Privrank for Social Media

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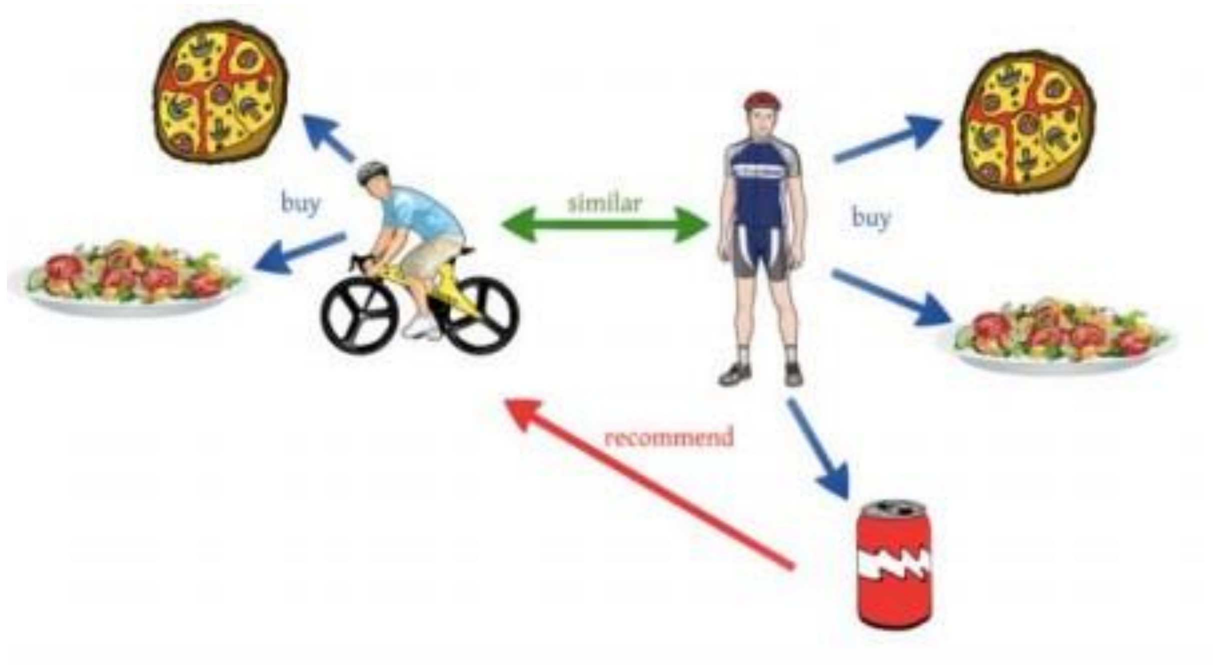
Priv-Rank for Social Media

Collaborative Filtering:

Most websites like Amazon, YouTube, and Netflix use collaborative filtering as a part of their sophisticated recommendation systems.

Collaborative filtering is based on the idea that similar users tend to have similar tastes.



Collaborative filtering systems have many forms, but many common systems can be reduced to two steps:

1. Look for users who share the same rating patterns with the active user (the user whom the prediction is for).
2. Use the ratings from those like-minded users found in step 1 to calculate a prediction for the active user

EXPLANATION:

1. Loading the dataset

We currently have a dataset of users containing 4 things. UserID, gender, age and posts they liked.

