as positive; otherwise cast to float
df["label"] = (df["rating"].astype(float) > 0).astype(np.float32)

#4) Simple embedding model
class TinyRec(nn.Module):
    def __init__(self, num_users, num_items, emb_dim=64):
        super().__init__()
        self.user_emb = nn.Embedding(num_users, emb_dim)
        self.item_emb = nn.Embedding(num_items, emb_dim)
        self.out = nn.Linear(emb_dim * 2, 1)
        self.sigmoid = nn.Sigmoid()

    def forward(self, u_idx, i_idx):
        u = self.user_emb(u_idx) # (B, d)
        i = self.item_emb(i_idx) # (B, d)
        x = torch.cat([u, i], dim=1) # (B, 2d)
```

```

logit = self.out(x) # (B, 1)
return self.sigmoid(logit).squeeze(1)

def train_subject(df_subj, subject, epochs=6, batch_size=256, lr=1e-3):
    if len(df_subj) < 50:
        print(f" Skipping {subject}: too few rows ({len(df_subj)}).")
        return

    #Random split (quick baseline)
    train_df, test_df = train_test_split(df_subj, test_size=0.2, random_state=42)

    #Tensors
    tr_users = torch.tensor(train_df["user_idx"].values, dtype=torch.long)
    tr_items = torch.tensor(train_df["item_idx"].values, dtype=torch.long)
    tr_y      = torch.tensor(train_df["label"].values,      dtype=torch.float32)

    te_users = torch.tensor(test_df["user_idx"].values, dtype=torch.long)
    te_items = torch.tensor(test_df["item_idx"].values, dtype=torch.long)
    te_y      = test_df["label"].values.astype(np.float32)

    model = TinyRec(num_users_total, num_items_total, emb_dim=64)
    opt = optim.Adam(model.parameters(), lr=lr)
    crit = nn.BCELoss()

    #Simple mini-batching
    def batches(U, I, Y, bs):
        n = len(Y)
        for s in range(0, n, bs):
            e = min(s+bs, n)
            yield U[s:e], I[s:e], Y[s:e]

    for ep in range(1, epochs+1):
        model.train()
        total_loss = 0.0
        for U, I, Y in batches(tr_users, tr_items, tr_y, batch_size):
            opt.zero_grad()
            pred = model(U, I)
            loss = crit(pred, Y)
            loss.backward()
            opt.step()
            total_loss += float(loss.item()) * len(Y)
        avg_loss = total_loss / len(tr_y)
        print(f"[{subject}] epoch {ep:02d} loss={avg_loss:.4f}")

    #Save
    save_path = os.path.join(SAVE_DIR, f"{subject}_tinyrec.pth")
    torch.save(model.state_dict(), save_path)
    print(f" saved {save_path}")

    # Quick accuracy on test split
    model.eval()
    with torch.no_grad():
        pred = model(te_users, te_items).cpu().numpy()
        acc = ( (pred >= 0.5).astype(np.float32) == te_y ).mean()
        print(f"[{subject}] test accuracy: {acc:.3f}")

    #Train per subject
    for subj, df_sub in df.groupby("subject"):
        print(f"\n=== Training baseline for subject: {subj} ===")
        train_subject(df_sub, subj, epochs=6, batch_size=256, lr=1e-3)

print("\n Baseline finished. Models stored in:", SAVE_DIR)

```

Users (global): 40 | Items (global): 40  
Subjects: ['biology', 'business', 'chemistry', 'ict']

```

=== Training baseline for subject: biology ===
[biology] epoch 01  loss=0.7961
[biology] epoch 02  loss=0.7800
[biology] epoch 03  loss=0.7641
[biology] epoch 04  loss=0.7485
[biology] epoch 05  loss=0.7332
[biology] epoch 06  loss=0.7181
    saved trained_models\biology_tinyrec.pth
[biology] test accuracy: 0.481

=== Training baseline for subject: business ===
[business] epoch 01  loss=0.7671
[business] epoch 02  loss=0.7505
[business] epoch 03  loss=0.7341
[business] epoch 04  loss=0.7180
[business] epoch 05  loss=0.7022
[business] epoch 06  loss=0.6867
    saved trained_models\business_tinyrec.pth
[business] test accuracy: 0.706

=== Training baseline for subject: chemistry ===
[chemistry] epoch 01  loss=0.8832
[chemistry] epoch 02  loss=0.8657
[chemistry] epoch 03  loss=0.8485
[chemistry] epoch 04  loss=0.8316
[chemistry] epoch 05  loss=0.8150
[chemistry] epoch 06  loss=0.7986
    saved trained_models\chemistry_tinyrec.pth
[chemistry] test accuracy: 0.481

=== Training baseline for subject: ict ===
[ict] epoch 01  loss=0.6427
[ict] epoch 02  loss=0.6286
[ict] epoch 03  loss=0.6148
[ict] epoch 04  loss=0.6012
[ict] epoch 05  loss=0.5879
[ict] epoch 06  loss=0.5748
    saved trained_models\ict_tinyrec.pth
[ict] test accuracy: 0.852

```

Baseline finished. Models stored in: trained\_models

```

In [2]: #Baseline embedding model per subject (metrics + more epochs)

import os
import numpy as np
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.metrics import precision_score, recall_score, f1_score, roc_auc_score, mean
import torch
import torch.nn as nn
import torch.optim as optim

INTERACTIONS = r"C:\Users\Rizwana\Downloads\interactions2.csv"
SAVE_DIR = "trained_models"
EPOCHS = 20
BATCH_SIZE = 256
LR = 1e-3
EMB_DIM = 64
os.makedirs(SAVE_DIR, exist_ok=True)

#Load & sanity
df = pd.read_csv(INTERACTIONS)
required = {"user_id", "subject", "topic_name"}

```

```

missing = required - set(df.columns)
if missing:
    raise ValueError(f"CSV is missing columns: {missing}")

#Optional rating
if "rating" not in df.columns:
    df["rating"] = 1.0

#Normalize subject labels
df["subject"] = df["subject"].str.lower().str.strip()

#Indices from columns
df["user_idx"] = df["user_id"].astype("category").cat.codes
df["item_key"] = df["topic_name"].astype(str).str.strip()
df["item_idx"] = df["item_key"].astype("category").cat.codes

num_users_total = int(df["user_idx"].nunique())
num_items_total = int(df["item_idx"].nunique())
print(f"Users (global): {num_users_total} | Items (global): {num_items_total}")
print("Subjects:", sorted(df["subject"].unique()))

#Label (binary)

df["label"] = (df["rating"].astype(float) > 0).astype(np.float32)

#Tiny embedding model
class TinyRec(nn.Module):
    def __init__(self, num_users, num_items, emb_dim=64):
        super().__init__()
        self.user_emb = nn.Embedding(num_users, emb_dim)
        self.item_emb = nn.Embedding(num_items, emb_dim)
        self.out = nn.Linear(emb_dim * 2, 1)
        self.sigmoid = nn.Sigmoid()

    def forward(self, u_idx, i_idx):
        u = self.user_emb(u_idx)      # (B, d)
        i = self.item_emb(i_idx)      # (B, d)
        x = torch.cat([u, i], dim=1)  # (B, 2d)
        logit = self.out(x)           # (B, 1)
        return self.sigmoid(logit).squeeze(1)

def train_subject(df_subj, subject, epochs=EPOCHS, batch_size=BATCH_SIZE, lr=LR):
    if len(df_subj) < 50:
        print(f" Skipping {subject}: too few rows ({len(df_subj)}).")
        return

    # User-stratified split (keeps users in both sets if possible; ok for baseline)
    train_df, test_df = train_test_split(df_subj, test_size=0.2, random_state=42)

    tr_users = torch.tensor(train_df["user_idx"].values, dtype=torch.long)
    tr_items = torch.tensor(train_df["item_idx"].values, dtype=torch.long)
    tr_y      = torch.tensor(train_df["label"].values,      dtype=torch.float32)

    te_users = torch.tensor(test_df["user_idx"].values, dtype=torch.long)
    te_items = torch.tensor(test_df["item_idx"].values, dtype=torch.long)
    te_y_np  = test_df["label"].values.astype(np.float32)

    model = TinyRec(num_users_total, num_items_total, emb_dim=EMB_DIM)
    opt = optim.Adam(model.parameters(), lr=lr)
    crit = nn.BCELoss()

    def batches(U, I, Y, bs):
        n = len(Y)
        for s in range(0, n, bs):
            e = min(s+bs, n)
            yield U[s:e], I[s:e], Y[s:e]

```

```

print(f"\n=== Training baseline for subject: {subject} ===")
for ep in range(1, epochs+1):
    model.train()
    total_loss = 0.0
    for U, I, Y in batches(tr_users, tr_items, tr_y, batch_size):
        opt.zero_grad()
        pred = model(U, I)
        loss = crit(pred, Y)
        loss.backward()
        opt.step()
        total_loss += float(loss.item()) * len(Y)
    avg_loss = total_loss / len(tr_y)
    if ep % 2 == 0 or ep == 1 or ep == epochs:
        print(f"[{subject}] epoch {ep:02d}  loss={avg_loss:.4f}")

#Save
save_path = os.path.join(SAVE_DIR, f"{subject}_tinyrec.pth")
torch.save(model.state_dict(), save_path)
print(f" saved {save_path}")

#Evaluation
model.eval()
with torch.no_grad():
    te_pred = model(te_users, te_items).cpu().numpy()
    te_pred_label = (te_pred >= 0.5).astype(np.float32)

# Metrics
acc = accuracy_score(te_y_np, te_pred_label)
prec = precision_score(te_y_np, te_pred_label, zero_division=0)
rec = recall_score(te_y_np, te_pred_label, zero_division=0)
f1 = f1_score(te_y_np, te_pred_label, zero_division=0)
try:
    auc = roc_auc_score(te_y_np, te_pred)
except ValueError:
    auc = float("nan")
rmse = np.sqrt(mean_squared_error(te_y_np, te_pred))

print(f"[{subject}] ACC={acc:.3f}  PREC={prec:.3f}  REC={rec:.3f}  F1={f1:.3f}  AUC="

return {
    "subject": subject,
    "acc": acc, "precision": prec, "recall": rec, "f1": f1, "auc": auc, "rmse": rmse
}

#Train & evaluate per subject
all_metrics = []
for subj, df_sub in df.groupby("subject"):
    m = train_subject(df_sub, subj)
    if m: all_metrics.append(m)

print("\n=== Summary ===")
if all_metrics:
    summary = pd.DataFrame(all_metrics).set_index("subject")
    display(summary)
else:
    print("No subjects trained.")

```

```

Users (global): 40 | Items (global): 40
Subjects: ['biology', 'business', 'chemistry', 'ict']

```

```

=== Training baseline for subject: biology ===
[biology] epoch 01  loss=0.8069
[biology] epoch 02  loss=0.7895
[biology] epoch 04  loss=0.7556
[biology] epoch 06  loss=0.7229

```

```

[biology] epoch 08 loss=0.6913
[biology] epoch 10 loss=0.6608
[biology] epoch 12 loss=0.6315
[biology] epoch 14 loss=0.6033
[biology] epoch 16 loss=0.5763
[biology] epoch 18 loss=0.5503
[biology] epoch 20 loss=0.5255
saved trained_models\biology_tinyrec.pth
[biology] ACC=0.788 PREC=1.000 REC=0.788 F1=0.882 AUC=nan RMSE=0.424

```

=== Training baseline for subject: business ===

```

[business] epoch 01 loss=0.7387
[business] epoch 02 loss=0.7205
[business] epoch 04 loss=0.6853
[business] epoch 06 loss=0.6514
[business] epoch 08 loss=0.6189
[business] epoch 10 loss=0.5880
[business] epoch 12 loss=0.5584
[business] epoch 14 loss=0.5303
[business] epoch 16 loss=0.5037
[business] epoch 18 loss=0.4783
[business] epoch 20 loss=0.4544
saved trained_models\business_tinyrec.pth
[business] ACC=0.784 PREC=1.000 REC=0.784 F1=0.879 AUC=nan RMSE=0.411

```

=== Training baseline for subject: chemistry ===

```

[chemistry] epoch 01 loss=0.7452
[chemistry] epoch 02 loss=0.7297
[chemistry] epoch 04 loss=0.6995
[chemistry] epoch 06 loss=0.6702
[chemistry] epoch 08 loss=0.6420
[chemistry] epoch 10 loss=0.6147
[chemistry] epoch 12 loss=0.5883
[chemistry] epoch 14 loss=0.5630
[chemistry] epoch 16 loss=0.5387
[chemistry] epoch 18 loss=0.5153
[chemistry] epoch 20 loss=0.4928
saved trained_models\chemistry_tinyrec.pth
[chemistry] ACC=0.907 PREC=1.000 REC=0.907 F1=0.951 AUC=nan RMSE=0.397

```

=== Training baseline for subject: ict ===

```

[ict] epoch 01 loss=0.7704
[ict] epoch 02 loss=0.7539
[ict] epoch 04 loss=0.7217
[ict] epoch 06 loss=0.6906
[ict] epoch 08 loss=0.6607
[ict] epoch 10 loss=0.6320
[ict] epoch 12 loss=0.6044
[ict] epoch 14 loss=0.5779
[ict] epoch 16 loss=0.5525
[ict] epoch 18 loss=0.5282
[ict] epoch 20 loss=0.5050
saved trained_models\ict_tinyrec.pth
[ict] ACC=0.852 PREC=1.000 REC=0.852 F1=0.920 AUC=nan RMSE=0.395

```

=== Summary ===

	acc	precision	recall	f1	auc	rmse
<b>subject</b>						
<b>biology</b>	0.788462	1.0	0.788462	0.881720	NaN	0.424377
<b>business</b>	0.784314	1.0	0.784314	0.879121	NaN	0.410583
<b>chemistry</b>	0.907407	1.0	0.907407	0.951456	NaN	0.397006



In [6]: *#Baseline embedding model per subject*

```
import os
import numpy as np
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.metrics import (
    precision_score, recall_score, f1_score,
    roc_auc_score, mean_squared_error, accuracy_score
)
import torch
import torch.nn as nn
import torch.optim as optim

INTERACTIONS = r"C:\Users\Rizwana\Desktop\studyclock project\interactions_real.csv"
SAVE_DIR = "trained_models"
EPOCHS = 20
BATCH_SIZE = 256
LR = 1e-3
EMB_DIM = 64
os.makedirs(SAVE_DIR, exist_ok=True)

#Loading and error handling
df = pd.read_csv(INTERACTIONS)
required = {"user_id", "subject", "topic_name"}
missing = required - set(df.columns)
if missing:
    raise ValueError(f"CSV is missing columns: {missing}")

if "rating" not in df.columns:
    df["rating"] = 1.0

df["subject"] = df["subject"].str.lower().str.strip()
df["user_idx"] = df["user_id"].astype("category").cat.codes
df["item_key"] = df["topic_name"].astype(str).str.strip()
df["item_idx"] = df["item_key"].astype("category").cat.codes
df["label"] = (df["rating"].astype(float) > 0).astype(np.float32)

num_users_total = int(df["user_idx"].nunique())
num_items_total = int(df["item_idx"].nunique())
print(f"Users={num_users_total} Items={num_items_total} Subjects={sorted(df['subject'])}")

#Model
class TinyRec(nn.Module):
    def __init__(self, num_users, num_items, emb_dim=64):
        super().__init__()
        self.user_emb = nn.Embedding(num_users, emb_dim)
        self.item_emb = nn.Embedding(num_items, emb_dim)
        self.out = nn.Linear(emb_dim * 2, 1)
        self.sigmoid = nn.Sigmoid()
    def forward(self, u_idx, i_idx):
        u = self.user_emb(u_idx)
        i = self.item_emb(i_idx)
        x = torch.cat([u, i], dim=1)
        return self.sigmoid(self.out(x)).squeeze(1)

def train_subject(df_subj, subject, epochs=EPOCHS, batch_size=BATCH_SIZE, lr=LR):
    if len(df_subj) < 50:
        print(f" Skipping {subject}: too few rows ({len(df_subj)})")
    return
```