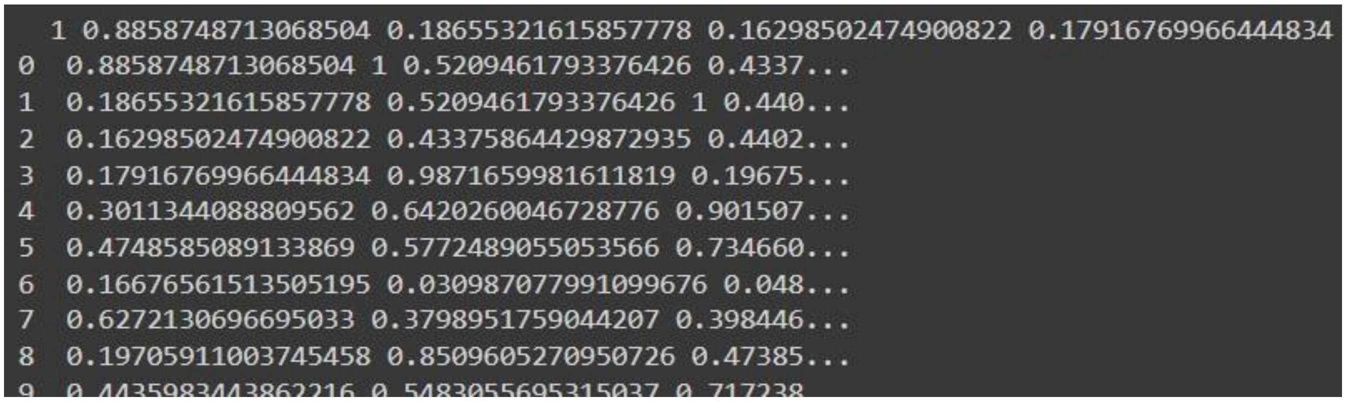
For privacy reasons, we did not take fields which could be used to back track to the original user like Name, DOB, etc.

2. Looking for similar users / Pre-processing the dataset

Firstly, we normalize the data using Standard Scalar.

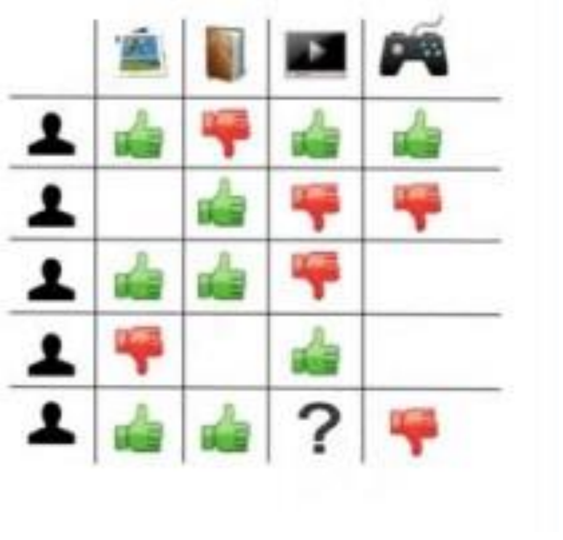
Then used the PCA (Principle Component Analysis) for dimensionality reduction from 3 to 1.

And then we created the similarity matrix, or we can say correlation matrix.



```
   1 0.8858748713068504 0.18655321615857778 0.16298502474900822 0.17916769966444834
0  0.8858748713068504 1 0.5209461793376426 0.4337...
1  0.18655321615857778 0.5209461793376426 1 0.440...
2  0.16298502474900822 0.43375864429872935 0.4402...
3  0.17916769966444834 0.9871659981611819 0.19675...
4  0.3011344088809562 0.6420260046728776 0.901507...
5  0.4748585089133869 0.5772489055053566 0.734660...
6  0.16676561513505195 0.030987077991099676 0.048...
7  0.6272130696695033 0.3798951759044207 0.398446...
8  0.19705911003745458 0.8509605270950726 0.47385...
9  0.4435983443862216 0.5483055695315037 0.717238
```

3. Recommend person to user



Now that we have users that are most similar to us, we need to find the likeability of each post not seen by our current user. For this we use the following likeliness equation:

$$\sum_{i=1}^{n} x_i \cdot r_i$$

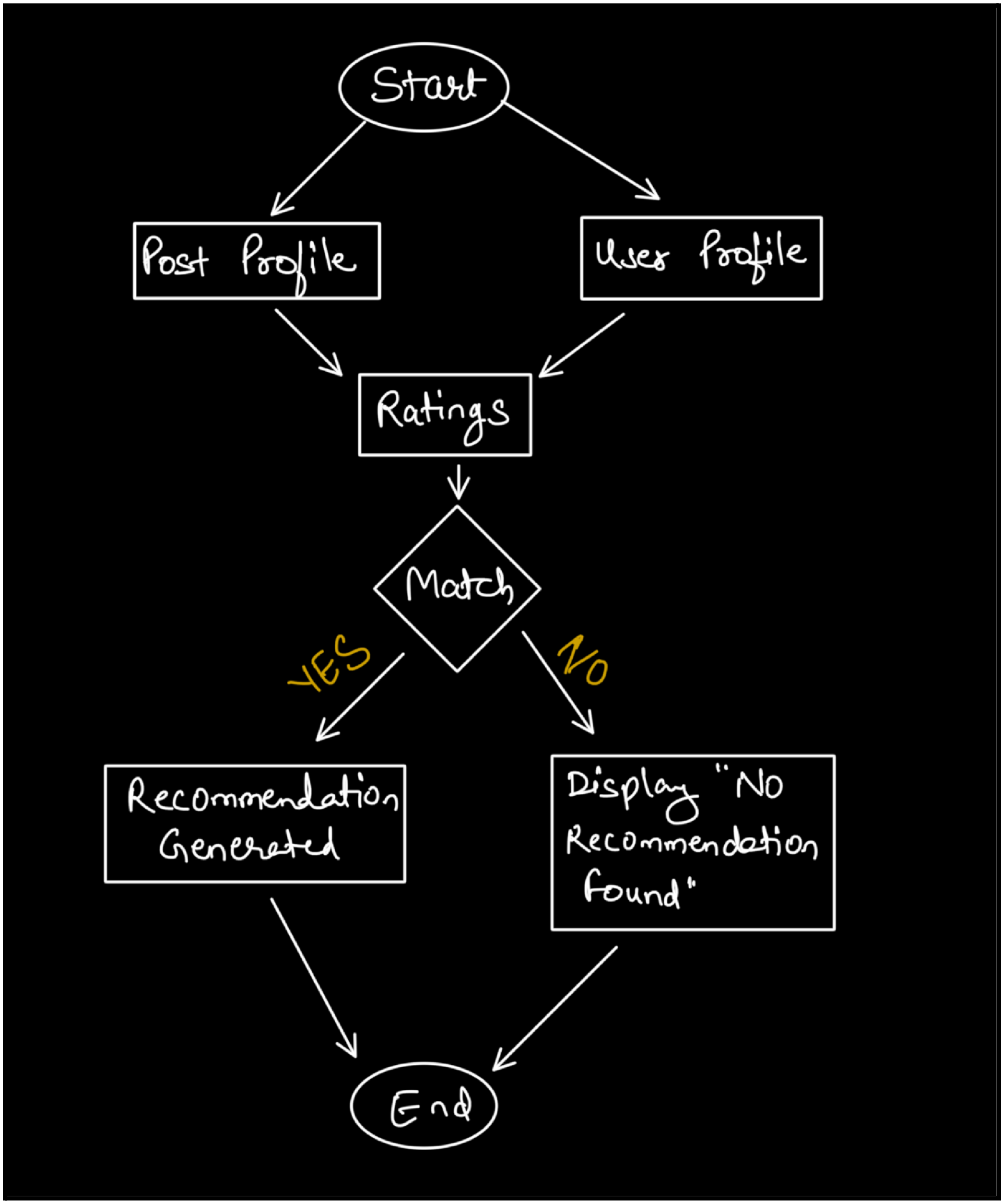
Here “x” is the likeability value of the current user, “i” is the user and “r” is the likeability of that person/user. We perform the above operation on every not visited post and then reverse sort the result. The first value i.e., pot with the highest value is the one which is most likely that the user will like.

What we did for Privacy?