```

#Class distribution
y_all = df_subj["label"].values
pos = int((y_all == 1).sum()); neg = int((y_all == 0).sum())
print(f"\n=== {subject.upper()} === class dist -> pos={pos} neg={neg}")

# Stratify only when both classes present
can_stratify = (pos > 0) and (neg > 0)
if can_stratify:
    train_df, test_df = train_test_split(
        df_subj, test_size=0.2, random_state=42, stratify=df_subj["label"]
    )
else:
    print("Only one class present. Using non-stratified split; AUC will be NaN.")
    train_df, test_df = train_test_split(df_subj, test_size=0.2, random_state=42)

tr_users = torch.tensor(train_df["user_idx"].values, dtype=torch.long)
tr_items = torch.tensor(train_df["item_idx"].values, dtype=torch.long)
tr_y = torch.tensor(train_df["label"].values, dtype=torch.float32)

te_users = torch.tensor(test_df["user_idx"].values, dtype=torch.long)
te_items = torch.tensor(test_df["item_idx"].values, dtype=torch.long)
te_y_np = test_df["label"].values.astype(np.float32)

model = TinyRec(num_users_total, num_items_total, emb_dim=EMB_DIM)
opt = torch.optim.Adam(model.parameters(), lr=lr)
crit = nn.BCELoss()

def batches(U, I, Y, bs):
    n = len(Y)
    for s in range(0, n, bs):
        e = min(s+bs, n)
        yield U[s:e], I[s:e], Y[s:e]

for ep in range(1, epochs+1):
    model.train()
    total = 0.0
    for U, I, Y in batches(tr_users, tr_items, tr_y, batch_size):
        opt.zero_grad()
        pred = model(U, I)
        loss = crit(pred, Y)
        loss.backward()
        nn.utils.clip_grad_norm_(model.parameters(), 1.0)
        opt.step()
        total += float(loss.item()) * len(Y)
    if ep in {1, 2, 5, 10, 15, epochs}:
        print(f"[{subject}] epoch {ep:02d} loss={total/len(tr_y):.4f}")

path = os.path.join(SAVE_DIR, f"{subject}_tinyrec.pth")
torch.save(model.state_dict(), path)
print(f" saved {path}")

#Evaluation
model.eval()
with torch.no_grad():
    te_prob = model(te_users, te_items).cpu().numpy()
    te_pred = (te_prob >= 0.5).astype(np.float32)

acc = accuracy_score(te_y_np, te_pred)
prec = precision_score(te_y_np, te_pred, zero_division=0)
rec = recall_score(te_y_np, te_pred, zero_division=0)
f1 = f1_score(te_y_np, te_pred, zero_division=0)
# AUC safe
try:
    auc = roc_auc_score(te_y_np, te_prob) if can_stratify else float("nan")
except ValueError:
    auc = float("nan")

```

```

rmse = np.sqrt(mean_squared_error(te_y_np, te_prob))

print(f"[{subject}] ACC={acc:.3f} PREC={prec:.3f} REC={rec:.3f} F1={f1:.3f} AUC=
return {"subject":subject, "acc":acc, "precision":prec, "recall":rec, "f1":f1, "auc"

#Train/Eval per subject
all_metrics = []
for subj, df_sub in df.groupby("subject"):
    m = train_subject(df_sub, subj)
    if m: all_metrics.append(m)

print("\n=== Summary ===")
if all_metrics:
    display(pd.DataFrame(all_metrics).set_index("subject"))
else:
    print("No subjects trained.")

```

Users=20 Items=73 Subjects=['biology', 'business', 'chemistry', 'ict']

```

=== BIOLOGY === class dist -> pos=84 neg=0
Only one class present. Using non-stratified split; AUC will be NaN.
[biology] epoch 01 loss=0.7189
[biology] epoch 02 loss=0.7028
[biology] epoch 05 loss=0.6559
[biology] epoch 10 loss=0.5834
[biology] epoch 15 loss=0.5174
[biology] epoch 20 loss=0.4574
saved trained_models\biology_tinyrec.pth
[biology] ACC=0.765 PREC=1.000 REC=0.765 F1=0.867 AUC=nan RMSE=0.371

=== BUSINESS === class dist -> pos=108 neg=0
Only one class present. Using non-stratified split; AUC will be NaN.
[business] epoch 01 loss=0.7038
[business] epoch 02 loss=0.6901
[business] epoch 05 loss=0.6503
[business] epoch 10 loss=0.5878
[business] epoch 15 loss=0.5301
[business] epoch 20 loss=0.4767
saved trained_models\business_tinyrec.pth
[business] ACC=0.773 PREC=1.000 REC=0.773 F1=0.872 AUC=nan RMSE=0.440

=== CHEMISTRY === class dist -> pos=68 neg=0
Only one class present. Using non-stratified split; AUC will be NaN.
[chemistry] epoch 01 loss=0.6069
[chemistry] epoch 02 loss=0.5921
[chemistry] epoch 05 loss=0.5493
[chemistry] epoch 10 loss=0.4836
[chemistry] epoch 15 loss=0.4244
[chemistry] epoch 20 loss=0.3714
saved trained_models\chemistry_tinyrec.pth
[chemistry] ACC=0.857 PREC=1.000 REC=0.857 F1=0.923 AUC=nan RMSE=0.347
Skipping ict: too few rows (40).

```

=== Summary ===

	acc	precision	recall	f1	auc	rmse
subject						
biology	0.764706	1.0	0.764706	0.866667	NaN	0.370679
business	0.772727	1.0	0.772727	0.871795	NaN	0.439777
chemistry	0.857143	1.0	0.857143	0.923077	NaN	0.346535

In [3]: `import pandas as pd`

```

from sklearn.model_selection import train_test_split
from sklearn.feature_extraction.text import TfidfVectorizer
import numpy as np
import tensorflow as tf
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Embedding, LSTM, Bidirectional, Dense, Dropout

df = pd.read_csv(r"C:\Users\Rizwana\Desktop\studyclock project\interactions_real.csv")
print(df.head())

#Create features (X) and labels (y)

df["X"] = df["subject"] + " " + df["topic_name"]

#Use ratings as the label
df["y"] = df["rating"]

print(df[["X", "y"]].head())

#Convert text into numerical vectors (TF-IDF)

vectorizer = TfidfVectorizer(max_features=5000) # limit to 5000 words
X = vectorizer.fit_transform(df["X"]).toarray()
y = df["y"].values

#Train/test split

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

#Build a BiLSTM model

X_train_seq = np.expand_dims(X_train, axis=-1)
X_test_seq = np.expand_dims(X_test, axis=-1)

model = Sequential()
model.add(Bidirectional(LSTM(64, return_sequences=False), input_shape=(X_train_seq.shape
model.add(Dropout(0.3))
model.add(Dense(64, activation="relu"))
model.add(Dense(1, activation="linear")) # regression (predict rating)

model.compile(optimizer="adam", loss="mse", metrics=["mae"])
model.summary()

#Train model

history = model.fit(
    X_train_seq, y_train,
    validation_data=(X_test_seq, y_test),
    epochs=5,
    batch_size=16
)

#Evaluate

loss, mae = model.evaluate(X_test_seq, y_test)
print(f"Test Loss: {loss}, Test MAE: {mae}")

```

user_id	subject	topic_name	rating	timestamp
---------	---------	------------	--------	-----------

```

0 user_1 ICT Unit 8 Safety and Security 4 1755302429
1 user_1 Business Chapter 16 Marketing Strategy 3 1755269216
2 user_1 Business Chapter 13 The Marketing Mix 1 1755422586
3 user_1 Biology Unit 3 Movement in and out of cells 2 1755636804
4 user_1 Business Chapter 23 Income Statements 4 1755710187

```

	X	Y
0	ICT Unit 8 Safety and Security	4
1	Business Chapter 16 Marketing Strategy	3
2	Business Chapter 13 The Marketing Mix	1
3	Biology Unit 3 Movement in and out of cells	2
4	Business Chapter 23 Income Statements	4

```

C:\Users\Rizwana\anaconda3\envs\finalproject\lib\site-packages\keras\src\layers\rnn\bidirectional.py:107: UserWarning: Do not pass an `input_shape`/`input_dim` argument to a layer. When using Sequential models, prefer using an `Input(shape)` object as the first layer in the model instead.
  super().__init__(**kwargs)

```

Model: "sequential"

Layer (type)	Output Shape	Param #
bidirectional (Bidirectional)	(None, 128)	33,792
dropout (Dropout)	(None, 128)	0
dense (Dense)	(None, 64)	8,256
dense_1 (Dense)	(None, 1)	65

Total params: 42,113 (164.50 KB)

Trainable params: 42,113 (164.50 KB)

Non-trainable params: 0 (0.00 B)

Epoch 1/5

```

15/15 ————— 5s 82ms/step - loss: 8.8850 - mae: 2.6274 - val_loss: 2.2944 - val_mae: 1.3195

```

Epoch 2/5

```

15/15 ————— 1s 37ms/step - loss: 2.8568 - mae: 1.3537 - val_loss: 1.9257 - val_mae: 1.1520

```

Epoch 3/5

```

15/15 ————— 1s 40ms/step - loss: 2.1027 - mae: 1.2435 - val_loss: 1.9708 - val_mae: 1.2237

```

Epoch 4/5

```

15/15 ————— 1s 39ms/step - loss: 2.0667 - mae: 1.2387 - val_loss: 1.7530 - val_mae: 1.1331

```

Epoch 5/5

```

15/15 ————— 1s 37ms/step - loss: 1.9379 - mae: 1.2050 - val_loss: 1.9385 - val_mae: 1.2111

```

```

2/2 ————— 0s 49ms/step - loss: 1.9385 - mae: 1.2111

```

Test Loss: 1.938524842262268, Test MAE: 1.2111347913742065

```

In [6]: import joblib

#save model in .keras format
model.save("bilstm_model.keras")

#save TF-IDF vectorizer separately
joblib.dump(vectorizer, "tfidf_vectorizer.pkl")

print("Model and vectorizer saved successfully")

```

Model and vectorizer saved successfully!

```

In [7]: import tensorflow as tf

```

```
import joblib

#load model
model = tf.keras.models.load_model("bilstm_model.keras")

#load vectorizer
vectorizer = joblib.load("tfidf_vectorizer.pkl")

print("Model and vectorizer reloaded successfully")
```

Model and vectorizer reloaded successfully

```
C:\Users\Rizwana\anaconda3\envs\finalproject\lib\site-packages\keras\src\saving\saving_1
ib.py:797: UserWarning: Skipping variable loading for optimizer 'rmsprop', because it ha
s 12 variables whereas the saved optimizer has 22 variables.
    saveable.load_own_variables(weights_store.get(inner_path))
```

```
In [11]: import numpy as np
import pandas as pd
import joblib
from tensorflow.keras.models import load_model

#Load model + vectorizer
model = load_model("bilstm_model.keras")
vectorizer = joblib.load("tfidf_vectorizer.pkl")

#Reload dataset
df = pd.read_csv(r"C:\Users\Rizwana\Desktop\studyclock project\interactions_real.csv")
all_topics = df['topic_name'].unique()

def predict_for_user(model, user_id, all_topics, interactions, vectorizer, k=5):
    # Topics user has already interacted with
    seen_topics = interactions[interactions['user_id'] == user_id]['topic_name'].unique()
    candidate_topics = [t for t in all_topics if t not in seen_topics]

    preds = []
    for topic in candidate_topics:
        #Recreate "subject topic_name"
        subject = interactions[interactions['topic_name'] == topic]['subject'].values[0]
        text = subject + " " + topic

        #Vectorize
        X_vec = vectorizer.transform([text]).toarray()
        X_seq = np.expand_dims(X_vec, axis=-1)

        #Predict
        score = model.predict(X_seq, verbose=0)[0][0]
        preds.append((topic, score))

    # Return top-K
    results = pd.DataFrame(preds, columns=["topic_name", "predicted_score"])
    return results.sort_values("predicted_score", ascending=False).head(k)

#Example: Top-5 recs for user_1
top_k_for_user1 = predict_for_user(model, "user_1", all_topics, df, vectorizer, k=5)
print("Top-K Recommendations for user_1:")
print(top_k_for_user1)
```

Top-K Recommendations for user\_1:

	topic_name	predicted_score
31	Unit 15 Air and Water	3.267026
51	Unit 18 Variation and selection	3.255251
25	Unit 12 Respiration	3.246816
3	Unit 15 Drugs	3.246668
4	Unit 13 Excretion	3.246009

```
In [12]: import numpy as np
```

```

import pandas as pd

#Prediction function

def predict_for_user(model, user_id, all_topics, interactions, vectorizer, k=5):
    # Topics already seen by the user
    seen_topics = interactions[interactions['user_id'] == user_id]['topic_name'].unique()
    candidate_topics = [t for t in all_topics if t not in seen_topics]

    preds = []
    for topic in candidate_topics:
        #Combine subject + topic
        subject = interactions[interactions['topic_name'] == topic]['subject'].values[0]
        text = subject + " " + topic

        #Vectorize + reshape for LSTM
        X_vec = vectorizer.transform([text]).toarray()
        X_seq = np.expand_dims(X_vec, axis=-1)

        #Predict score
        score = model.predict(X_seq, verbose=0)[0][0]
        preds.append((topic, score))

    #Return top-K predictions
    results = pd.DataFrame(preds, columns=["topic_name", "predicted_score"])
    return results.sort_values("predicted_score", ascending=False).head(k)

#Generate Top-K for multiple users

unique_users = df["user_id"].unique()
print("Available Users:", unique_users)

#Pick first 5 users
sample_users = unique_users[:5]

all_topics = df['topic_name'].unique()

recommendations = {} # store results for all users

for user in sample_users:
    top_k = predict_for_user(model, user, all_topics, df, vectorizer, k=5)
    recommendations[user] = top_k

    print(f"\nTop-5 Recommendations for {user}:")
    print(top_k)

#Combine into one DataFrame
all_recs = []
for user, recs in recommendations.items():
    temp = recs.copy()
    temp.insert(0, "user_id", user)
    all_recs.append(temp)

all_recs_df = pd.concat(all_recs, ignore_index=True)
all_recs_df.to_csv("user_recommendations.csv", index=False)
print("\nSaved recommendations for multiple users to user_recommendations.csv")

```

```

Available Users: ['user_1' 'user_2' 'user_3' 'user_4' 'user_5' 'user_6' 'user_7' 'user_
8'
'user_9' 'user_10' 'user_11' 'user_12' 'user_13' 'user_14' 'user_15'
'user_16' 'user_17' 'user_18' 'user_19' 'user_20']

```

```

Top-5 Recommendations for user_1:

```



	topic_name	predicted_score
31	Unit 15 Air and Water	3.267026
51	Unit 18 Variation and selection	3.255251
25	Unit 12 Respiration	3.246816
3	Unit 15 Drugs	3.246668
4	Unit 13 Excretion	3.246009

Top-5 Recommendations for user\_2:

	topic_name	predicted_score
31	Unit 15 Air and Water	3.267026
51	Unit 18 Variation and selection	3.255251
25	Unit 12 Respiration	3.246816
24	Unit 18 The Variety of Organic Chemicals	3.244677
22	Unit 12 The Periodic Table	3.243503

Top-5 Recommendations for user\_3:

	topic_name	predicted_score
31	Unit 15 Air and Water	3.267026
51	Unit 18 Variation and selection	3.255251
25	Unit 12 Respiration	3.246816
16	Unit 15 Drugs	3.246668
17	Unit 13 Excretion	3.246009

Top-5 Recommendations for user\_4:

	topic_name	predicted_score
31	Unit 15 Air and Water	3.267026
51	Unit 18 Variation and selection	3.255251
14	Unit 15 Drugs	3.246668
15	Unit 13 Excretion	3.246009
53	Chapter 25 Analysis of Accountants	3.241866

Top-5 Recommendations for user\_5:

	topic_name	predicted_score
51	Unit 18 Variation and selection	3.255251
31	Unit 12 Respiration	3.246816
14	Unit 13 Excretion	3.246009
29	Unit 12 The Periodic Table	3.243503
53	Chapter 25 Analysis of Accountants	3.241866

Saved recommendations for multiple users to user\_recommendations.csv