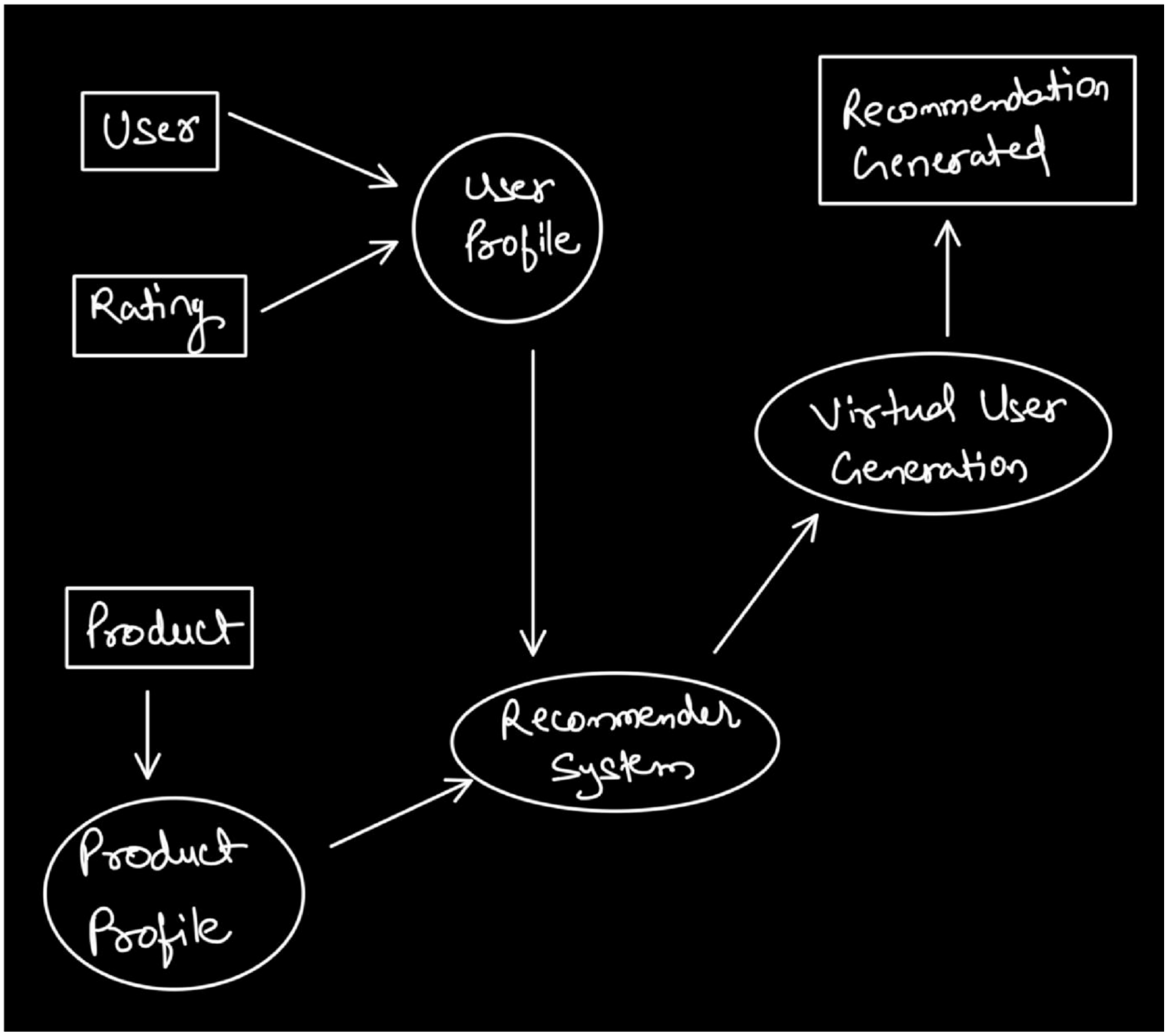
We obfuscated the data 10 - 20% like converting the likes to dislikes and vice versa. So, we could not easily backtrack to the user from their choices. This process was done on the user’s end.

This also allows to prevent inference attacks such as based on user preference we might be able to infer their gender etc., thereby increasing privacy as done in PrivRank research paper.