```
In [17]: import pandas as pd
import numpy as np
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.metrics.pairwise import cosine_similarity

from surprise import SVD, Dataset, Reader
from surprise.model_selection import train_test_split
from surprise import accuracy

df = pd.read_csv(r"C:\Users\Rizwana\Desktop\studyclock project\interactions_real.csv")

#Collaborative Filtering (SVD)

print("Collaborative Filtering (SVD) Evaluation")

#Encode IDs
df["user_id_encoded"] = df["user_id"].astype("category").cat.codes
df["topic_id_encoded"] = df["topic_name"].astype("category").cat.codes

# Surprise Dataset
reader = Reader(rating_scale=(1, 5))
data = Dataset.load_from_df(df[["user_id_encoded", "topic_id_encoded", "rating"]], reader)
```

```

#Train/test split
trainset, testset = train_test_split(data, test_size=0.2, random_state=42)

#Train model
algo = SVD()
algo.fit(trainset)

#Predict
predictions = algo.test(testset)

#Evaluate
print("RMSE:", accuracy.rmse(predictions))
print("MAE:", accuracy.mae(predictions))

#3. Content-Based (TF-IDF + Cosine)

print("Content-Based Similarity Analysis")

subject_similarity = {}
subject_tables = {}

for subject in df["subject"].unique():
    subj_df = df[df["subject"] == subject]

    # Use summary_text if available, else topic_name
    if "summary_text" in subj_df.columns:
        texts = subj_df["summary_text"].astype(str).tolist()
    else:
        texts = subj_df["topic_name"].astype(str).tolist()

    topics = subj_df["topic_name"].tolist()

    # Local vectorizer per subject
    vectorizer = TfidfVectorizer()
    tfidf_matrix = vectorizer.fit_transform(texts)

    # Cosine similarity
    sim_matrix = cosine_similarity(tfidf_matrix)

    # Store as DataFrame
    df_sim = pd.DataFrame(sim_matrix, index=topics, columns=topics)
    subject_similarity[subject] = sim_matrix
    subject_tables[subject] = df_sim

    print(f"\n--- Similarity Table for {subject.upper()} ---")
    print(df_sim.head()) # show only first few rows to avoid too much output

    # Save CSV
    filename = f"{subject}_similarity_matrix.csv"
    df_sim.to_csv(filename)
    print(f"Saved {filename}")

```

Collaborative Filtering (SVD) Evaluation

RMSE: 1.4161

RMSE: 1.416146255187813

MAE: 1.2351

MAE: 1.2350898227967984

Content-Based Similarity Analysis

--- Similarity Table for ICT ---

	Unit 8 Safety and Security \
Unit8 Safety and Security	1.000000
Unit2 Input and Output Devices	0.151798

Unit 8 Safety and Security	1.000000
Unit 5 The effects of using ICT	0.044965
Unit 5 The effects of using ICT	0.044965
Unit 2 Input and Output Devices \	
Unit 8 Safety and Security	0.151798
Unit 2 Input and Output Devices	1.000000
Unit 8 Safety and Security	0.151798
Unit 5 The effects of using ICT	0.038578
Unit 5 The effects of using ICT	0.038578
Unit 8 Safety and Security \	
Unit 8 Safety and Security	1.000000
Unit 2 Input and Output Devices	0.151798
Unit 8 Safety and Security	1.000000
Unit 5 The effects of using ICT	0.044965
Unit 5 The effects of using ICT	0.044965
Unit 5 The effects of using ICT \	
Unit 8 Safety and Security	0.044965
Unit 2 Input and Output Devices	0.038578
Unit 8 Safety and Security	0.044965
Unit 5 The effects of using ICT	1.000000
Unit 5 The effects of using ICT	1.000000
Unit 5 The effects of using ICT \	
Unit 8 Safety and Security	0.044965
Unit 2 Input and Output Devices	0.038578
Unit 8 Safety and Security	0.044965
Unit 5 The effects of using ICT	1.000000
Unit 5 The effects of using ICT	1.000000
Unit 2 Input and Output Devices \	
Unit 8 Safety and Security	0.151798
Unit 2 Input and Output Devices	1.000000
Unit 8 Safety and Security	0.151798
Unit 5 The effects of using ICT	0.038578
Unit 5 The effects of using ICT	0.038578
Unit 7 Systems Analysis and Design \	
Unit 8 Safety and Security	0.135774
Unit 2 Input and Output Devices	0.116487
Unit 8 Safety and Security	0.135774
Unit 5 The effects of using ICT	0.034505
Unit 5 The effects of using ICT	0.034505
Unit 2 Input and Output Devices \	
Unit 8 Safety and Security	0.151798
Unit 2 Input and Output Devices	1.000000
Unit 8 Safety and Security	0.151798
Unit 5 The effects of using ICT	0.038578
Unit 5 The effects of using ICT	0.038578
Unit 7 Systems Analysis and Design \	
Unit 8 Safety and Security	0.135774
Unit 2 Input and Output Devices	0.116487
Unit 8 Safety and Security	0.135774
Unit 5 The effects of using ICT	0.034505
Unit 5 The effects of using ICT	0.034505
Unit 8 Safety and Security ... \	
Unit 8 Safety and Security	1.000000 ...
Unit 2 Input and Output Devices	0.151798 ...
Unit 8 Safety and Security	1.000000 ...
Unit 5 The effects of using ICT	0.044965 ...
Unit 5 The effects of using ICT	0.044965 ...

	Unit 7 Systems Analysis and Design \	
Unit 8 Safety and Security		0.135774
Unit 2 Input and Output Devices		0.116487
Unit 8 Safety and Security		0.135774
Unit 5 The effects of using ICT		0.034505
Unit 5 The effects of using ICT		0.034505

	Unit 6 ICT Applications \	
Unit 8 Safety and Security		0.064541
Unit 2 Input and Output Devices		0.055373
Unit 8 Safety and Security		0.064541
Unit 5 The effects of using ICT		0.266438
Unit 5 The effects of using ICT		0.266438

	Unit 7 Systems Analysis and Design \	
Unit 8 Safety and Security		0.135774
Unit 2 Input and Output Devices		0.116487
Unit 8 Safety and Security		0.135774
Unit 5 The effects of using ICT		0.034505
Unit 5 The effects of using ICT		0.034505

	Unit 3 Storage Devices and Media \	
Unit 8 Safety and Security		0.146816
Unit 2 Input and Output Devices		0.325087
Unit 8 Safety and Security		0.146816
Unit 5 The effects of using ICT		0.037312
Unit 5 The effects of using ICT		0.037312

	Unit 8 Safety and Security \	
Unit 8 Safety and Security		1.000000
Unit 2 Input and Output Devices		0.151798
Unit 8 Safety and Security		1.000000
Unit 5 The effects of using ICT		0.044965
Unit 5 The effects of using ICT		0.044965

	Unit 6 ICT Applications \	
Unit 8 Safety and Security		0.064541
Unit 2 Input and Output Devices		0.055373
Unit 8 Safety and Security		0.064541
Unit 5 The effects of using ICT		0.266438
Unit 5 The effects of using ICT		0.266438

	Unit 2 Input and Output Devices \	
Unit 8 Safety and Security		0.151798
Unit 2 Input and Output Devices		1.000000
Unit 8 Safety and Security		0.151798
Unit 5 The effects of using ICT		0.038578
Unit 5 The effects of using ICT		0.038578

	Unit 3 Storage Devices and Media \	
Unit 8 Safety and Security		0.146816
Unit 2 Input and Output Devices		0.325087
Unit 8 Safety and Security		0.146816
Unit 5 The effects of using ICT		0.037312
Unit 5 The effects of using ICT		0.037312

	Unit 8 Safety and Security \	
Unit 8 Safety and Security		1.000000
Unit 2 Input and Output Devices		0.151798
Unit 8 Safety and Security		1.000000
Unit 5 The effects of using ICT		0.044965
Unit 5 The effects of using ICT		0.044965

	Unit 5 The effects of using ICT	
Unit 8 Safety and Security		0.044965

Unit 2 Input and Output Devices	0.038578
Unit 8 Safety and Security	0.044965
Unit 5 The effects of using ICT	1.000000
Unit 5 The effects of using ICT	1.000000

[5 rows x 40 columns]

Saved ICT\_similarity\_matrix.csv

--- Similarity Table for BUSINESS ---

	Chapter 16 Marketing Strategy \
Chapter 16 Marketing Strategy	1.000000
Chapter 13 The Marketing Mix	0.197224
Chapter 23 Income Statements	0.023768
Chapter 20 Location Decisions	0.019459
Chapter 21 Business Finance - Needs and Sources	0.017816
	Chapter 13 The Marketing Mix \
Chapter 16 Marketing Strategy	0.197224
Chapter 13 The Marketing Mix	1.000000
Chapter 23 Income Statements	0.024814
Chapter 20 Location Decisions	0.020315
Chapter 21 Business Finance - Needs and Sources	0.018600
	Chapter 23 Income Statements \
Chapter 16 Marketing Strategy	0.023768
Chapter 13 The Marketing Mix	0.024814
Chapter 23 Income Statements	1.000000
Chapter 20 Location Decisions	0.019002
Chapter 21 Business Finance - Needs and Sources	0.017398
	Chapter 20 Location Decisions \
Chapter 16 Marketing Strategy	0.019459
Chapter 13 The Marketing Mix	0.020315
Chapter 23 Income Statements	0.019002
Chapter 20 Location Decisions	1.000000
Chapter 21 Business Finance - Needs and Sources	0.014243
	Chapter 21 Business Finance - Needs and Sources \
Chapter 16 Marketing Strategy	0.017816
Chapter 13 The Marketing Mix	0.018600
Chapter 23 Income Statements	0.017398
Chapter 20 Location Decisions	0.014243
Chapter 21 Business Finance - Needs and Sources	1.000000
	Chapter 7 Organisation and management \
Chapter 16 Marketing Strategy	0.026311
Chapter 13 The Marketing Mix	0.027468
Chapter 23 Income Statements	0.025693
Chapter 20 Location Decisions	0.021035
Chapter 21 Business Finance - Needs and Sources	0.086080
	Chapter 10 Marketing, Competition and the Customer \
Chapter 16 Marketing Strategy	

0.140918  
Chapter 13 The Marketing Mix  
0.279909  
Chapter 23 Income Statements  
0.017730  
Chapter 20 Location Decisions  
0.014515  
Chapter 21 Business Finance - Needs and Sources  
0.059400

Chapter 24 Balance Sheets \

Chapter 16 Marketing Strategy	0.023768
Chapter 13 The Marketing Mix	0.024814
Chapter 23 Income Statements	0.023210
Chapter 20 Location Decisions	0.019002
Chapter 21 Business Finance - Needs and Sources	0.017398

Chapter 23 Income Statements \

Chapter 16 Marketing Strategy	0.023768
Chapter 13 The Marketing Mix	0.024814
Chapter 23 Income Statements	1.000000
Chapter 20 Location Decisions	0.019002
Chapter 21 Business Finance - Needs and Sources	0.017398

Chapter 8 Recruitment, Selection and Training \

Chapter 16 Marketing Strategy	0.023625
Chapter 13 The Marketing Mix	0.024665
Chapter 23 Income Statements	0.023071
Chapter 20 Location Decisions	0.018888
Chapter 21 Business Finance - Needs and Sources	0.077294

...

Chapter 16 Marketing Strategy	...
Chapter 13 The Marketing Mix	...
Chapter 23 Income Statements	...
Chapter 20 Location Decisions	...
Chapter 21 Business Finance - Needs and Sources	...

Chapter 10 Marketing, Competition and the Customer \

Chapter 16 Marketing Strategy	0.140918
Chapter 13 The Marketing Mix	0.279909
Chapter 23 Income Statements	0.017730
Chapter 20 Location Decisions	0.014515
Chapter 21 Business Finance - Needs and Sources	0.059400

Chapter 23 Income Statements \

Chapter 16 Marketing Strategy	0.023768
Chapter 13 The Marketing Mix	0.024814
Chapter 23 Income Statements	1.000000
Chapter 20 Location Decisions	0.019002
Chapter 21 Business Finance - Needs and Sources	0.017398

Chapter 22 Cash flow forecasting and working capital \

Chapter 16 Marketing Strategy  
0.013629  
Chapter 13 The Marketing Mix  
0.014229  
Chapter 23 Income Statements  
0.013309  
Chapter 20 Location Decisions  
0.010896  
Chapter 21 Business Finance - Needs and Sources  
0.044590

Chapter 17 Production of Goods and Serv

ices \

Chapter 16 Marketing Strategy	0.01
9604	
Chapter 13 The Marketing Mix	0.02
0466	
Chapter 23 Income Statements	0.01
9143	
Chapter 20 Location Decisions	0.01
5673	
Chapter 21 Business Finance - Needs and Sources	0.06
4136	

Chapter 8 Recruitment, Selection and Tr

aining \

Chapter 16 Marketing Strategy	0.
023625	
Chapter 13 The Marketing Mix	0.
024665	
Chapter 23 Income Statements	0.
023071	
Chapter 20 Location Decisions	0.
018888	
Chapter 21 Business Finance - Needs and Sources	0.
077294	

Chapter 17 Production of Goods and Serv

ices \

Chapter 16 Marketing Strategy	0.01
9604	
Chapter 13 The Marketing Mix	0.02
0466	
Chapter 23 Income Statements	0.01
9143	
Chapter 20 Location Decisions	0.01
5673	
Chapter 21 Business Finance - Needs and Sources	0.06
4136	

Chapter 4 Types of Business Organisatio

n \

Chapter 16 Marketing Strategy	0.02235
7	
Chapter 13 The Marketing Mix	0.02334
1	
Chapter 23 Income Statements	0.02183
3	
Chapter 20 Location Decisions	0.01787
4	
Chapter 21 Business Finance - Needs and Sources	0.10744
6	

Chapter 16 Marketing Strategy \

Chapter 16 Marketing Strategy	1.000000
Chapter 13 The Marketing Mix	0.197224



Chapter 23 Income Statements	0.023768
Chapter 20 Location Decisions	0.019459
Chapter 21 Business Finance - Needs and Sources	0.017816

# Chapter 28 Business and the Internation

al Economy \

Chapter 16 Marketing Strategy	0.018305
Chapter 13 The Marketing Mix	0.152989
Chapter 23 Income Statements	0.017875
Chapter 20 Location Decisions	0.014634
Chapter 21 Business Finance - Needs and Sources	0.134458

# Chapter 25 Analysis of Accountants

Chapter 16 Marketing Strategy	0.021304
Chapter 13 The Marketing Mix	0.022242
Chapter 23 Income Statements	0.020804
Chapter 20 Location Decisions	0.017032
Chapter 21 Business Finance - Needs and Sources	0.015594

[5 rows x 108 columns]  
 Saved Business\_similarity\_matrix.csv

## --- Similarity Table for BIOLOGY ---

	Unit 3 Movement in and out of cells \
Unit 3 Movement in and out of cells	1.000000
Unit 7 Animal Nutrition	0.021557
Unit 8 Plant Transport	0.026379
Unit 17 Inheritance	0.024619
Unit 2 Cells	0.421808

	Unit 7 Animal Nutrition \
Unit 3 Movement in and out of cells	0.021557
Unit 7 Animal Nutrition	1.000000
Unit 8 Plant Transport	0.036859
Unit 17 Inheritance	0.034399
Unit 2 Cells	0.051105

	Unit 8 Plant Transport \
Unit 3 Movement in and out of cells	0.026379
Unit 7 Animal Nutrition	0.036859
Unit 8 Plant Transport	1.000000
Unit 17 Inheritance	0.042094
Unit 2 Cells	0.062537

	Unit 17 Inheritance	Unit 2 Cells \
Unit 3 Movement in and out of cells	0.024619	0.421808
Unit 7 Animal Nutrition	0.034399	0.051105
Unit 8 Plant Transport	0.042094	0.062537
Unit 17 Inheritance	1.000000	0.058365
Unit 2 Cells	0.058365	1.000000

	Unit 15 Drugs	Unit 13 Excretion \
Unit 3 Movement in and out of cells	0.024619	0.024619
Unit 7 Animal Nutrition	0.034399	0.034399
Unit 8 Plant Transport	0.042094	0.042094
Unit 17 Inheritance	0.039286	0.039286
Unit 2 Cells	0.058365	0.058365

	Unit 8 Plant Transport \
Unit 3 Movement in and out of cells	0.026379
Unit 7 Animal Nutrition	0.036859

Unit 8 Plant Transport	1.000000		
Unit 17 Inheritance	0.042094		
Unit 2 Cells	0.062537		
		Unit 9 Transport in humans \	
Unit 3 Movement in and out of cells	0.211623		
Unit 7 Animal Nutrition	0.031860		
Unit 8 Plant Transport	0.423397		
Unit 17 Inheritance	0.036386		
Unit 2 Cells	0.054056		
		Unit 10 Diseases and Immunity ... \	
Unit 3 Movement in and out of cells	0.101728	...	
Unit 7 Animal Nutrition	0.026783	...	
Unit 8 Plant Transport	0.032775	...	
Unit 17 Inheritance	0.030588	...	
Unit 2 Cells	0.045443	...	
		Unit 4 Biological Molecules \	
Unit 3 Movement in and out of cells	0.022532		
Unit 7 Animal Nutrition	0.031484		
Unit 8 Plant Transport	0.038527		
Unit 17 Inheritance	0.035956		
Unit 2 Cells	0.053418		
		Unit 14 Coordination and Response \	
Unit 3 Movement in and out of cells	0.101728		
Unit 7 Animal Nutrition	0.026783		
Unit 8 Plant Transport	0.032775		
Unit 17 Inheritance	0.030588		
Unit 2 Cells	0.045443		
		Unit 17 Inheritance Unit 15 Drugs \	
Unit 3 Movement in and out of cells	0.024619	0.024619	
Unit 7 Animal Nutrition	0.034399	0.034399	
Unit 8 Plant Transport	0.042094	0.042094	
Unit 17 Inheritance	1.000000	0.039286	
Unit 2 Cells	0.058365	0.058365	
		Unit 10 Diseases and Immunity \	
Unit 3 Movement in and out of cells	0.101728		
Unit 7 Animal Nutrition	0.026783		
Unit 8 Plant Transport	0.032775		
Unit 17 Inheritance	0.030588		
Unit 2 Cells	0.045443		
		Unit 10 Diseases and Immunity \	
Unit 3 Movement in and out of cells	0.101728		
Unit 7 Animal Nutrition	0.026783		
Unit 8 Plant Transport	0.032775		
Unit 17 Inheritance	0.030588		
Unit 2 Cells	0.045443		
		Unit 13 Excretion \	
Unit 3 Movement in and out of cells	0.024619		
Unit 7 Animal Nutrition	0.034399		
Unit 8 Plant Transport	0.042094		
Unit 17 Inheritance	0.039286		
Unit 2 Cells	0.058365		
		Unit 1 Characteristics and Classification of Living	
Organisms \			
Unit 3 Movement in and out of cells			0.231778
Unit 7 Animal Nutrition			0.019488

Unit 8 Plant Transport	0.023848
Unit 17 Inheritance	0.022256
Unit 2 Cells	0.033065

	Unit 14 Coordination and Response \
Unit 3 Movement in and out of cells	0.101728
Unit 7 Animal Nutrition	0.026783
Unit 8 Plant Transport	0.032775
Unit 17 Inheritance	0.030588
Unit 2 Cells	0.045443

	Unit 16 Reproduction
Unit 3 Movement in and out of cells	0.021330
Unit 7 Animal Nutrition	0.029804
Unit 8 Plant Transport	0.036472
Unit 17 Inheritance	0.034038
Unit 2 Cells	0.050569

[5 rows x 84 columns]

Saved Biology\_similarity\_matrix.csv

--- Similarity Table for CHEMISTRY ---

	Unit 17 Organic chemistry and petrochemicals
ls \	
Unit 17 Organic chemistry and petrochemicals	1.0000
00	
Unit 2 Atoms, Elements and Compounds	0.1018
29	
Unit 11 Making and identifying salts	0.0937
11	
Unit 20 Natural Polymers	0.0246
57	
Unit 9 Chemical Reactions	0.0352
59	

	Unit 2 Atoms, Elements and Compounds \
Unit 17 Organic chemistry and petrochemicals	0.101829
Unit 2 Atoms, Elements and Compounds	1.000000
Unit 11 Making and identifying salts	0.099106
Unit 20 Natural Polymers	0.026077
Unit 9 Chemical Reactions	0.037289

	Unit 11 Making and identifying salts \
Unit 17 Organic chemistry and petrochemicals	0.093711
Unit 2 Atoms, Elements and Compounds	0.099106
Unit 11 Making and identifying salts	1.000000
Unit 20 Natural Polymers	0.023998
Unit 9 Chemical Reactions	0.034316

	Unit 20 Natural Polymers \
Unit 17 Organic chemistry and petrochemicals	0.024657
Unit 2 Atoms, Elements and Compounds	0.026077
Unit 11 Making and identifying salts	0.023998
Unit 20 Natural Polymers	1.000000
Unit 9 Chemical Reactions	0.042951

	Unit 9 Chemical Reactions \
Unit 17 Organic chemistry and petrochemicals	0.035259
Unit 2 Atoms, Elements and Compounds	0.037289
Unit 11 Making and identifying salts	0.034316
Unit 20 Natural Polymers	0.042951
Unit 9 Chemical Reactions	1.000000

	Unit 1 Particles and Purification \	
Unit 17 Organic chemistry and petrochemicals	0.126868	
Unit 2 Atoms, Elements and Compounds	0.134172	
Unit 11 Making and identifying salts	0.123476	
Unit 20 Natural Polymers	0.032489	
Unit 9 Chemical Reactions	0.046458	
	Unit 14 Metal Extraction \	
Unit 17 Organic chemistry and petrochemicals	0.022380	
Unit 2 Atoms, Elements and Compounds	0.023668	
Unit 11 Making and identifying salts	0.021781	
Unit 20 Natural Polymers	0.027262	
Unit 9 Chemical Reactions	0.038983	
	Unit 17 Organic chemistry and petrochemicals	
ls \		
Unit 17 Organic chemistry and petrochemicals		1.0000
00		
Unit 2 Atoms, Elements and Compounds		0.1018
29		
Unit 11 Making and identifying salts		0.0937
11		
Unit 20 Natural Polymers		0.0246
57		
Unit 9 Chemical Reactions		0.0352
59		
	Unit 9 Chemical Reactions \	
Unit 17 Organic chemistry and petrochemicals	0.035259	
Unit 2 Atoms, Elements and Compounds	0.037289	
Unit 11 Making and identifying salts	0.034316	
Unit 20 Natural Polymers	0.042951	
Unit 9 Chemical Reactions	1.000000	
	Unit 17 Organic chemistry and petrochemicals	
ls \		
Unit 17 Organic chemistry and petrochemicals		1.0000
00		
Unit 2 Atoms, Elements and Compounds		0.1018
29		
Unit 11 Making and identifying salts		0.0937
11		
Unit 20 Natural Polymers		0.0246
57		
Unit 9 Chemical Reactions		0.0352
59		
	... Unit 14 Metal Extraction \	
Unit 17 Organic chemistry and petrochemicals	...	0.022380
Unit 2 Atoms, Elements and Compounds	...	0.023668
Unit 11 Making and identifying salts	...	0.021781
Unit 20 Natural Polymers	...	0.027262
Unit 9 Chemical Reactions	...	0.038983
	Unit 18 The Variety of Organic Chemicals	
\		
Unit 17 Organic chemistry and petrochemicals		0.169278
Unit 2 Atoms, Elements and Compounds		0.020919
Unit 11 Making and identifying salts		0.019251
Unit 20 Natural Polymers		0.024095
Unit 9 Chemical Reactions		0.034455

Unit 17 Organic chemistry and petrochemicals	0.022380
Unit 2 Atoms, Elements and Compounds	0.023668
Unit 11 Making and identifying salts	0.021781
Unit 20 Natural Polymers	0.027262
Unit 9 Chemical Reactions	0.038983
Unit 14 Metal Extraction \	
Unit 17 Organic chemistry and petrochemicals	0.093711
Unit 2 Atoms, Elements and Compounds	0.099106
Unit 11 Making and identifying salts	1.000000
Unit 20 Natural Polymers	0.023998
Unit 9 Chemical Reactions	0.034316
Unit 11 Making and identifying salts \	
Unit 17 Organic chemistry and petrochemicals	0.093711
Unit 2 Atoms, Elements and Compounds	0.099106
Unit 11 Making and identifying salts	1.000000
Unit 20 Natural Polymers	0.023998
Unit 9 Chemical Reactions	0.034316
Unit 16 The Chemical Industry \	
Unit 17 Organic chemistry and petrochemicals	0.024240
Unit 2 Atoms, Elements and Compounds	0.025636
Unit 11 Making and identifying salts	0.023592
Unit 20 Natural Polymers	0.029528
Unit 9 Chemical Reactions	0.298069
Unit 8 Speed of Reaction \	
Unit 17 Organic chemistry and petrochemicals	0.024105
Unit 2 Atoms, Elements and Compounds	0.025493
Unit 11 Making and identifying salts	0.023461
Unit 20 Natural Polymers	0.029364
Unit 9 Chemical Reactions	0.041990
Unit 19 Polymers \	
Unit 17 Organic chemistry and petrochemicals	0.029840
Unit 2 Atoms, Elements and Compounds	0.031558
Unit 11 Making and identifying salts	0.029042
Unit 20 Natural Polymers	0.348734
Unit 9 Chemical Reactions	0.051979
Unit 18 The Variety of Organic Chemicals \	
Unit 17 Organic chemistry and petrochemicals	0.169278
Unit 2 Atoms, Elements and Compounds	0.020919
Unit 11 Making and identifying salts	0.019251
Unit 20 Natural Polymers	0.024095
Unit 9 Chemical Reactions	0.034455
Unit 17 Organic chemistry and petrochemicals \	
Unit 17 Organic chemistry and petrochemicals	1.000000
Unit 2 Atoms, Elements and Compounds	0.101829
Unit 11 Making and identifying salts	0.093711
Unit 20 Natural Polymers	0.024657
Unit 9 Chemical Reactions	0.035259
Unit 2 Atoms, Elements and Compounds	
Unit 17 Organic chemistry and petrochemicals	0.101829
Unit 2 Atoms, Elements and Compounds	1.000000
Unit 11 Making and identifying salts	0.099106

[5 rows x 68 columns]  
Saved Chemistry\_similarity\_matrix.csv

```
In [15]: import pandas as pd
from surprise import SVD, Dataset, Reader
from surprise.model_selection import train_test_split
from surprise import accuracy

df = pd.read_csv(r"C:\Users\Rizwana\Desktop\studyclock project\interactions_real.csv")

#Encoding
df["user_id_encoded"] = df["user_id"].astype("category").cat.codes
df["topic_id_encoded"] = df["topic_name"].astype("category").cat.codes

#Create mappings for easy lookup
topic_map = df.drop_duplicates("topic_id_encoded").set_index("topic_id_encoded")["topic_
user_map = df.drop_duplicates("user_id").set_index("user_id")["user_id_encoded"].to_dict

#Surprise Dataset
reader = Reader(rating_scale=(1, 5))
data = Dataset.load_from_df(df[["user_id_encoded", "topic_id_encoded", "rating"]], reader)

#Train/test split
trainset, testset = train_test_split(data, test_size=0.2, random_state=42)

#Train SVD model
algo = SVD()
algo.fit(trainset)

#Evaluate
predictions = algo.test(testset)
print("RMSE:", accuracy.rmse(predictions))
print("MAE:", accuracy.mae(predictions))

#Recommendation function

def get_top_n_recommendations(user_id, n=5):
    user_inner_id = user_map[user_id]
    all_topic_ids = df["topic_id_encoded"].unique()
    interacted_items = df[df["user_id_encoded"] == user_inner_id]["topic_id_encoded"].to

    preds = []
    for item in all_topic_ids:
        if item not in interacted_items:
            # Pass string IDs to Surprise
            pred = algo.predict(str(user_inner_id), str(item))
            preds.append((item, pred.est))

    preds.sort(key=lambda x: x[1], reverse=True)
    return [(topic_map[item], score) for item, score in preds[:n]]

#Show recommendations

results = []
for user in ["user_1", "user_2", "user_3", "user_4", "user_5"]:
    print(f"\nTop-5 Recommendations for {user}:")
    recs = get_top_n_recommendations(user, n=5)
    for topic, score in recs:
        print(f"{topic:30} {score:.4f}")
```

```

results.append({"user_id": user, "topic_name": topic, "predicted_score": score})

recs_df = pd.DataFrame(results)
recs_df.to_csv("svd_recommendations.csv", index=False)
print("Recommendations saved to svd_recommendations.csv")

RMSE: 1.3966
RMSE: 1.3966440109000955
MAE: 1.2131
MAE: 1.2131064141822392

Top-5 Recommendations for user_1:
Unit 17 Inheritance          2.9250
Unit 2 Cells                 2.9250
Chapter 10 Marketing, Competition and the Customer  2.9250
Unit 15 Drugs                2.9250
Unit 13 Excretion            2.9250

Top-5 Recommendations for user_2:
Chapter 16 Marketing Strategy  2.9250
Chapter 13 The Marketing Mix    2.9250
Unit 3 Movement in and out of cells  2.9250
Chapter 20 Location Decisions  2.9250
Unit 17 Organic chemistry and petrochemicals  2.9250

Top-5 Recommendations for user_3:
Unit 8 Safety and Security      2.9250
Chapter 16 Marketing Strategy  2.9250
Unit 3 Movement in and out of cells  2.9250
Chapter 23 Income Statements    2.9250
Chapter 20 Location Decisions    2.9250

Top-5 Recommendations for user_4:
Unit 8 Safety and Security      2.9250
Chapter 16 Marketing Strategy  2.9250
Chapter 13 The Marketing Mix    2.9250
Unit 3 Movement in and out of cells  2.9250
Chapter 23 Income Statements    2.9250

Top-5 Recommendations for user_5:
Unit 8 Safety and Security      2.9250
Chapter 16 Marketing Strategy  2.9250
Unit 3 Movement in and out of cells  2.9250
Chapter 23 Income Statements    2.9250
Chapter 20 Location Decisions    2.9250
Recommendations saved to svd_recommendations.csv

```

In [22]: `pip install seaborn`

```

Collecting seaborn
  Using cached seaborn-0.13.2-py3-none-any.whl.metadata (5.4 kB)
Requirement already satisfied: numpy!=1.24.0,>=1.20 in c:\users\rizwana\anaconda3\envs\finalproject\lib\site-packages (from seaborn) (1.24.3)
Requirement already satisfied: pandas>=1.2 in c:\users\rizwana\anaconda3\envs\finalproject\lib\site-packages (from seaborn) (2.3.1)
Collecting matplotlib!=3.6.1,>=3.4 (from seaborn)
  Downloading matplotlib-3.10.5-cp310-cp310-win_amd64.whl.metadata (11 kB)
Collecting contourpy>=1.0.1 (from matplotlib!=3.6.1,>=3.4->seaborn)
  Downloading contourpy-1.3.2-cp310-cp310-win_amd64.whl.metadata (5.5 kB)
Collecting cycler>=0.10 (from matplotlib!=3.6.1,>=3.4->seaborn)
  Downloading cycler-0.12.1-py3-none-any.whl.metadata (3.8 kB)
Collecting fonttools>=4.22.0 (from matplotlib!=3.6.1,>=3.4->seaborn)
  Downloading fonttools-4.59.1-cp310-cp310-win_amd64.whl.metadata (111 kB)
Collecting kiwisolver>=1.3.1 (from matplotlib!=3.6.1,>=3.4->seaborn)
  Downloading kiwisolver-1.4.9-cp310-cp310-win_amd64.whl.metadata (6.4 kB)

```

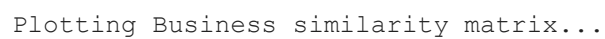