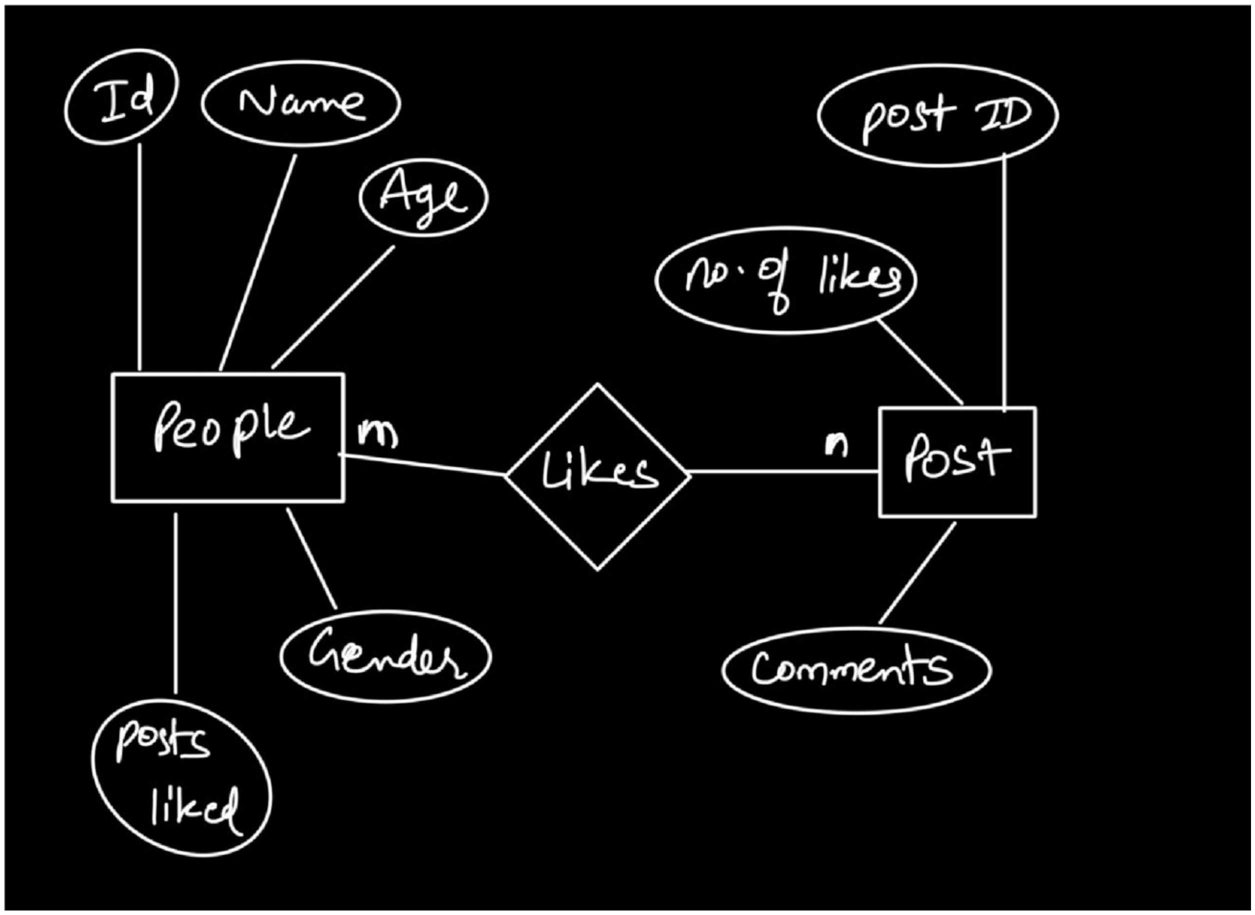
Flowchart:


Start
Post Profile
User Profile
Ratings
Match
YES
NO
Recommendation Generated
Display "NO Recommendation found"
End