```

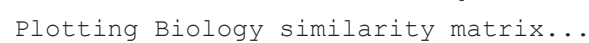
Requirement already satisfied: packaging>=20.0 in c:\users\rizwana\anaconda3\envs\finalproject\lib\site-packages (from matplotlib!=3.6.1,>=3.4->seaborn) (25.0)
Requirement already satisfied: pillow>=8 in c:\users\rizwana\anaconda3\envs\finalproject\lib\site-packages (from matplotlib!=3.6.1,>=3.4->seaborn) (11.3.0)
Collecting pyparsing>=2.3.1 (from matplotlib!=3.6.1,>=3.4->seaborn)
  Downloading pyparsing-3.2.3-py3-none-any.whl.metadata (5.0 kB)
Requirement already satisfied: python-dateutil>=2.7 in c:\users\rizwana\anaconda3\envs\finalproject\lib\site-packages (from matplotlib!=3.6.1,>=3.4->seaborn) (2.9.0.post0)
Requirement already satisfied: pytz>=2020.1 in c:\users\rizwana\anaconda3\envs\finalproject\lib\site-packages (from pandas>=1.2->seaborn) (2025.2)
Requirement already satisfied: tzdata>=2022.7 in c:\users\rizwana\anaconda3\envs\finalproject\lib\site-packages (from pandas>=1.2->seaborn) (2025.2)
Requirement already satisfied: six>=1.5 in c:\users\rizwana\anaconda3\envs\finalproject\lib\site-packages (from python-dateutil>=2.7->matplotlib!=3.6.1,>=3.4->seaborn) (1.17.0)
Using cached seaborn-0.13.2-py3-none-any.whl (294 kB)
Downloading matplotlib-3.10.5-cp310-cp310-win_amd64.whl (8.1 MB)
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----- 7.3/8.1 MB 3.0 MB/s eta 0:00:01
----- 7.9/8.1 MB 2.9 MB/s eta 0:00:01
----- 8.1/8.1 MB 2.7 MB/s 0:00:03
Downloading contourpy-1.3.2-cp310-cp310-win_amd64.whl (221 kB)
Downloading cycler-0.12.1-py3-none-any.whl (8.3 kB)
Downloading fonttools-4.59.1-cp310-cp310-win_amd64.whl (2.3 MB)
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----- 1.8/2.3 MB 457.5 kB/s eta 0:00:01
----- 1.8/2.3 MB 457.5 kB/s eta 0:00:01
----- 2.1/2.3 MB 466.0 kB/s eta 0:00:01
----- 2.3/2.3 MB 472.1 kB/s 0:00:04
Downloading kiwisolver-1.4.9-cp310-cp310-win_amd64.whl (73 kB)
Downloading pyparsing-3.2.3-py3-none-any.whl (111 kB)
Installing collected packages: pyparsing, kiwisolver, fonttools, cycler, contourpy, matplotlib, seaborn
----- 0/7 [pyparsing]
----- 2/7 [fonttools]
----- 2/7 [fonttools]
----- 2/7 [fonttools]

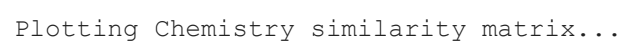
```



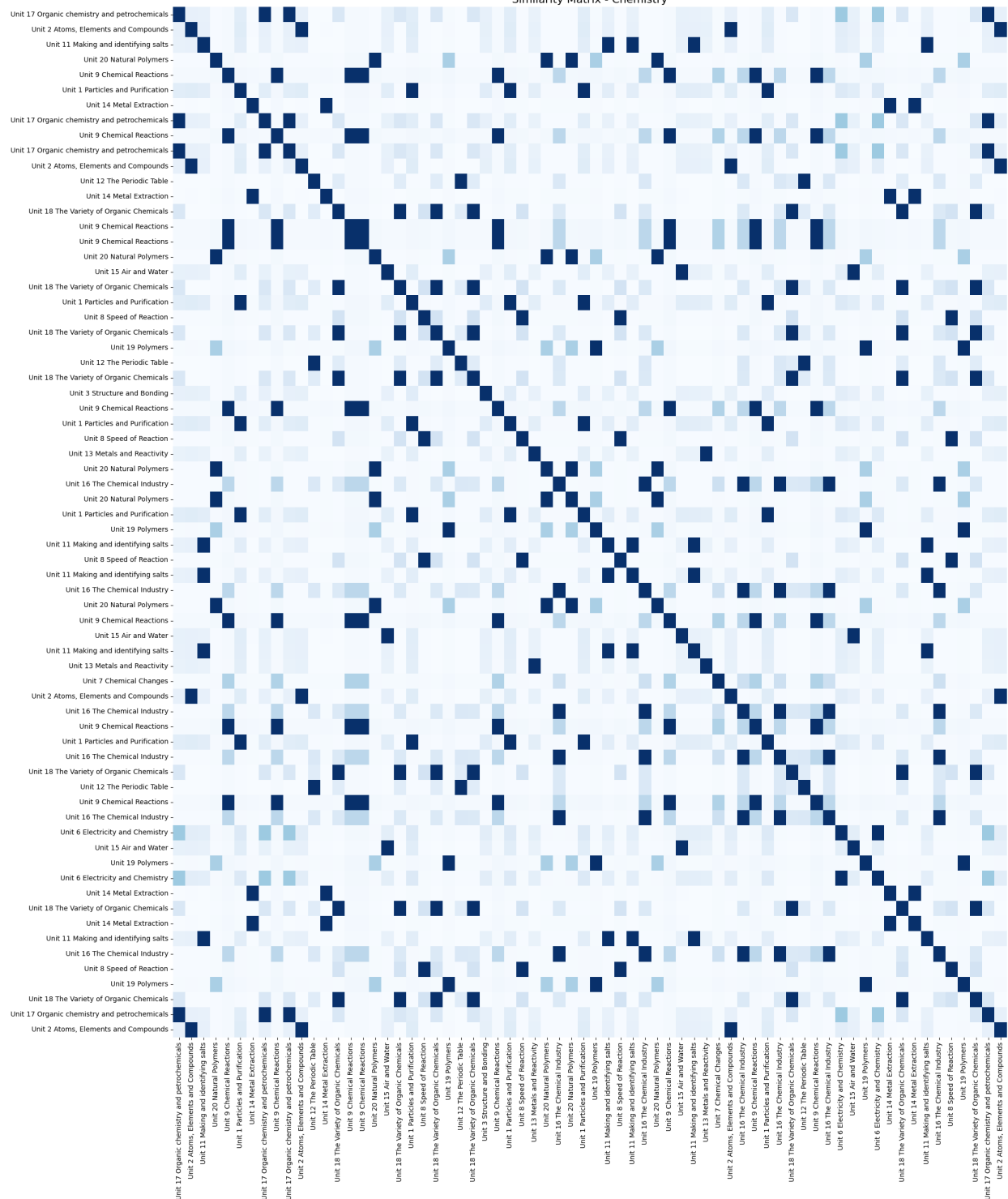


```
Plotting Business similarity matrix...
```





Plotting Chemistry similarity matrix...



```
In [2]: import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from surprise import SVD, Dataset, Reader, accuracy
from surprise.model_selection import train_test_split, cross_validate
from sklearn.metrics import precision_score, recall_score, ndcg_score
import warnings
warnings.filterwarnings('ignore')

df = pd.read_csv(r"C:\Users\Rizwana\Desktop\studyclock project\interactions_real.csv")

#Encoding
df["user_id_encoded"] = df["user_id"].astype("category").cat.codes
df["topic_id_encoded"] = df["topic_name"].astype("category").cat.codes
```

```

#Create mappings for easy lookup
topic_map = df.drop_duplicates("topic_id_encoded").set_index("topic_id_encoded")["topic_
user_map = df.drop_duplicates("user_id").set_index("user_id")["user_id_encoded"].to_dict

#Surprise Dataset
reader = Reader(rating_scale=(1, 5))
data = Dataset.load_from_df(df[["user_id_encoded", "topic_id_encoded", "rating"]], reader)

#Train/test split
trainset, testset = train_test_split(data, test_size=0.2, random_state=42)

#Train SVD model
algo = SVD(random_state=42)
algo.fit(trainset)

#Evaluate
predictions = algo.test(testset)
rmse = accuracy.rmse(predictions)
mae = accuracy.mae(predictions)

print(" SVD MODEL EVALUATION")
print("=" * 50)
print(f"RMSE: {rmse:.4f}")
print(f"MAE: {mae:.4f}")

# 1. PREDICTION ERROR ANALYSIS
print("\n PREDICTION ERROR ANALYSIS")
print("=" * 50)

# Extract actual and predicted ratings
actual_ratings = [pred.r_ui for pred in predictions]
predicted_ratings = [pred.est for pred in predictions]
errors = [abs(pred.r_ui - pred.est) for pred in predictions]

print(f"Average prediction error: {np.mean(errors):.4f}")
print(f"Max prediction error: {np.max(errors):.4f}")
print(f"Min prediction error: {np.min(errors):.4f}")

# Visualization: Prediction vs Actual
plt.figure(figsize=(12, 10))

# Scatter plot of actual vs predicted
plt.subplot(2, 2, 1)
plt.scatter(actual_ratings, predicted_ratings, alpha=0.6, s=30)
plt.plot([1, 5], [1, 5], 'r--', alpha=0.8) # Perfect prediction line
plt.xlabel('Actual Rating')
plt.ylabel('Predicted Rating')
plt.title('Actual vs Predicted Ratings')
plt.grid(True, alpha=0.3)

# Error distribution
plt.subplot(2, 2, 2)
plt.hist(errors, bins=30, alpha=0.7, color='orange', edgecolor='black')
plt.xlabel('Absolute Error')
plt.ylabel('Frequency')
plt.title('Distribution of Prediction Errors')
plt.grid(True, alpha=0.3)

# Error by rating value
error_by_rating = pd.DataFrame({
    'actual': actual_ratings,
    'error': errors
}).groupby('actual')['error'].mean()

plt.subplot(2, 2, 3)
error_by_rating.plot(kind='bar', color='skyblue', edgecolor='black')

```



```

plt.xlabel('Actual Rating')
plt.ylabel('Average Absolute Error')
plt.title('Error by Rating Value')
plt.xticks(rotation=0)
plt.grid(True, alpha=0.3)

# Residual plot
residuals = [pred.est - pred.r_ui for pred in predictions]
plt.subplot(2, 2, 4)
plt.scatter(predicted_ratings, residuals, alpha=0.6, s=30)
plt.axhline(y=0, color='r', linestyle='--', alpha=0.8)
plt.xlabel('Predicted Rating')
plt.ylabel('Residuals (Predicted - Actual)')
plt.title('Residual Plot')
plt.grid(True, alpha=0.3)

plt.tight_layout()
plt.savefig('svd_prediction_analysis.png', dpi=300, bbox_inches='tight')
plt.show()

# 2. CROSS-VALIDATION FOR ROBUST EVALUATION
print("\n CROSS-VALIDATION RESULTS")
print("=" * 50)

cv_results = cross_validate(algo, data, measures=['RMSE', 'MAE'], cv=5, verbose=False)

print("Cross-validation RMSE scores:", [f"{score:.4f}" for score in cv_results['test_rmse']])
print("Cross-validation MAE scores:", [f"{score:.4f}" for score in cv_results['test_mae']])
print(f"Mean RMSE: {np.mean(cv_results['test_rmse']):.4f} (±{np.std(cv_results['test_rmse']):.4f})")
print(f"Mean MAE: {np.mean(cv_results['test_mae']):.4f} (±{np.std(cv_results['test_mae']):.4f})")

# 3. TOP-N RECOMMENDATION EVALUATION
print("\n TOP-N RECOMMENDATION EVALUATION")
print("=" * 50)

# Create binary relevance (rating >= 4 is relevant)
df['relevant'] = (df['rating'] >= 4).astype(int)

# Recommendation function with relevance
def get_top_n_recommendations_with_relevance(user_id, n=5):
    user_inner_id = user_map[user_id]
    all_topic_ids = df["topic_id_encoded"].unique()
    interacted_items = df[df["user_id_encoded"] == user_inner_id]["topic_id_encoded"].to_list()

    preds = []
    for item in all_topic_ids:
        if item not in interacted_items:
            pred = algo.predict(str(user_inner_id), str(item))
            preds.append((item, pred.est))

    preds.sort(key=lambda x: x[1], reverse=True)

    # Get relevance information
    recommendations = []
    for item, score in preds[:n]:
        topic_name = topic_map[item]
        # Check if this topic would be relevant (has high rating from other users)
        avg_rating = df[df['topic_id_encoded'] == item]['rating'].mean()
        relevant = 1 if avg_rating >= 4 else 0
        recommendations.append({
            'topic_name': topic_name,
            'predicted_score': score,
            'relevance': relevant
        })

    return recommendations

```

```

# Evaluate precision and recall for top-N recommendations
def evaluate_top_n(precision_at=5):
    precisions = []
    recalls = []

    test_users = df['user_id'].unique()[0:20] # Evaluate on first 20 users for efficiency

    for user in test_users:
        recs = get_top_n_recommendations_with_relevance(user, n=precision_at)
        relevant_rec = sum(1 for rec in recs if rec['relevance'] == 1)

        precision = relevant_rec / precision_at
        # For recall, we need the total number of relevant items for this user
        user_relevant_items = len(df[(df['user_id'] == user) & (df['relevance'] == 1)])
        recall = relevant_rec / user_relevant_items if user_relevant_items > 0 else 0

        precisions.append(precision)
        recalls.append(recall)

    return np.mean(precisions), np.mean(recalls)

precision, recall = evaluate_top_n(5)
print(f"Precision@5: {precision:.4f}")
print(f"Recall@5: {recall:.4f}")

# 4. USER AND ITEM ANALYSIS
print("\n USER AND ITEM ANALYSIS")
print("=" * 50)

# User activity analysis
user_activity = df.groupby('user_id_encoded').agg({
    'rating': 'count',
    'rating': 'mean'
}).rename(columns={'rating': 'avg_rating'})
user_activity['interaction_count'] = df.groupby('user_id_encoded').size()

# Topic popularity analysis
topic_popularity = df.groupby('topic_id_encoded').agg({
    'rating': 'count',
    'rating': 'mean'
}).rename(columns={'rating': 'avg_rating'})
topic_popularity['interaction_count'] = df.groupby('topic_id_encoded').size()

print("User activity statistics:")
print(user_activity.describe().round(3))
print("\nTopic popularity statistics:")
print(topic_popularity.describe().round(3))

# Visualization: User and item analysis
plt.figure(figsize=(15, 10))

# User interaction distribution
plt.subplot(2, 3, 1)
plt.hist(user_activity['interaction_count'], bins=30, alpha=0.7, color='lightblue', edge
plt.xlabel('Number of Interactions per User')
plt.ylabel('Frequency')
plt.title('User Interaction Distribution')
plt.grid(True, alpha=0.3)

# Topic interaction distribution
plt.subplot(2, 3, 2)
plt.hist(topic_popularity['interaction_count'], bins=30, alpha=0.7, color='lightgreen',
plt.xlabel('Number of Interactions per Topic')
plt.ylabel('Frequency')
plt.title('Topic Interaction Distribution')

```