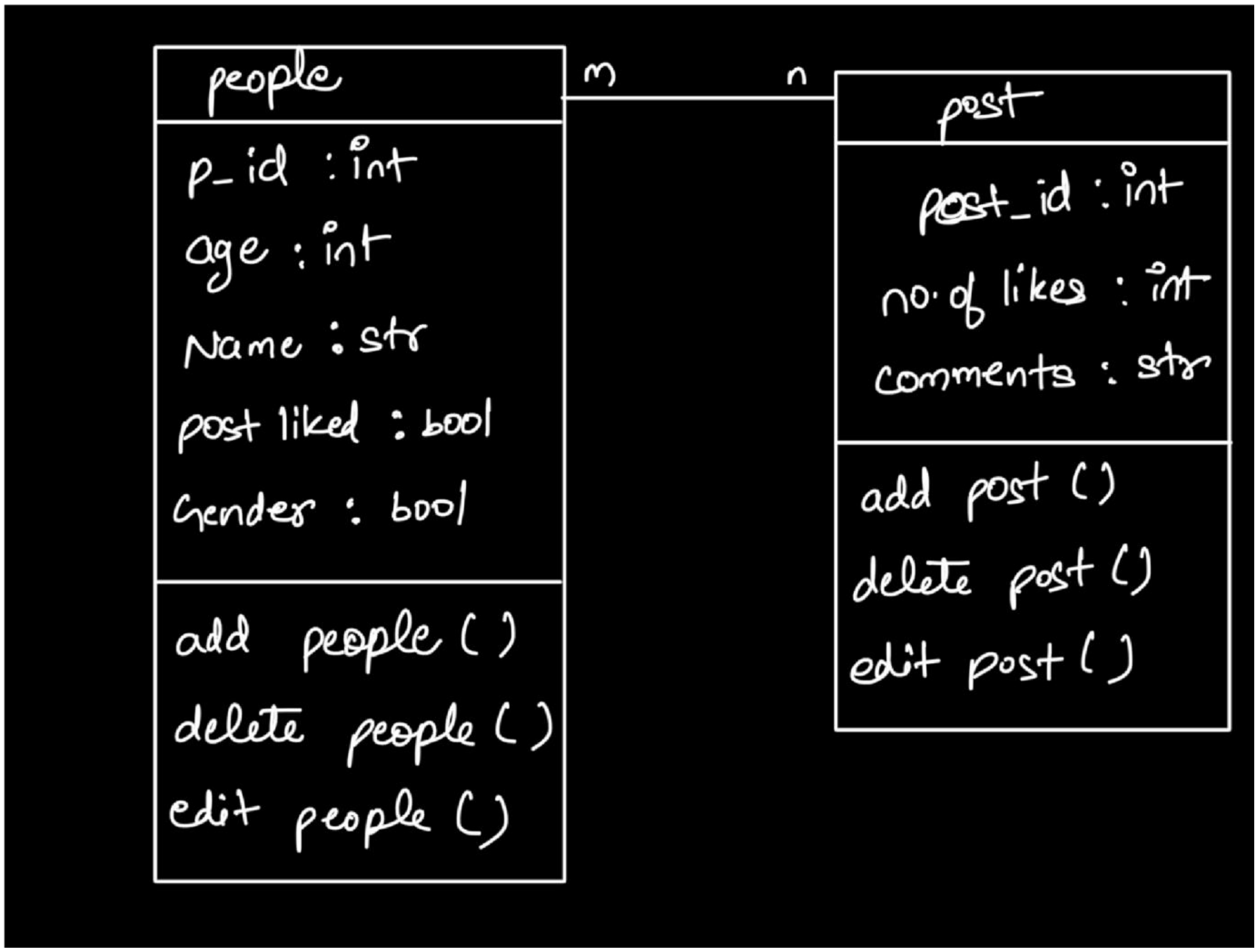
Data Flow Diagram:



ER- Diagram:


Id
Name
Age
People
m
Likes
n
Post
post ID
no. of likes
Gender
posts liked
Comments

UML Diagram:



Code:

From *pre-process.py* file:

```python
import csv
import random



def write_csv(matrix):
    with open('similarity.csv', 'w', newline='') as file:
        writer = csv.writer(file, delimiter=' ')
        for row in matrix:
            writer.writerow(row)
```

```
def f():
    N = 1000 # 1000 -> N; Also need to change in main.py; obfuscation()
call
    res = [[1 for _ in range(0, N)] for _ in range(0, N)]
    for i in range(0, N):
        for j in range(i, N):
            if i != j:
                x = random.random()
                res[i][j] = x
                res[j][i] = x
    return res


result = f()
write_csv(result)
```

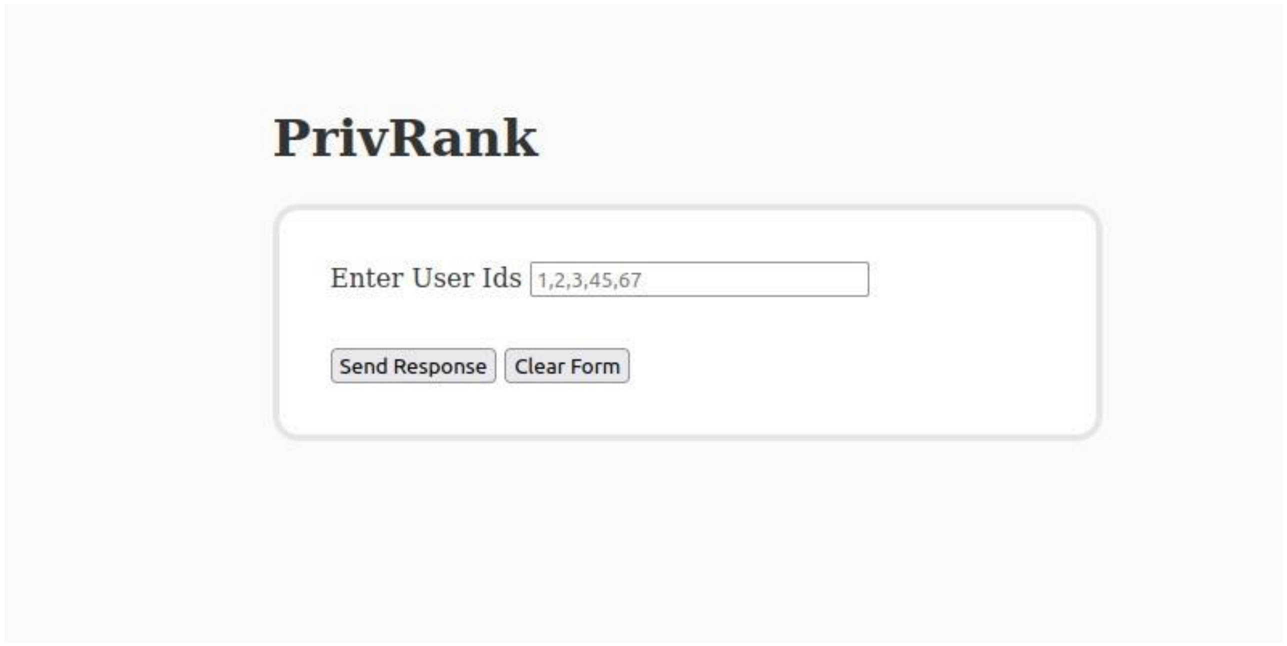
From *main.py* file:

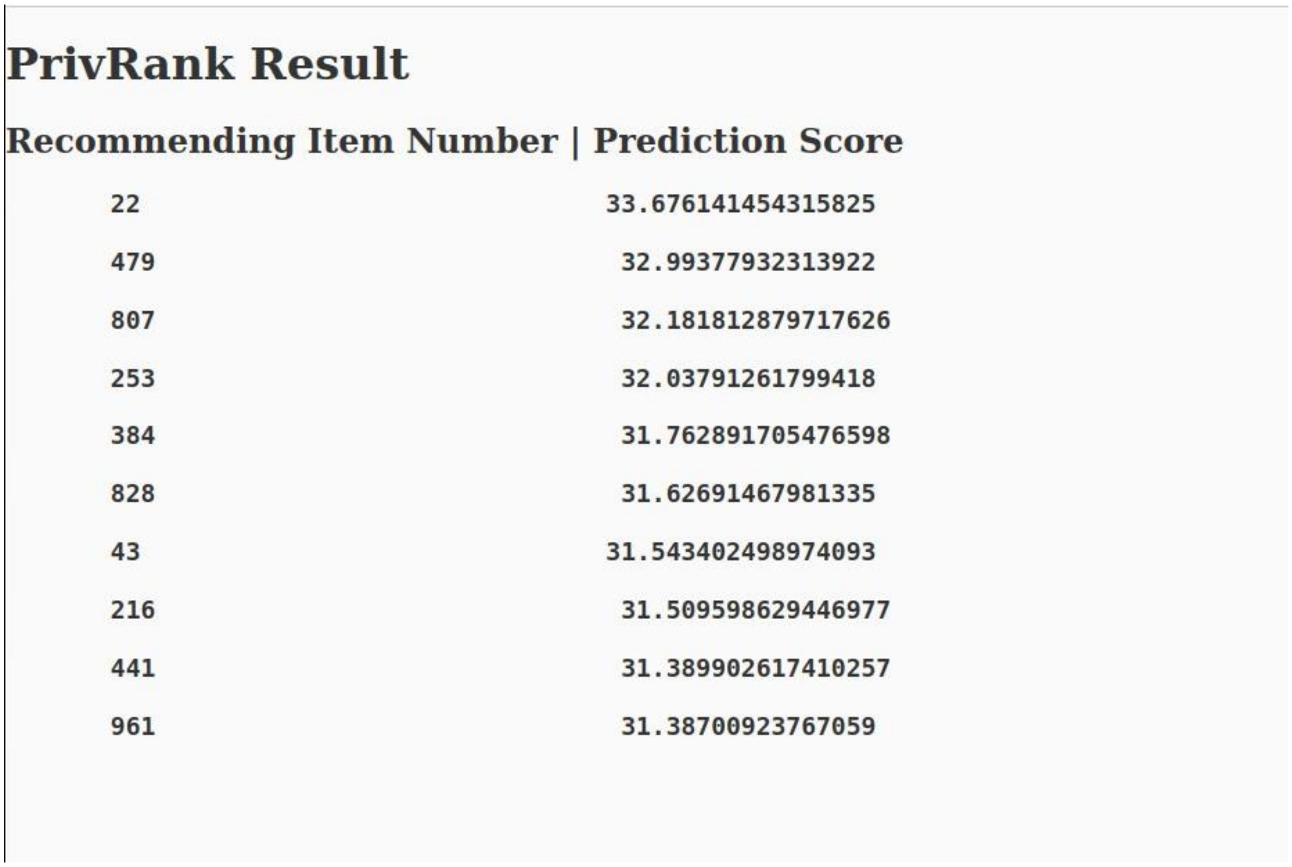
```
import csv
import random
from fastapi import FastAPI, Request, Form
from fastapi.responses import HTMLResponse
from fastapi.staticfiles import StaticFiles
from fastapi.templating import Jinja2Templates


app = FastAPI()

templates = Jinja2Templates(directory="templates")
app.mount("/static", StaticFiles(directory="static"), name="static")


@app.get("/", response_class=HTMLResponse)
```

```
async def input_form(request: Request):
    return templates.TemplateResponse("form.html", {"request": request})


@app.post("/", response_class=HTMLResponse)
```

```
async def recommended_users(request: Request,
                            liked_users: str = Form(...)):
    recommended_users_arr = liked_users.split(',')
    recommended_users_arr = [int(e) for e in recommended_users_arr]

    # 1000 -> N; Also need to change in preprocess.py
    recommended_users_arr = obfuscation(recommended_users_arr, 10, 1000)
    recommended_users_arr = predict(recommended_users_arr)
    res = []
    for id, score in recommended_users_arr:
        res.append(f"       {id}                              {score}")
    return templates.TemplateResponse("result.html", {"request": request,
"res": res})


def predict(arr):
    arr=set(arr)
    matrix=get_similarity_matrix()
    N=len(matrix)

    scores=[[0, i] for i in range(0, N)]
    for liked_item in arr:
        for idx in range(0, N):
            scores[idx][0] += matrix[liked_item][idx]
    scores.sort(reverse=True)
    res=[]
    for score, val in scores:
        if val not in arr:
            res += [[val, score]]
        if len(res) == 10:
            break
    return res



def get_similarity_matrix():
    with open('similarity.csv', newline='') as file:
        reader=csv.reader(file, delimiter=' ')
        matrix=[]
        for row in reader:
            matrix += [[float(e) for e in row]]
        return matrix



def obfuscation(arr, THRESHOLD, N):
    THRESHOLD=int((THRESHOLD*N)/100)
    THRESHOLD=min(THRESHOLD, N)
    indexes=random.sample(range(0, N), THRESHOLD)
    res=set()

    for idx in set(indexes+arr):
        if random.randint(0, 1):
            res.add(idx)
    return sorted(res)
```

Output:





PrivRank Result

Recommending Item Number | Prediction Score

```
    22                       33.676141454315825
    479                       32.99377932313922
    807                       32.181812879717626
    253                       32.03791261799418
    384                       31.762891705476598
    828                       31.62691467981335
    43                       31.543402498974093
    216                       31.509598629446977
    441                       31.389902617410257
    961                       31.38700923767059
```