```

plt.grid(True, alpha=0.3)

# Rating distribution
plt.subplot(2, 3, 3)
rating_counts = df['rating'].value_counts().sort_index()
plt.bar(rating_counts.index, rating_counts.values, alpha=0.7, color='salmon', edgecolor=
plt.xlabel('Rating')
plt.ylabel('Count')
plt.title('Rating Distribution')
plt.xticks(range(1, 6))
plt.grid(True, alpha=0.3)

# User rating distribution
plt.subplot(2, 3, 4)
plt.hist(user_activity['avg_rating'], bins=20, alpha=0.7, color='gold', edgecolor='black'
plt.xlabel('Average User Rating')
plt.ylabel('Frequency')
plt.title('User Rating Behavior')
plt.grid(True, alpha=0.3)

# Topic rating distribution
plt.subplot(2, 3, 5)
plt.hist(topic_popularity['avg_rating'], bins=20, alpha=0.7, color='purple', edgecolor='
plt.xlabel('Average Topic Rating')
plt.ylabel('Frequency')
plt.title('Topic Rating Quality')
plt.grid(True, alpha=0.3)

# Cold start problem analysis
user_interaction_counts = df.groupby('user_id_encoded').size()
cold_users = sum(user_interaction_counts < 5) # Users with few interactions
cold_topics = sum(topic_popularity['interaction_count'] < 5) # Topics with few interact

plt.subplot(2, 3, 6)
categories = ['Cold Users (<5 interactions)', 'Cold Topics (<5 interactions)']
values = [cold_users, cold_topics]
plt.bar(categories, values, alpha=0.7, color=['orange', 'red'], edgecolor='black')
plt.ylabel('Count')
plt.title('Cold Start Problem Analysis')
plt.xticks(rotation=45, ha='right')
plt.grid(True, alpha=0.3)

plt.tight_layout()
plt.savefig('svd_user_item_analysis.png', dpi=300, bbox_inches='tight')
plt.show()

# 5. RECOMMENDATION DIVERSITY ANALYSIS
print("\ RECOMMENDATION DIVERSITY ANALYSIS")
print("=" * 50)

# Analyze how diverse recommendations are across users
all_recommendations = []
test_users = df['user_id'].unique()[:30]

for user in test_users:
    recs = get_top_n_recommendations(user, n=5)
    for topic, score in recs:
        all_recommendations.append(topic)

# Calculate recommendation frequency
rec_frequency = pd.Series(all_recommendations).value_counts()
print("Top 10 most frequently recommended topics:")
print(rec_frequency.head(10))

print(f"\nRecommendation diversity: {len(rec_frequency)} unique topics recommended")
print(f"Gini coefficient of recommendation distribution: {1 - sum((rec_frequency / rec_f

```

```

# 6. SAVE COMPREHENSIVE EVALUATION RESULTS
evaluation_results = {
    'rmse': rmse,
    'mae': mae,
    'precision_at_5': precision,
    'recall_at_5': recall,
    'avg_prediction_error': np.mean(errors),
    'cv_mean_rmse': np.mean(cv_results['test_rmse']),
    'cv_mean_mae': np.mean(cv_results['test_mae']),
    'cold_users': cold_users,
    'cold_topics': cold_topics,
    'recommendation_diversity': len(rec_frequency),
    'avg_user_interactions': user_activity['interaction_count'].mean(),
    'avg_topic_interactions': topic_popularity['interaction_count'].mean()
}

results_df = pd.DataFrame(list(evaluation_results.items()), columns=['metric', 'value'])
results_df.to_csv('svd_evaluation_metrics.csv', index=False)

print("\nCOMPREHENSIVE EVALUATION COMPLETED!")
print("=" * 50)
print("Evaluation metrics saved to 'svd_evaluation_metrics.csv'")
print("Visualizations saved as PNG files")
print("\ SUMMARY:")
for metric, value in evaluation_results.items():
    if isinstance(value, float):
        print(f"{metric:<25}: {value:.4f}")
    else:
        print(f"{metric:<25}: {value}")

# 7. GENERATE SAMPLE RECOMMENDATIONS FOR DEMONSTRATION
print(" SAMPLE RECOMMENDATIONS")
print("=" * 50)

sample_users = ["user_1", "user_2", "user_3", "user_4", "user_5"]
results = []

for user in sample_users:
    print(f"\nTop-5 Recommendations for {user}:")
    recs = get_top_n_recommendations(user, n=5)
    for topic, score in recs:
        print(f" {topic:35} {score:.4f}")
        results.append({"user_id": user, "topic_name": topic, "predicted_score": score})

recs_df = pd.DataFrame(results)
recs_df.to_csv("svd_recommendations.csv", index=False)
print(" Recommendations saved to 'svd_recommendations.csv'")

```

RMSE: 1.4136

MAE: 1.2309

SVD MODEL EVALUATION

=====

RMSE: 1.4136

MAE: 1.2309

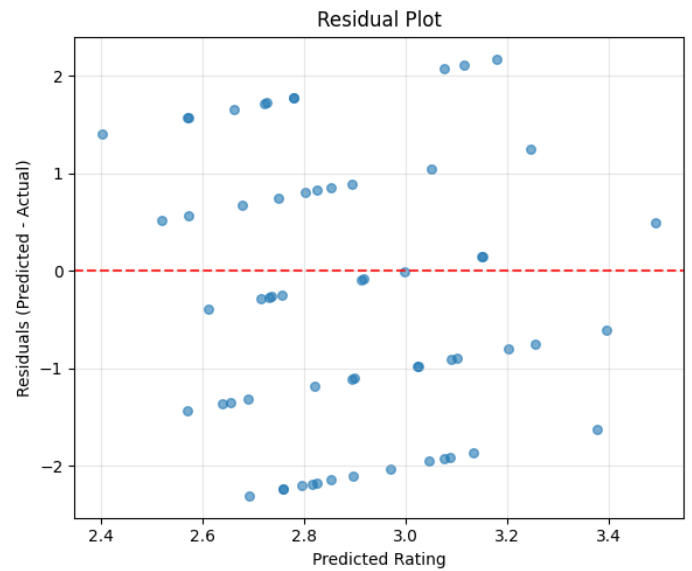
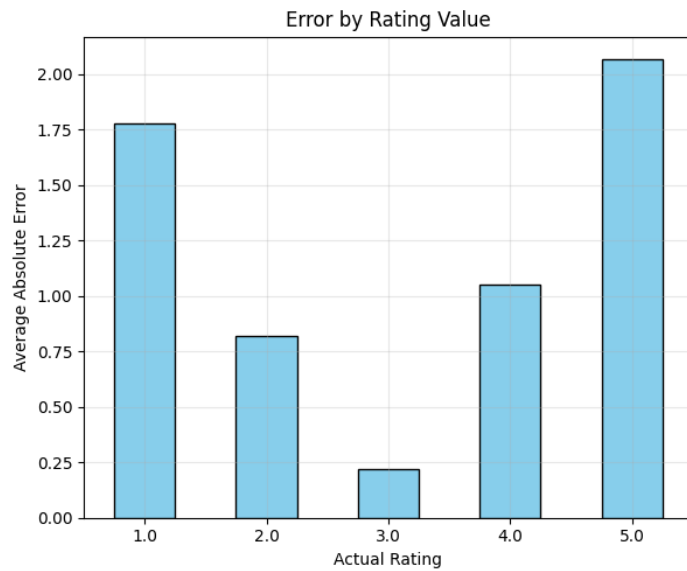
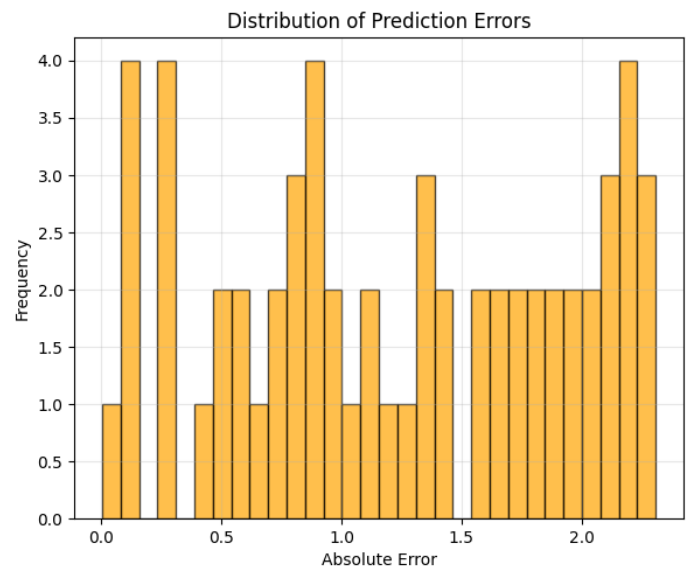
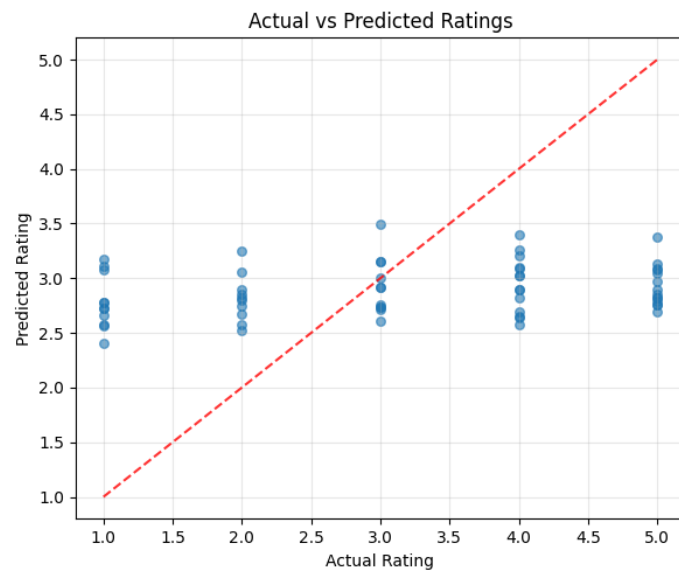
PREDICTION ERROR ANALYSIS

=====

Average prediction error: 1.2309

Max prediction error: 2.3092

Min prediction error: 0.0022



#### CROSS-VALIDATION RESULTS

```
=====
Cross-validation RMSE scores: ['1.5240', '1.2743', '1.4741', '1.4845', '1.3133']
Cross-validation MAE scores: ['1.2974', '1.0991', '1.3067', '1.2839', '1.1215']
Mean RMSE: 1.4140 (±0.1004)
Mean MAE: 1.2217 (±0.0916)
```

#### TOP-N RECOMMENDATION EVALUATION

```
=====
Precision@5: 0.1400
Recall@5: 0.1427
```

#### USER AND ITEM ANALYSIS

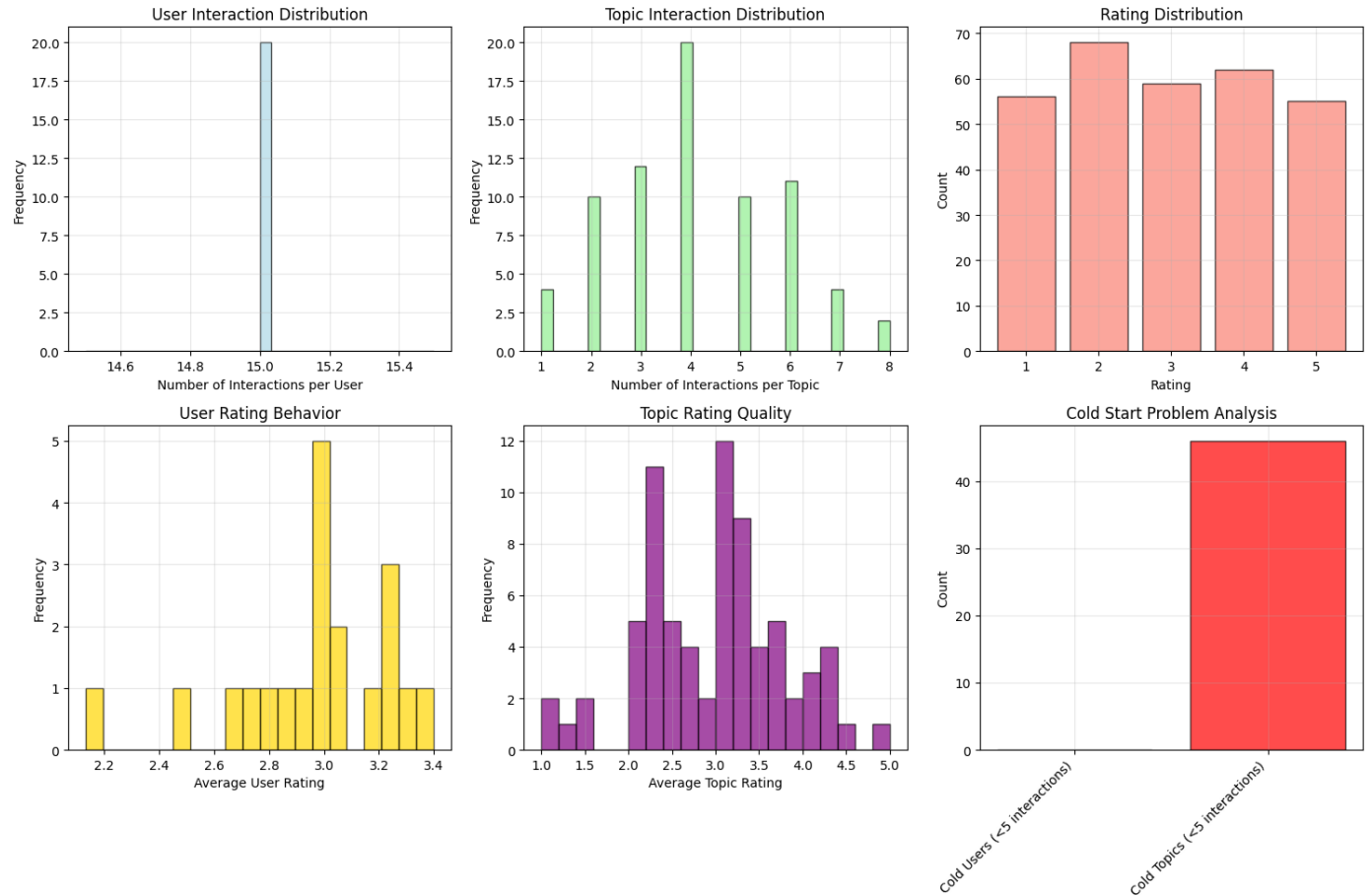
```
=====
User activity statistics:
```

	avg_rating	interaction_count
count	20.000	20.0
mean	2.973	15.0
std	0.308	0.0
min	2.133	15.0
25%	2.850	15.0
50%	3.000	15.0
75%	3.217	15.0
max	3.400	15.0

```
Topic popularity statistics:
```

	avg_rating	interaction_count
count	73.000	73.000
mean	2.945	4.110

std	0.818	1.704
min	1.000	1.000
25%	2.400	3.000
50%	3.000	4.000
75%	3.500	5.000
max	5.000	8.000



## \ RECOMMENDATION DIVERSITY ANALYSIS

=====

```
-----
NameError                                Traceback (most recent call last)
Cell In[2], line 271
    268 test_users = df['user_id'].unique()[ :30]
    270 for user in test_users:
--> 271     recs = get_top_n_recommendations(user, n=5)
    272     for topic, score in recs:
    273         all_recommendations.append(topic)

NameError: name 'get_top_n_recommendations' is not defined
```

# Hybrid Recommender without BiLSTM

```
In [26]: import pandas as pd
import numpy as np
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.metrics.pairwise import cosine_similarity

df = pd.read_csv(r"C:\Users\Rizwana\Desktop\studyoclock project\interactions_real.csv")

#Build TF-IDF similarity (per subject)
tfidf = TfidfVectorizer(stop_words="english")

subject_sim_matrices = {}
for subject in df["subject"].unique():
    subject_topics = df[df["subject"] == subject]["topic_name"].unique()
```

```

tfidf_matrix = tfidf.fit_transform(subject_topics)
cosine_sim = cosine_similarity(tfidf_matrix)
subject_sim_matrices[subject] = {
    "topics": subject_topics,
    "matrix": cosine_sim
}

#Hybrid Recommendation Function
def hybrid_recommend(user_id, topic_name, top_k=5, alpha=0.5, beta=0.5):
    # Identify the subject of the selected topic
    if topic_name not in df["topic_name"].values:
        return f"Topic '{topic_name}' not found!"

    subject = df[df["topic_name"] == topic_name]["subject"].iloc[0]
    sim_data = subject_sim_matrices[subject]
    topics = sim_data["topics"]
    cosine_sim = sim_data["matrix"]

    # Content similarity
    idx = np.where(topics == topic_name)[0][0]
    cos_sim = cosine_sim[idx]

    content_scores = pd.DataFrame({
        "topic_name": topics,
        "content_score": cos_sim
    })

    #Collaborative Filtering
    cf_scores = []
    for t in topics:
        pred = df[(df["user_id"] == user_id) & (df["topic_name"] == t)]["rating"].mean()
        if np.isnan(pred):
            pred = df[df["topic_name"] == t]["rating"].mean()
        cf_scores.append(pred)
    content_scores["cf_score"] = cf_scores

    # Hybrid score
    content_scores["hybrid_score"] = (
        alpha * content_scores["content_score"] +
        beta * content_scores["cf_score"]
    )

    #Rank and return
    recs = content_scores.sort_values(by="hybrid_score", ascending=False).head(top_k)
    return subject, recs[["topic_name", "content_score", "cf_score", "hybrid_score"]]

print("=== Biology Example ===")
subject, recs = hybrid_recommend("user_5", "Unit 12 Respiration", top_k=5)
print(f"Subject: {subject}")
print(recs.to_string(index=False, float_format="%.3f"))
print() # Empty line for spacing

print("=== Chemistry Example ===")
subject, recs = hybrid_recommend("user_7", "Unit 12 The Periodic Table", top_k=5)
print(f"Subject: {subject}")
print(recs.to_string(index=False, float_format="%.3f"))

```

=== Biology Example ===

Subject: Biology

	topic_name	content_score	cf_score	hybrid_score
	Unit 12 Respiration	1.000	4.250	2.625
	Unit 7 Animal Nutrition	0.044	5.000	2.522
Unit 20 Microorganisms and biotechnology		0.034	4.250	2.142
	Unit 6 Plant Nutrition	0.047	4.000	2.023
	Unit 17 Inheritance	0.042	4.000	2.021

=== Chemistry Example ===

Subject: Chemistry

	topic_name	content_score	cf_score	hybrid_score
	Unit 7 Chemical Changes	0.042	4.000	2.021
	Unit 3 Structure and Bonding	0.038	4.000	2.019
	Unit 16 The Chemical Industry	0.034	3.833	1.934
	Unit 14 Metal Extraction	0.032	3.750	1.891
	Unit 20 Natural Polymers	0.033	3.400	1.716

```
In [28]: import pandas as pd
import numpy as np
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.metrics.pairwise import cosine_similarity

# Load the data
df = pd.read_csv(r"C:\Users\Rizwana\Desktop\studyclock project\interactions_real.csv")

# Build TF-IDF similarity (per subject)
tfidf = TfidfVectorizer(stop_words="english")

subject_sim_matrices = {}
for subject in df["subject"].unique():
    subject_topics = df[df["subject"] == subject]["topic_name"].unique()
    tfidf_matrix = tfidf.fit_transform(subject_topics)
    cosine_sim = cosine_similarity(tfidf_matrix)
    subject_sim_matrices[subject] = {
        "topics": subject_topics,
        "matrix": cosine_sim
    }

# Hybrid Recommendation Function
def hybrid_recommend(user_id, topic_name, top_k=5, alpha=0.5, beta=0.5):
    # Identify the subject of the selected topic
    if topic_name not in df["topic_name"].values:
        raise ValueError(f"Topic '{topic_name}' not found!")

    subject = df[df["topic_name"] == topic_name]["subject"].iloc[0]
    sim_data = subject_sim_matrices[subject]
    topics = sim_data["topics"]
    cosine_sim = sim_data["matrix"]

    # Content similarity
    idx = np.where(topics == topic_name)[0][0]
    cos_sim = cosine_sim[idx]

    content_scores = pd.DataFrame({
        "topic_name": topics,
        "content_score": cos_sim
    })

    # Collaborative Filtering
    cf_scores = []
    for t in topics:
        pred = df[(df["user_id"] == user_id) & (df["topic_name"] == t)]["rating"].mean()
        if np.isnan(pred):
            pred = df[df["topic_name"] == t]["rating"].mean()
        cf_scores.append(pred)
    content_scores["cf_score"] = cf_scores

    # Hybrid score
    content_scores["hybrid_score"] = (
        alpha * content_scores["content_score"] +
        beta * content_scores["cf_score"]
    )
```



```

# Rank and return
recs = content_scores.sort_values(by="hybrid_score", ascending=False).head(top_k)
return recs[["topic_name", "content_score", "cf_score", "hybrid_score"]]

# -----
# Generate recommendations for ALL users and topics
# -----
all_results = []

for user in df["user_id"].unique():
    for topic in df["topic_name"].unique():
        try:
            # Get recommendations for this user-topic combination
            recs = hybrid_recommend(user, topic, top_k=5)

            # Add input user and topic to the results
            recs = recs.copy()
            recs["input_user"] = user
            recs["input_topic"] = topic

            all_results.append(recs)

        except Exception as e:
            print(f"Skipping {user}, {topic} due to error: {e}")
            continue

# Combine into one DataFrame
if all_results:
    final_rec = pd.concat(all_results, ignore_index=True)

    # Reorder columns for readability
    final_rec = final_rec[["input_user", "input_topic", "topic_name", "content_score",

    # Save to CSV
    final_rec.to_csv("all_hybrid_recommendations.csv", index=False)

    print("Exported all recommendations to all_hybrid_recommendations.csv")
    print(f"Total recommendations generated: {len(final_rec)}")

    # -----
    # Show a quick sample
    # -----
    print("Example Recommendations:")
    print(final_rec.head(15).to_string(index=False, float_format="%.3f"))
else:
    print("No recommendations were generated. Check for errors above.")

```

Exported all recommendations to all\_hybrid\_recommendations.csv

Total recommendations generated: 7300

Example Recommendations:

input_user	input_topic	topic_name
content_score	cf_score	hybrid_score
user_1	Unit 8 Safety and Security	Unit 8 Safety and Security
1.000	4.000	2.500
user_1	Unit 8 Safety and Security	Unit 2 Input and Output Devices
0.070	4.000	2.035
user_1	Unit 8 Safety and Security	Unit 1 Types and Components of Computer Systems
0.061	3.667	1.864
user_1	Unit 8 Safety and Security	Unit 5 The effects of using ICT
0.070	2.857	1.464
user_1	Unit 8 Safety and Security	Unit 3 Storage Devices and Media
0.070	2.833	1.452
user_1	Chapter 16 Marketing Strategy	Chapter 15 The Marketing Mix
0.223	4.333	2.278
user_1	Chapter 16 Marketing Strategy	Chapter 14 The Marketing Mix
0.223	4.250	2.237

user_1	Chapter 16 Marketing Strategy	Chapter 25 Analysis of Accountants
0.027	4.400	2.213
user_1	Chapter 16 Marketing Strategy	Chapter 23 Income Statements
0.027	4.000	2.013
user_1	Chapter 16 Marketing Strategy	Chapter 16 Marketing Strategy
1.000	3.000	2.000
user_1	Chapter 13 The Marketing Mix	Chapter 15 The Marketing Mix
0.517	4.333	2.425
user_1	Chapter 13 The Marketing Mix	Chapter 14 The Marketing Mix
0.517	4.250	2.384
user_1	Chapter 13 The Marketing Mix	Chapter 25 Analysis of Accountants
0.029	4.400	2.215
user_1	Chapter 13 The Marketing Mix	Chapter 23 Income Statements
0.029	4.000	2.015
user_1	Chapter 13 The Marketing Mix	Chapter 24 Balance Sheets
0.029	3.667	1.848

```
In [30]: import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.metrics import mean_squared_error, mean_absolute_error, precision_score, re
from sklearn.model_selection import train_test_split
import warnings
warnings.filterwarnings('ignore')

final_recs = pd.read_csv("all_hybrid_recommendations.csv")

df = pd.read_csv(r"C:\Users\Rizwana\Desktop\studyclock project\interactions_real.csv")

#Statistics and overview
print("BASIC STATISTICS")
print("=" * 50)
print(f"Total recommendations generated: {len(final_recs):,}")
print(f"Number of unique users: {final_recs['input_user'].nunique()}")
print(f"Number of unique topics: {final_recs['topic_name'].nunique()}")
print(f"Number of input topics: {final_recs['input_topic'].nunique()}")
print()

#SCORE DISTRIBUTION ANALYSIS
print("SCORE DISTRIBUTION")
print("=" * 50)
print("Hybrid Score Statistics:")
print(final_recs['hybrid_score'].describe().round(3))
print("\nContent Score Statistics:")
print(final_recs['content_score'].describe().round(3))
print("\nCF Score Statistics:")
print(final_recs['cf_score'].describe().round(3))

#Visualization: Score Distributions
plt.figure(figsize=(15, 5))

plt.subplot(1, 3, 1)
sns.histplot(final_recs['hybrid_score'], bins=30, kde=True)
plt.title('Distribution of Hybrid Scores')
plt.xlabel('Hybrid Score')

plt.subplot(1, 3, 2)
sns.histplot(final_recs['content_score'], bins=30, kde=True)
plt.title('Distribution of Content Scores')
plt.xlabel('Content Score')

plt.subplot(1, 3, 3)
```

```

sns.histplot(final_recs['cf_score'], bins=30, kde=True)
plt.title('Distribution of CF Scores')
plt.xlabel('CF Score')

plt.tight_layout()
plt.savefig('score_distributions.png', dpi=300, bbox_inches='tight')
plt.show()

#CORRELATION ANALYSIS
print("CORRELATION ANALYSIS")
print("=" * 50)
correlation_matrix = final_recs[['hybrid_score', 'content_score', 'cf_score']].corr()
print("Correlation Matrix:")
print(correlation_matrix.round(3))

plt.figure(figsize=(8, 6))
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm', center=0, fmt='.3f')
plt.title('Correlation between Recommendation Scores')
plt.savefig('correlation_heatmap.png', dpi=300, bbox_inches='tight')
plt.show()

#TOP-N RECOMMENDATION ANALYSIS
#Create a binary relevance column (assuming ratings > 3 are relevant)
df['relevant'] = (df['rating'] >= 3).astype(int)

#Merge recommendations with actual interactions to find relevant items
eval_data = final_recs.merge(
    df[['user_id', 'topic_name', 'rating', 'relevant']],
    left_on=['input_user', 'topic_name'],
    right_on=['user_id', 'topic_name'],
    how='left'
)

eval_data['relevant'] = eval_data['relevant'].fillna(0) # Not interacted = not relevant

# 5. PRECISION AND RECALL AT K
def precision_recall_at_k(df, k=5):
    results = []
    for user in df['input_user'].unique():
        user_recs = df[df['input_user'] == user].nlargest(k, 'hybrid_score')
        relevant_count = user_recs['relevant'].sum()
        precision = relevant_count / k if k > 0 else 0
        recall = relevant_count / df[(df['input_user'] == user) & (df['relevant'] == 1)]
        results.append({'user': user, 'precision': precision, 'recall': recall})
    return pd.DataFrame(results)

precision_recall_df = precision_recall_at_k(eval_data, k=5)

print("PRECISION AND RECALL AT K=5")
print("=" * 50)
print(f"Average Precision@5: {precision_recall_df['precision'].mean():.3f}")
print(f"Average Recall@5: {precision_recall_df['recall'].mean():.3f}")

#NDCG (Normalized Discounted Cumulative Gain)
def calculate_ndcg(df, k=5):
    ndcg_scores = []
    for user in df['input_user'].unique():
        user_recs = df[df['input_user'] == user].nlargest(k, 'hybrid_score')
        relevance_scores = user_recs['relevant'].values
        # Calculate ideal DCG
        ideal_relevance = np.sort(relevance_scores)[::-1] # Sort in descending order
        dcg = sum((2 ** rel - 1) / np.log2(idx + 2) for idx, rel in enumerate(relevance_scores))
        idcg = sum((2 ** rel - 1) / np.log2(idx + 2) for idx, rel in enumerate(ideal_relevance))
        ndcg = dcg / idcg if idcg > 0 else 0
        ndcg_scores.append(ndcg)
    return np.mean(ndcg_scores)

```

```

avg_ndcg = calculate_ndcg(eval_data, k=5)
print(f"Average NDCG@5: {avg_ndcg:.3f}")

#USER ENGAGEMENT ANALYSIS
user_engagement = eval_data.groupby('input_user').agg({
    'hybrid_score': 'mean',
    'relevant': 'sum',
    'topic_name': 'count'
}).rename(columns={'topic_name': 'total_recommendations', 'relevant': 'relevant_recommendations'})

user_engagement['engagement_rate'] = user_engagement['relevant_recommendations'] / user_engagement['total_recommendations']

print("USER ENGAGEMENT ANALYSIS")
print("=" * 50)
print("Top 10 Most Engaged Users:")
print(user_engagement.nlargest(10, 'engagement_rate')[['engagement_rate', 'relevant_recommendations', 'total_recommendations']])

#Visualization: User Engagement
plt.figure(figsize=(12, 5))

plt.subplot(1, 2, 1)
sns.histplot(user_engagement['engagement_rate'], bins=20, kde=True)
plt.title('Distribution of User Engagement Rates')
plt.xlabel('Engagement Rate')

plt.subplot(1, 2, 2)
sns.scatterplot(data=user_engagement, x='hybrid_score', y='engagement_rate', alpha=0.6)
plt.title('Hybrid Score vs Engagement Rate')
plt.xlabel('Average Hybrid Score')
plt.ylabel('Engagement Rate')

plt.tight_layout()
plt.savefig('user_engagement_analysis.png', dpi=300, bbox_inches='tight')
plt.show()

#TOPIC POPULARITY ANALYSIS
topic_popularity = final_recs['topic_name'].value_counts().head(15)
topic_quality = eval_data.groupby('topic_name')['relevant'].mean().sort_values(ascending=False)

plt.figure(figsize=(15, 6))

plt.subplot(1, 2, 1)
sns.barplot(y=topic_popularity.index, x=topic_popularity.values)
plt.title('Top 15 Most Frequently Recommended Topics')
plt.xlabel('Number of Recommendations')

plt.subplot(1, 2, 2)
sns.barplot(y=topic_quality.index, x=topic_quality.values)
plt.title('Top 15 Highest Quality Topics (Relevance Rate)')
plt.xlabel('Relevance Rate')

plt.tight_layout()
plt.savefig('topic_analysis.png', dpi=300, bbox_inches='tight')
plt.show()

#HYBRID MODEL COMPONENT ANALYSIS
component_analysis = final_recs[['content_score', 'cf_score', 'hybrid_score']].describe()

print("HYBRID MODEL COMPONENT ANALYSIS")
print("=" * 50)
print(component_analysis)

#Visualization: Component influence
plt.figure(figsize=(12, 5))

```

```

plt.subplot(1, 2, 1)
sns.scatterplot(data=final_recs.sample(1000), x='content_score', y='cf_score',
                hue='hybrid_score', palette='viridis', alpha=0.6)
plt.title('Content vs CF Scores Colored by Hybrid Score')
plt.xlabel('Content Score')
plt.ylabel('CF Score')

plt.subplot(1, 2, 2)
sns.boxplot(data=final_recs[['content_score', 'cf_score', 'hybrid_score']])
plt.title('Distribution of All Score Types')
plt.xticks(rotation=45)

plt.tight_layout()
plt.savefig('component_analysis.png', dpi=300, bbox_inches='tight')
plt.show()

#Conclusion
print("\n" + "=" * 60)
print(" COMPREHENSIVE EVALUATION REPORT")
print("=" * 60)
print(f"Total Recommendations: {len(final_recs):,}")
print(f"Average Precision@5: {precision_recall_df['precision'].mean():.3f}")
print(f"Average Recall@5: {precision_recall_df['recall'].mean():.3f}")
print(f"Average NDCG@5: {avg_ndcg:.3f}")
print(f"Average User Engagement Rate: {user_engagement['engagement_rate'].mean():.3f}")
print(f"Average Hybrid Score: {final_recs['hybrid_score'].mean():.3f}")
print(f"Content-CF Correlation: {correlation_matrix.loc['content_score', 'cf_score']:.3f}")

#Save evaluation metrics to CSV
evaluation_metrics = pd.DataFrame({
    'metric': ['Precision@5', 'Recall@5', 'NDCG@5', 'Engagement_Rate', 'Avg_Hybrid_Score'],
    'value': [
        precision_recall_df['precision'].mean(),
        precision_recall_df['recall'].mean(),
        avg_ndcg,
        user_engagement['engagement_rate'].mean(),
        final_recs['hybrid_score'].mean(),
        correlation_matrix.loc['content_score', 'cf_score']
    ]
})

evaluation_metrics.to_csv('evaluation_metrics.csv', index=False)
print("Evaluation metrics saved to evaluation_metrics.csv")
print("All visualizations saved as PNG files")

```

## BASIC STATISTICS

=====

Total recommendations generated: 7,300  
 Number of unique users: 20  
 Number of unique topics: 67  
 Number of input topics: 73

## SCORE DISTRIBUTION

=====

### Hybrid Score Statistics:

count	7300.000
mean	2.158
std	0.277
min	1.231
25%	2.012
50%	2.140
75%	2.417
max	3.000

Name: hybrid\_score, dtype: float64

### Content Score Statistics:

```

count      7300.000
mean       0.166
std        0.308
min        0.014
25%        0.029
50%        0.038
75%        0.058
max        1.000
Name: content_score, dtype: float64

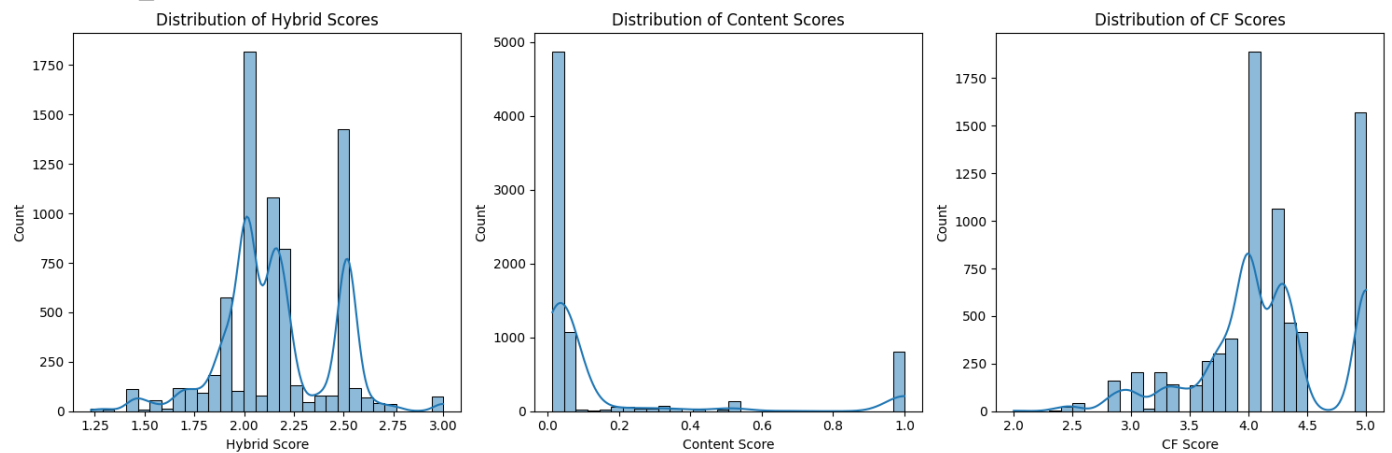
```

#### CF Score Statistics:

```

count      7300.000
mean       4.150
std        0.582
min        2.000
25%        3.833
50%        4.000
75%        4.400
max        5.000
Name: cf_score, dtype: float64

```

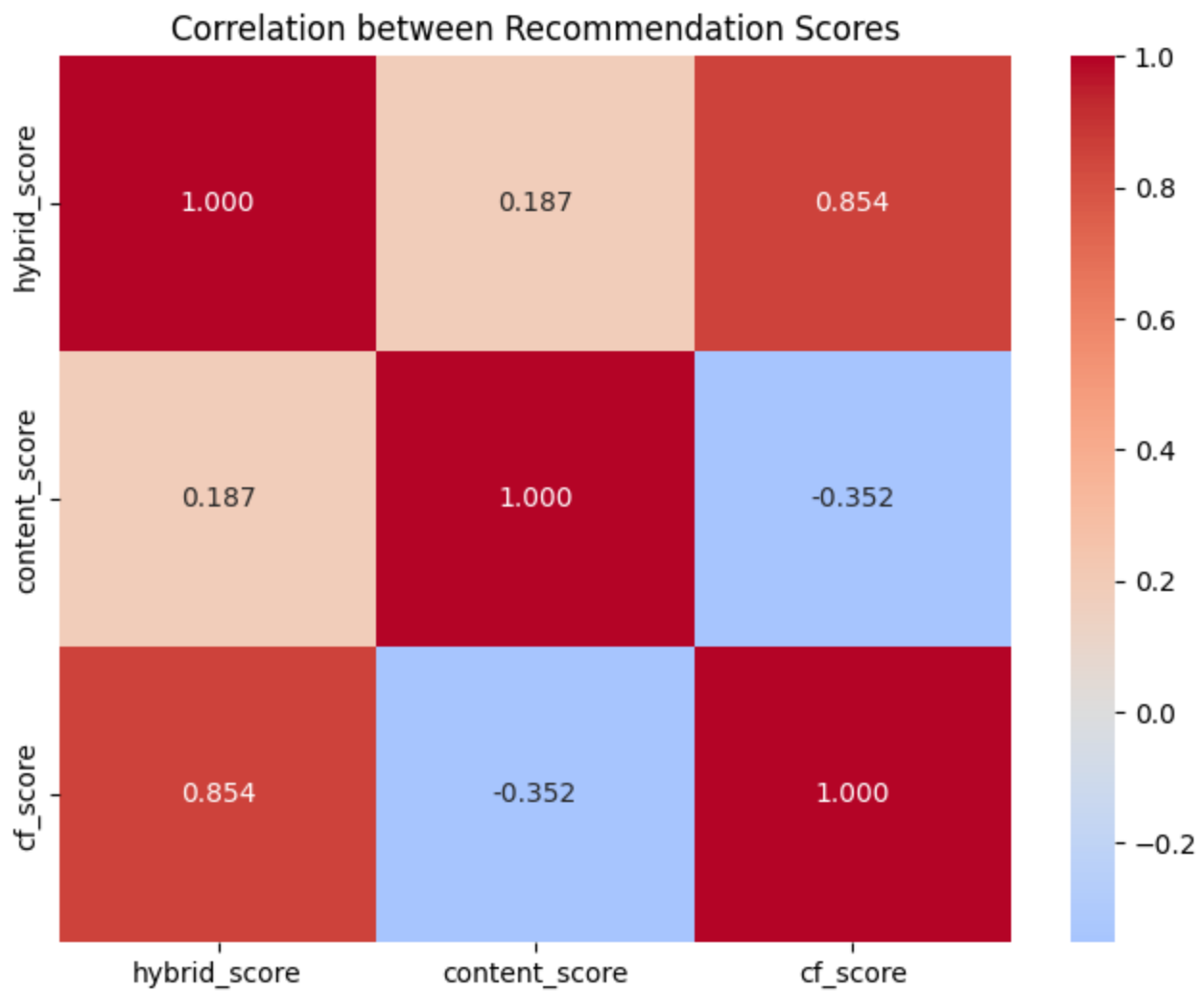


#### CORRELATION ANALYSIS

=====

#### Correlation Matrix:

	hybrid_score	content_score	cf_score
hybrid_score	1.000	0.187	0.854
content_score	0.187	1.000	-0.352
cf_score	0.854	-0.352	1.000



#### PRECISION AND RECALL AT K=5

=====

Average Precision@5: 0.590

Average Recall@5: 0.026

Average NDCG@5: 0.748

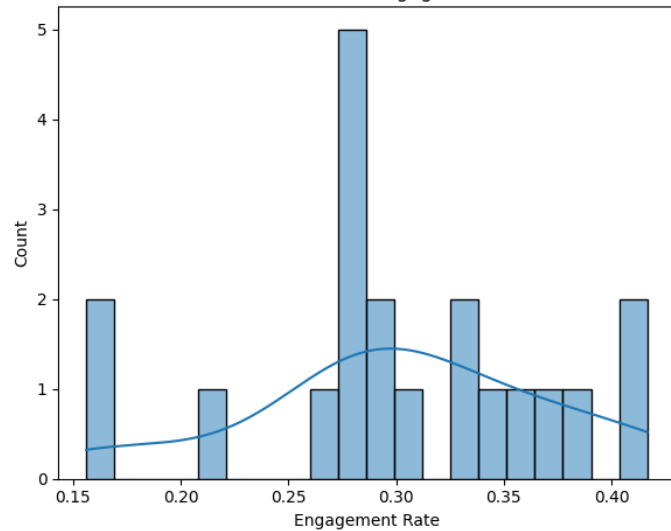
#### USER ENGAGEMENT ANALYSIS

=====

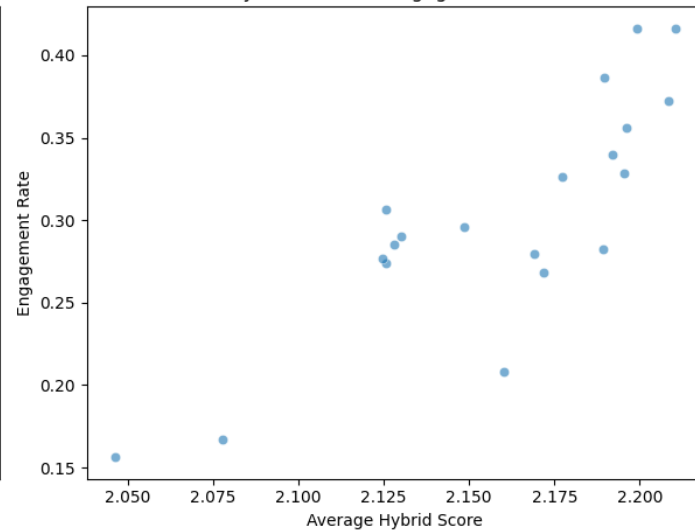
Top 10 Most Engaged Users:

input_user	engagement_rate	relevant_recommendations
user_11	0.416	152.0
user_8	0.416	152.0
user_7	0.386	141.0
user_17	0.373	136.0
user_3	0.356	130.0
user_2	0.340	124.0
user_6	0.329	120.0
user_16	0.326	119.0
user_4	0.307	112.0
user_15	0.296	108.0

Distribution of User Engagement Rates



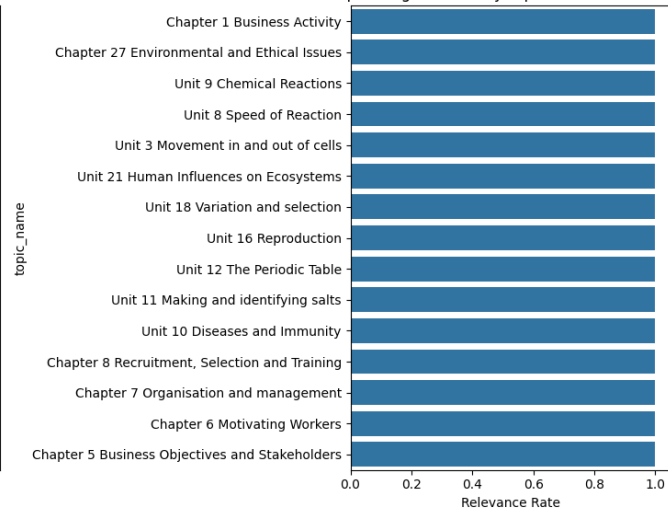
Hybrid Score vs Engagement Rate



Top 15 Most Frequently Recommended Topics



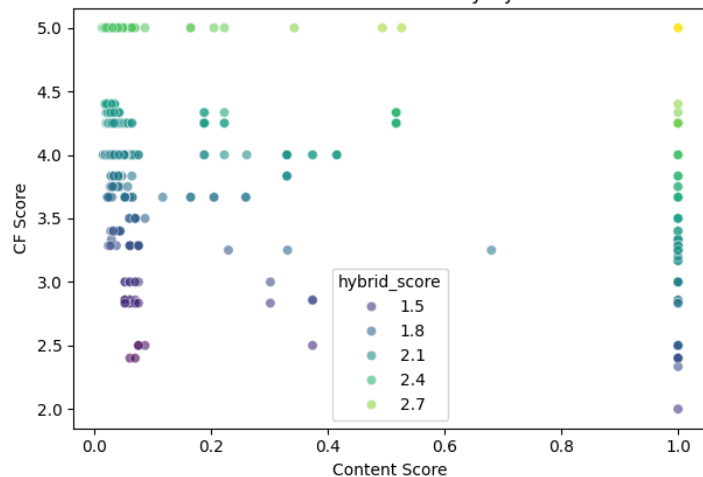
Top 15 Highest Quality Topics (Relevance Rate)



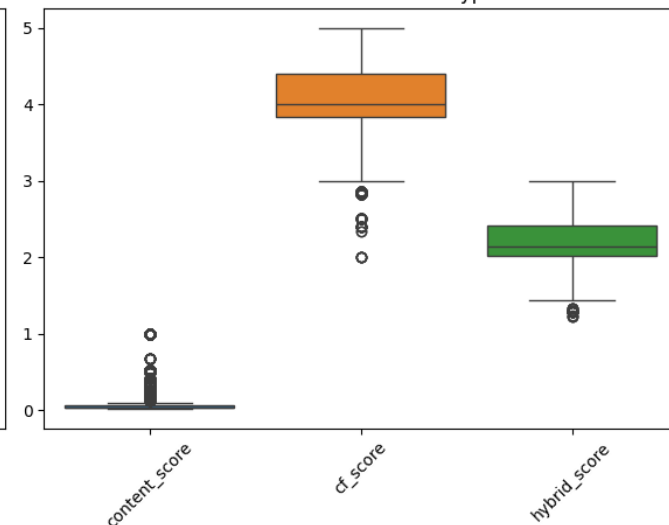
## HYBRID MODEL COMPONENT ANALYSIS

	content_score	cf_score	hybrid_score
count	7300.000	7300.000	7300.000
mean	0.166	4.150	2.158
std	0.308	0.582	0.277
min	0.014	2.000	1.231
25%	0.029	3.833	2.012
50%	0.038	4.000	2.140
75%	0.058	4.400	2.417
max	1.000	5.000	3.000

Content vs CF Scores Colored by Hybrid Score



Distribution of All Score Types





# COMPREHENSIVE EVALUATION REPORT

=====

Total Recommendations: 7,300  
Average Precision@5: 0.590  
Average Recall@5: 0.026  
Average NDCG@5: 0.748  
Average User Engagement Rate: 0.302  
Average Hybrid Score: 2.158  
Content-CF Correlation: -0.352  
Evaluation metrics saved to evaluation\_metrics.csv  
All visualizations saved as PNG files

In [ ]: