Recommender Systems

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Recommender Systems

- Algorithms suggesting relevant items to users
- Recommender system is an essential part in industry area

NETFLIX

  - 80% of movies watched came from recommendations

YouTube

  - 60% of video clicks came from recommendations

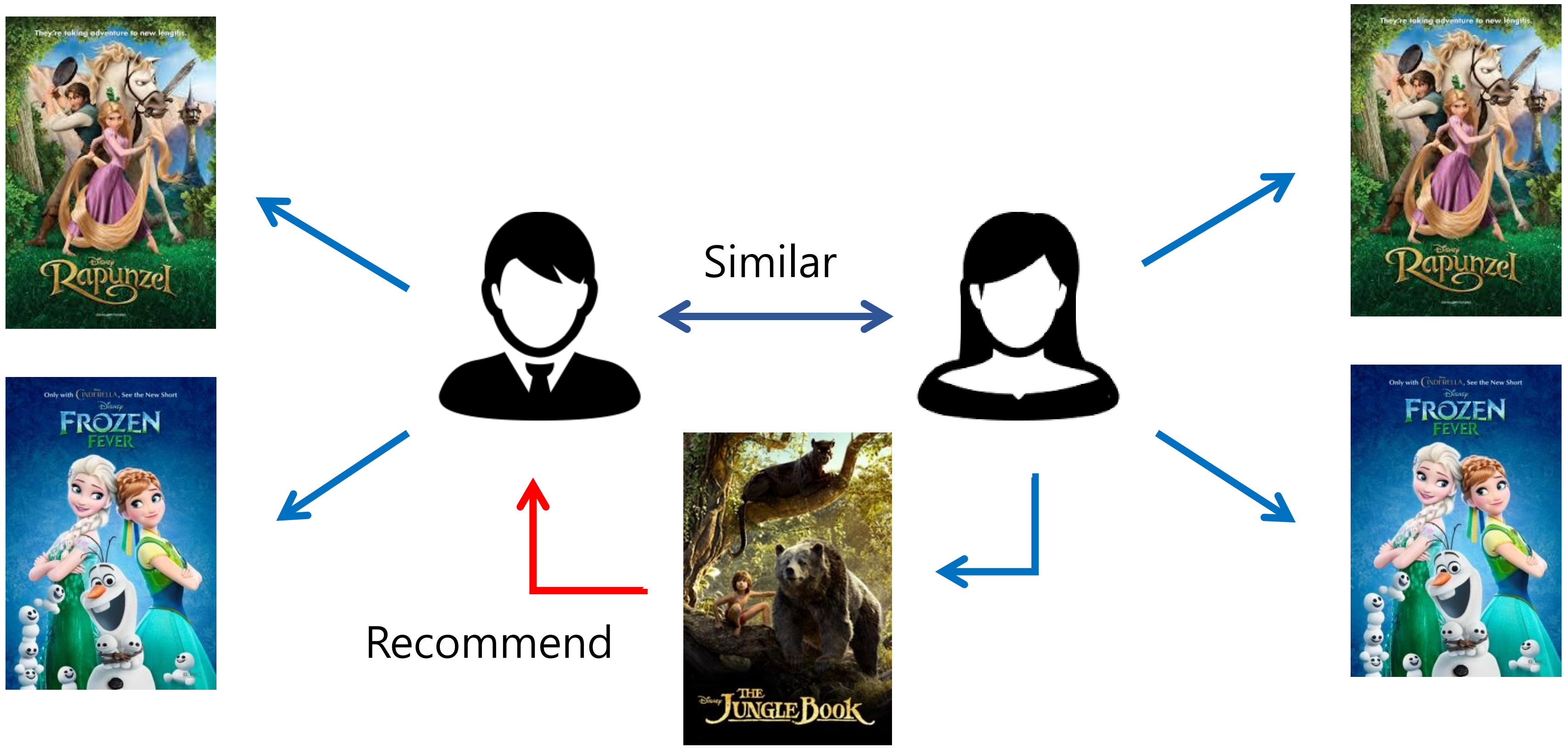
Recommendation Systems

- Recommend the items by predicting unknown rating values

			
	?	?	★ × 1
	★ × 5	?	?
	?	★ × 3	?

Collaborative Filtering

- Recommend items to users based on other users with similar patterns of selected items



Matrix Factorization (행렬 분해법)

- Matrix factorization is one of the popular method for recommendation systems
  - [M. Andriy and R.Salakhutdinov: NIPS 2008]
  - [X. He, H. Zhang, M. Kan and T. Chua: SIGIR 2016]
- The method predicts unknown rating values from incomplete rating matrix R

	I_1	$\cdots$	I_j	$\cdots$	I_M
u_1	5	$\cdots$	?	$\cdots$	?
$\vdots$	$\vdots$	$\cdots$	$\vdots$	$\cdots$	$\vdots$
u_i	?	$\cdots$	?	$\cdots$	3
$\vdots$	$\vdots$	$\cdots$	$\vdots$	$\cdots$	$\vdots$
u_N	5	$\cdots$	1	$\cdots$	1

Incomplete rating matrix
$R \in \mathbb{R}^{N \times M}$

Matrix Factorization (행렬 분해법)

- Matrix factorization
  - The latent models of users and items are represented k-dimensional vector
  - u_i^T : i-th user's latent vector, v_j : j-th item's latent vector
  - The estimated value of rating $\hat{r}_{ij}$ is approximated by $u_i^T v_j$ ($\hat{r}_{ij} = u_i^T v_j$)

	I_1	$\cdots$	I_j	$\cdots$	I_M
u_1	5	$\cdots$	?	$\cdots$	?
$\vdots$	$\vdots$	$\cdots$	$\vdots$	$\cdots$	$\vdots$
u_i	?	$\cdots$	?	$\cdots$	3
$\vdots$	$\vdots$	$\cdots$	$\vdots$	$\cdots$	$\vdots$
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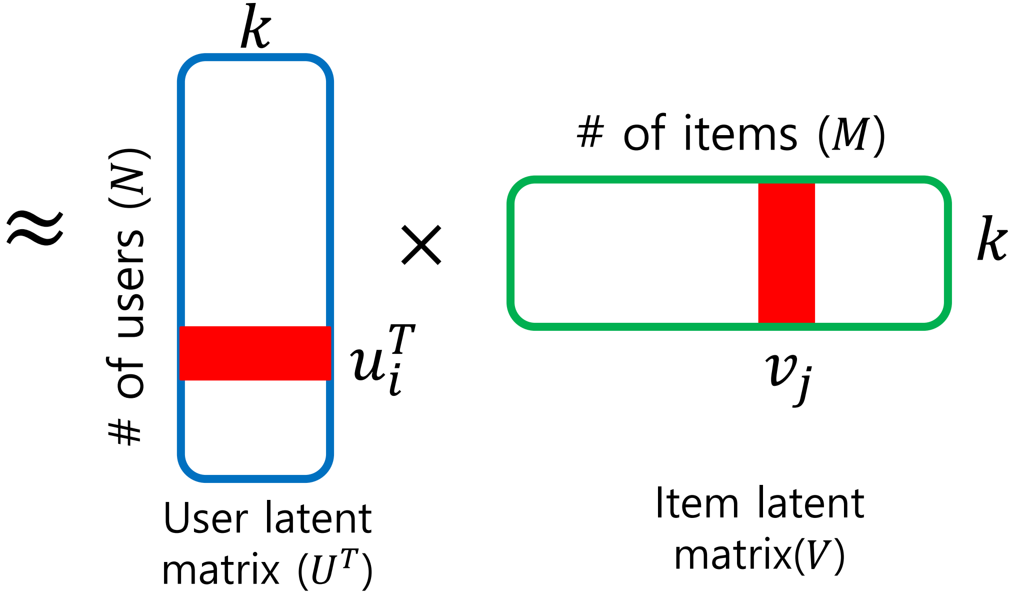
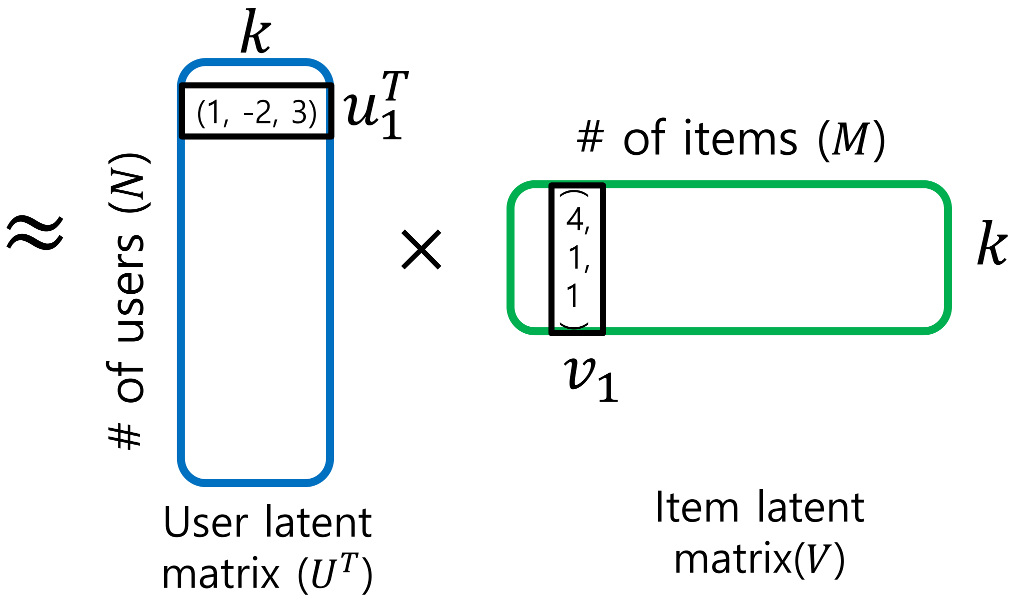


Matrix Factorization

- The goal of Matrix factorization
  - Predict unknown rating values
  - Find latent models of users (U) and items (V)
  - The estimated value of rating $\hat{r}_{ij}$ is approximated by $u_i^T v_j$ ($\hat{r}_{ij} = u_i^T v_j$)

	I_1	…	I_j	…	I_M
u_1	5	…	?	…	?
⋮	⋮	…	⋮	…	⋮
u_i	?	…	?	…	3
⋮	⋮	…	⋮	…	⋮
u_N	5	…	1	…	1



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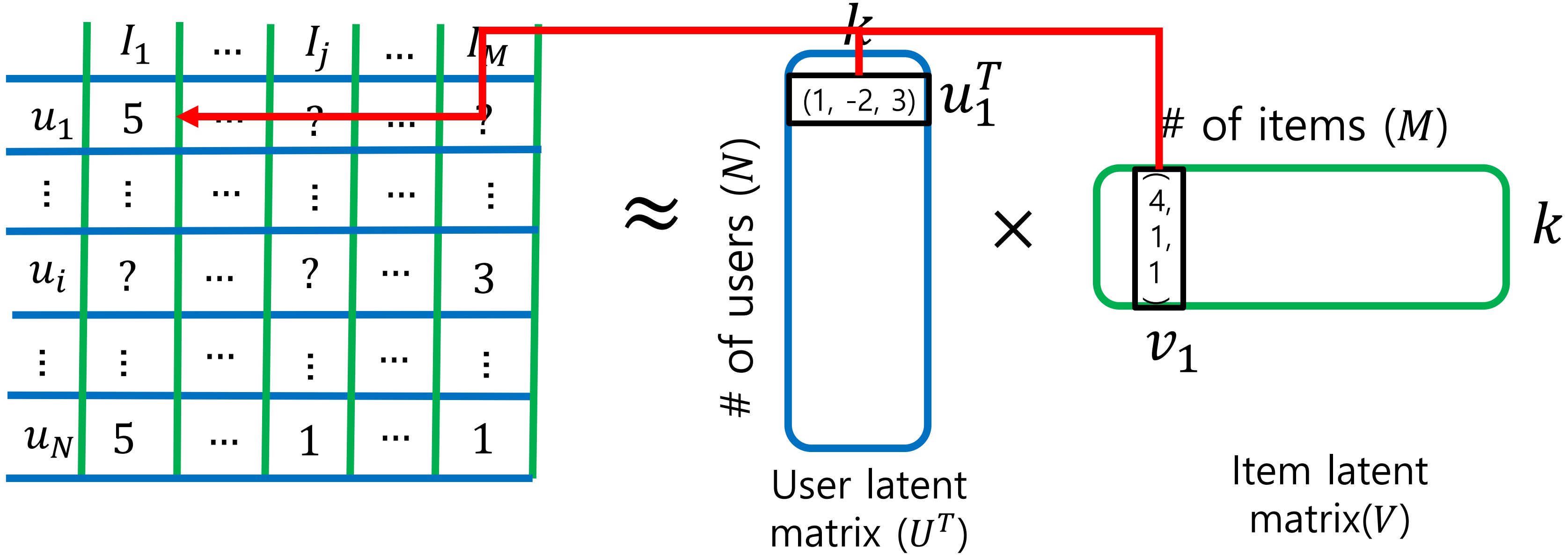

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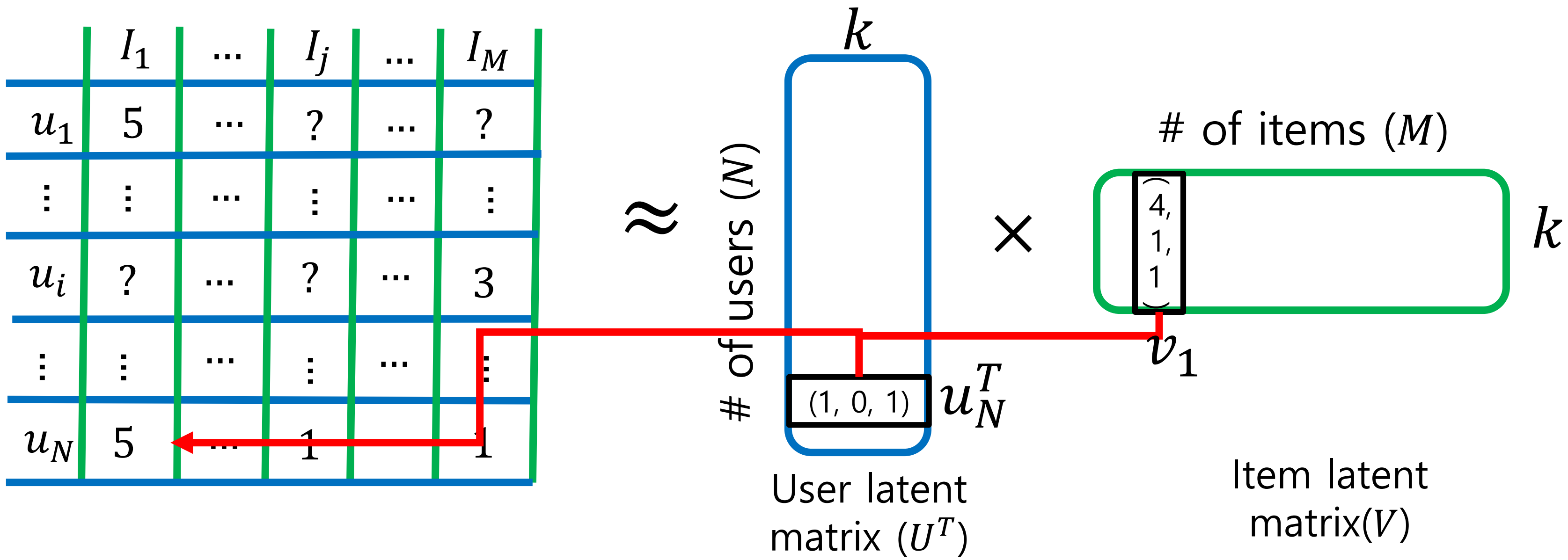

Matrix Factorization

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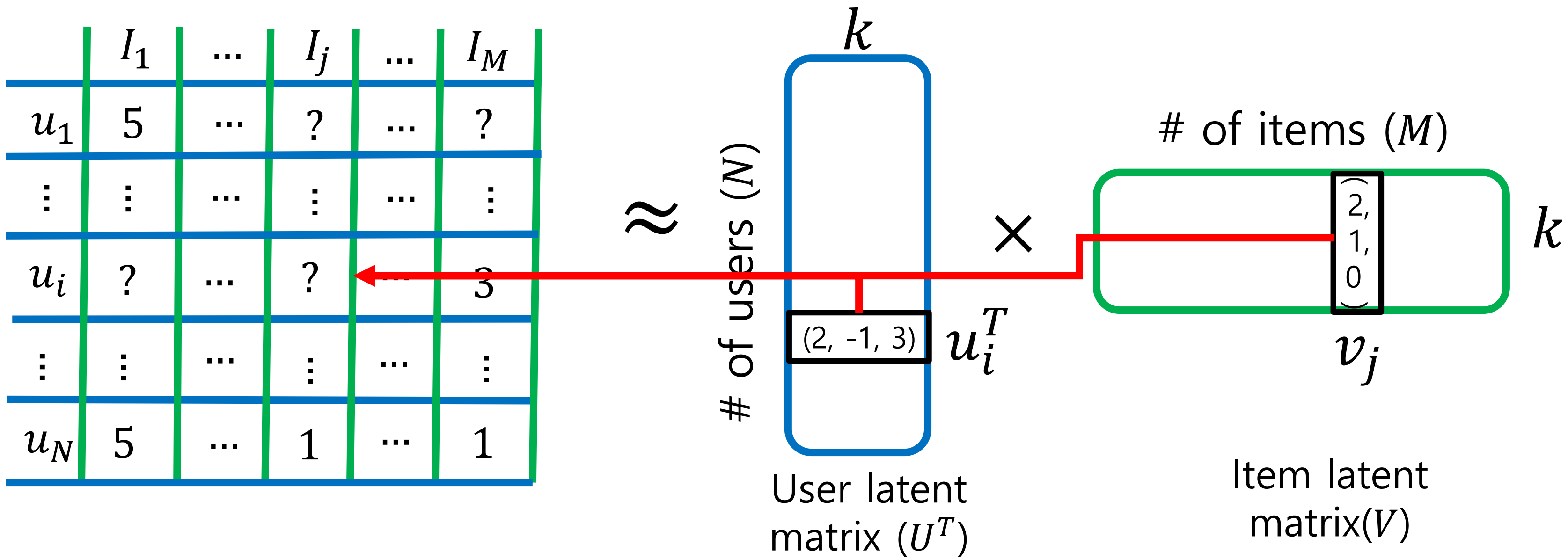

Matrix Factorization

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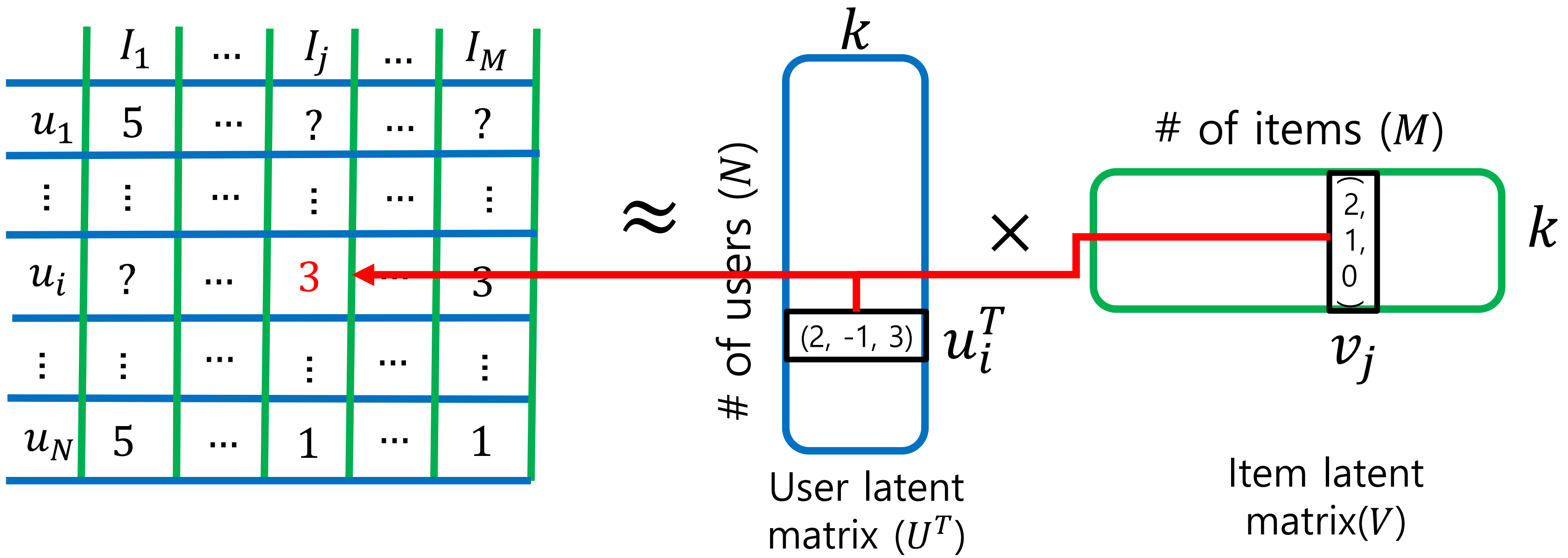
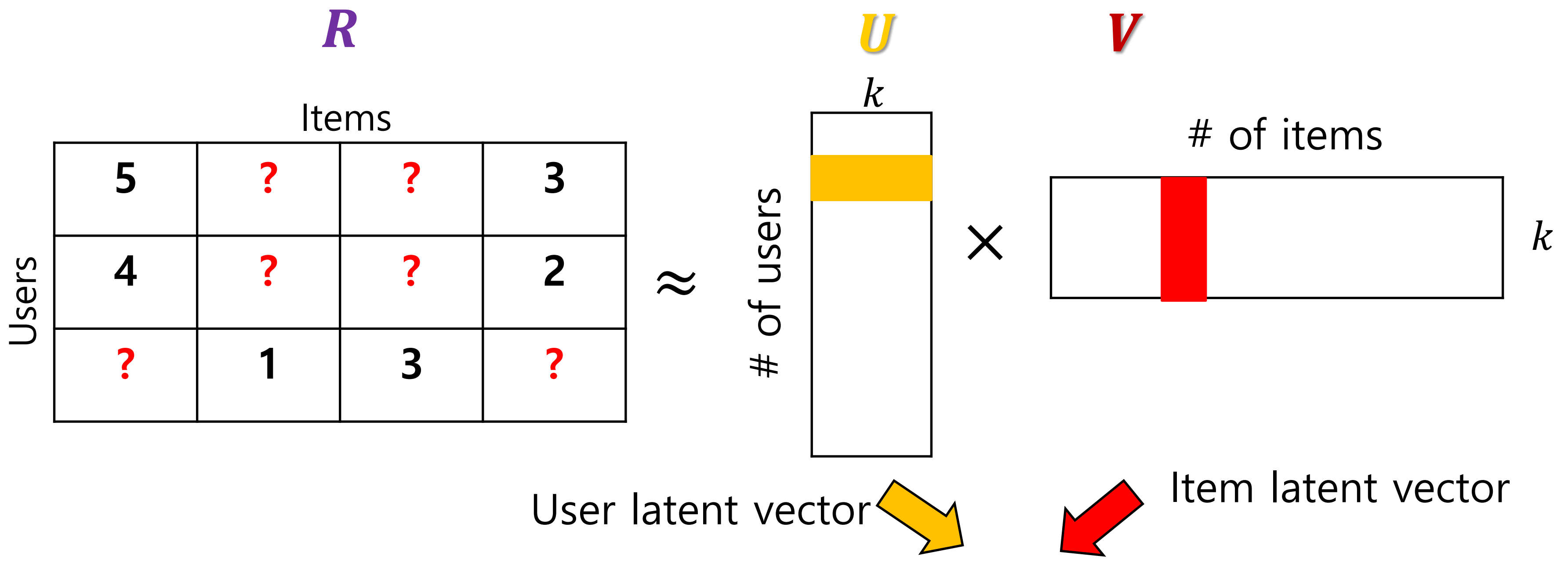


Matrix Factorization

- A popular model-based collaborative filtering
- Matrix factorization is introduced because of sparsity of real data



$$r_{ij} \approx u_i^T v_j$$

Matrix Factorization

- Given
  - Sparse rating matrix $R \in \mathbb{R}^{N \times M}$
- Minimize
  - $J(\boldsymbol{U}, \boldsymbol{V}) = \sum_i^N \sum_j^M I_{ij} \left(r_{ij} - \boldsymbol{u}_i^T \boldsymbol{v}_j \right)^2$
  - where
    - Latent user matrix $\boldsymbol{U} = [\boldsymbol{u}_1 \quad \cdots \quad \boldsymbol{u}_N] \in \mathbb{R}^{k \times N}$
    - Latent item matrix $\boldsymbol{V} = [\boldsymbol{v}_1 \quad \cdots \quad \boldsymbol{v}_M] \in \mathbb{R}^{k \times M}$
    - I_{ij} means indicator function s.t
      - $I_{ij} = 1$ if user i rated item j
      - $I_{ij} = 0$, otherwise

Matrix Factorization

- $J(\boldsymbol{U},\boldsymbol{V}) = \sum_i^N \sum_j^M I_{ij} e_{ij}^2$

  where $e_{ij} = r_{ij} - u_i^T v_j = r_{ij} - \sum_{k=1}^K u_{ik} v_{kj}$
- Gradient descent

$$\frac{\partial}{\partial u_{ik}} e_{ij}^2 = 2e_{ij} \frac{\partial e_{ij}}{\partial u_{ik}} = -2e_{ij} v_{kj}$$
$$\frac{\partial}{\partial v_{kj}} e_{ij}^2 = 2e_{ij} \frac{\partial e_{ij}}{\partial v_{kj}} = -2e_{ij} u_{ik}$$

$$u_{ik} \leftarrow u_{ik} - \eta \left(\frac{\partial}{\partial u_{ik}} e_{ij}^2 \right) = u_{ik} + 2\eta e_{ij} v_{kj}$$
$$v_{kj} \leftarrow v_{kj} - \eta \left(\frac{\partial}{\partial v_{kj}} e_{ij}^2 \right) = v_{kj} + 2\eta e_{ij} u_{ik}$$

Binary Matrix Factorization

- Problem definition
  - Given
    - Binary matrix $I \in \mathbb{R}^{N \times M}$
  - Minimize
    - $J(\boldsymbol{U}, \boldsymbol{V}) = \sum_i^N \sum_j^M \left(I_{ij} - u_i^T v_j\right)^2$
    - where
      - Latent user matrix $U \in \mathbb{R}^{k \times N}$
      - Latent item matrix $V \in \mathbb{R}^{k \times M}$
      - I_{ij} means indicator function s.t
        - $I_{ij} = 1$ if user i rated item j
        - $I_{ij} = 0$, otherwise
- Application
  - Click-stream data,

Implementing MF with PyTorch

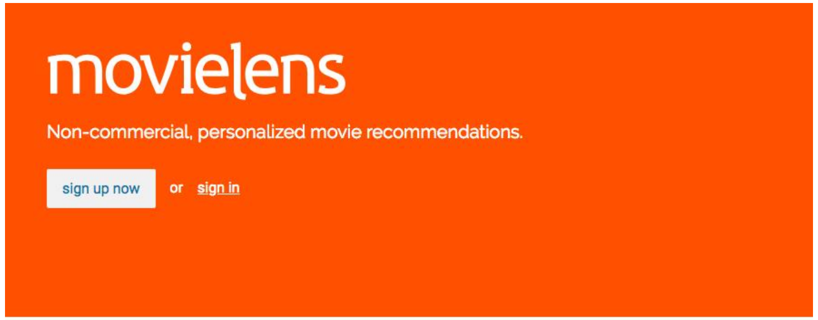
[참고: 우노!](https://wooono.tistory.com/150)

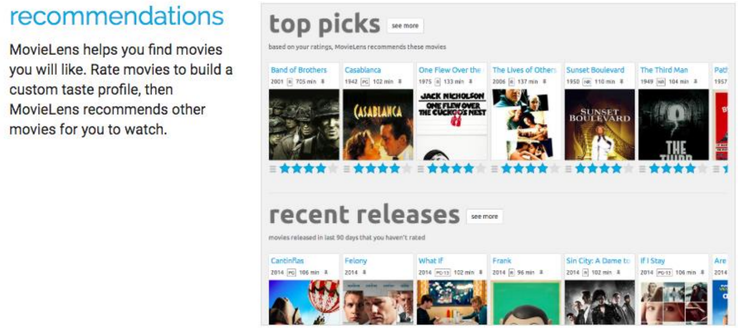
https://wooono.tistory.com/150

MovieLens Dataset

- https://grouplens.org/datasets/movielens/
- # ratings: **100k**, 1M, 10M, 20M, 25M

Version	Users	Movies	Ratings	Released	Format
100k	1k	1.7k	100k	4/1998	Txt
1M	6k	4k	1M	2/2003	Csv
10M	72k	10k	10M	1/2009	Csv
20M	138k	27k	20M	4/2015	Csv
Latest	230k	27k	21M	4/2015	Csv





Load MovieLens dataset

```python
import torch
import pandas as pd
import torch.nn.functional as F
import matplotlib.pyplot as plt
from torch import nn
from torch.utils.data import Dataset, DataLoader
```

```python
class MovieLensDataset(Dataset):
    def __init__(self, datapath):
        self.data_pd = pd.read_csv(datapath, sep="\t", names=['user', 'movie', 'rating', 'timestamp'])
        self.items = torch.LongTensor(self.data_pd['movie'])
        self.users = torch.LongTensor(self.data_pd['user'])
        self.ratings = torch.FloatTensor(self.data_pd['rating'])

    def __len__(self):
        return len(self.ratings)
    def __getitem__(self,idx):
        return self.users[idx], self.items[idx], self.ratings[idx]

    def get_datasize(self):
        return self.users.max()+1, self.items.max()+1, len(self.ratings)

train_data = MovieLensDataset("datasets/ml-100k/ua.base")
test_data = MovieLensDataset("datasets/ml-100k/ua.test")

batch_size = 128
train_loader = DataLoader(train_data, batch_size = batch_size, shuffle = True)
test_loader = DataLoader(test_data, batch_size = batch_size, shuffle = False)
```

Initialization

```
n_users, n_items, n_ratings = train_data.get_datasize()
_, _, n_ratings_test = test_data.get_datasize()
```

```
class MF(nn.Module):

    def __init__(self, num_users, num_items, rank = 10):
        super().__init__()
        self.U = torch.nn.Parameter(torch.randn(num_users, rank))
        self.V = torch.nn.Parameter(torch.randn(num_items, rank))

    def forward(self, users, items):
        ratings = torch.sum(self.U[users]*self.V[items], dim = -1)
        return ratings
```

```
mf_model = MF(n_users, n_items, rank = 16)
optimizer = torch.optim.Adam(mf_model.parameters(), lr= 0.01)
criterion = nn.MSELoss()
```

Training

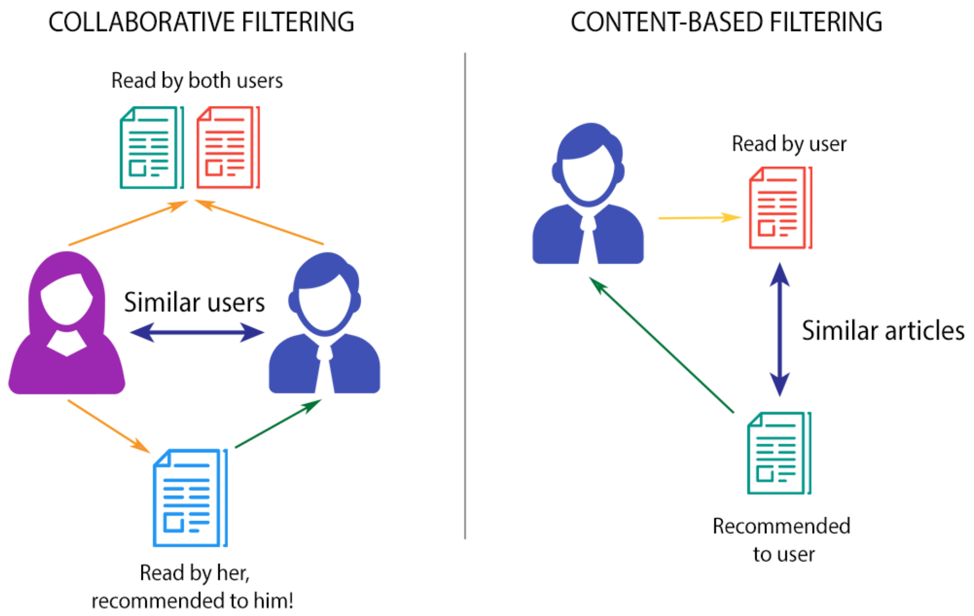
```
for epoch in range(20):
    cost = 0
    for users, items, ratings in train_loader:
        optimizer.zero_grad()
        ratings_pred = mf_model(users,items)
        loss = criterion(ratings_pred ,ratings)
        loss.backward()
        optimizer.step()
        cost += loss.item() * len(ratings)


    cost/=n_ratings

    print(f"Epoch: {epoch}")
    print("train cost: {:.6f}" .format(cost))

    #print(ratings_pred[:5])
    #print(ratings[:5])

    cost_test = 0
    for users, items, ratings in test_loader:
        ratings_pred = mf_model(users,items)
        loss = criterion(ratings_pred ,ratings)
        cost_test += loss.item() * len(ratings)

    cost_test/=n_ratings_test
    print("test cost: {:6f}".format(cost_test))
    #print(ratings_pred[:5])
```

```
Epoch: 0
train cost: 21.231961
test cost: 17.587405
Epoch: 1
train cost: 7.298090
test cost: 5.693044
Epoch: 2
train cost: 1.651690
test cost: 3.067293
Epoch: 3
train cost: 1.063861
test cost: 2.386656
Epoch: 4
train cost: 0.898847
test cost: 2.094314
Epoch: 5
train cost: 0.834799
test cost: 1.957692
Epoch: 6
train cost: 0.801918
test cost: 1.903030
Epoch: 7
train cost: 0.775600
test cost: 1.886208
Epoch: 8
train cost: 0.753672
test cost: 1.838627
Epoch: 9
train cost: 0.731245
test cost: 1.810325
```

Recommender Systems with Deep Learning

Hybrid recommender systems

Types of Recommender Systems



Suffer from Cold start and Sparsity

Limited to recommending content of the same type as the user is already using

Types of Recommender Systems

Collaborative filtering

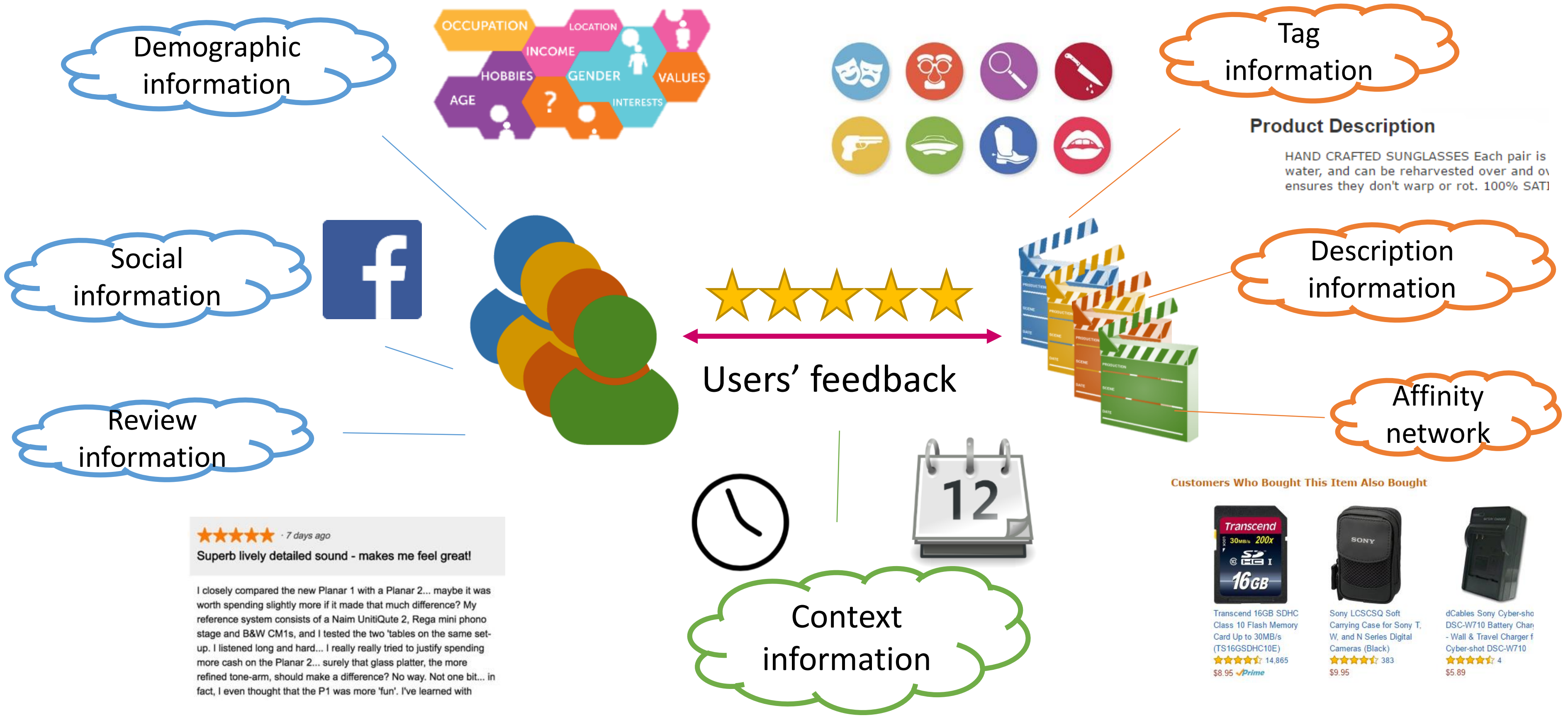
+

Content-based filtering

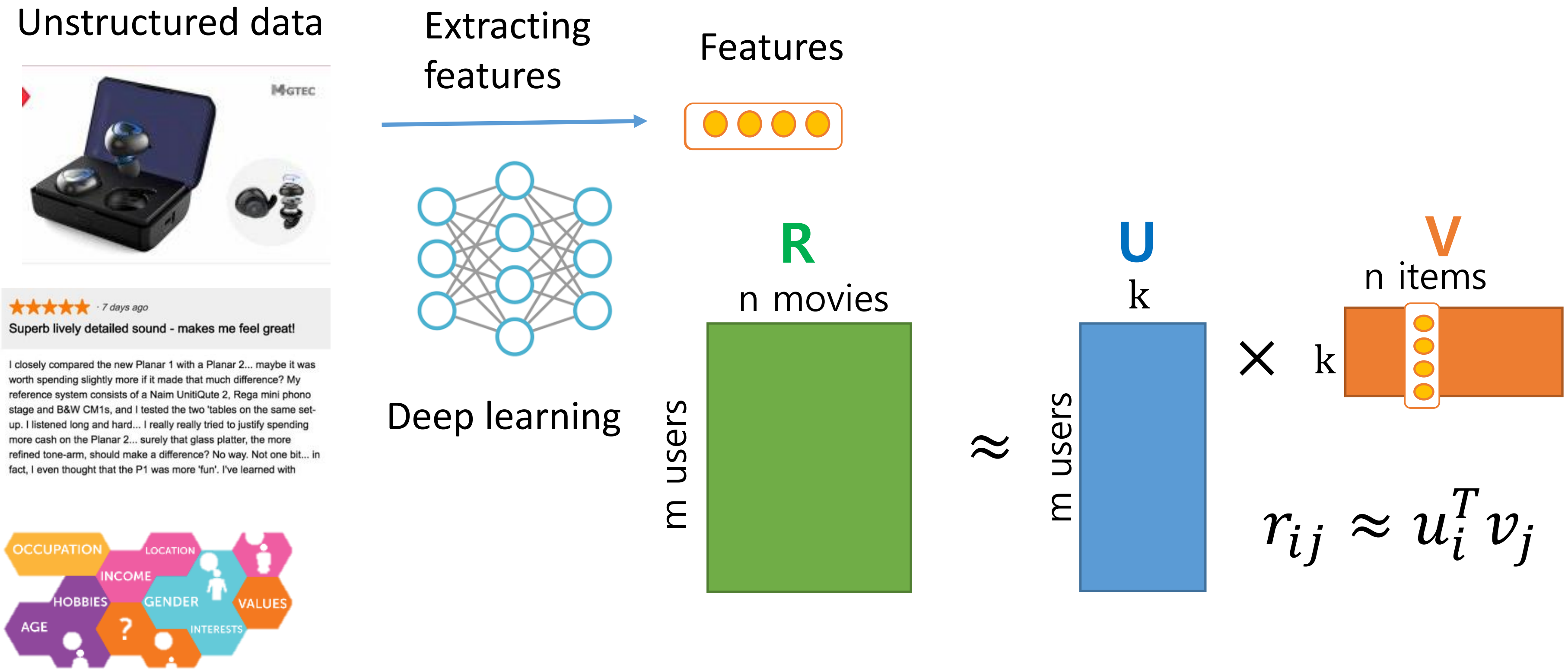
=

Hybrid Recommender System

Hybrid Recommender System



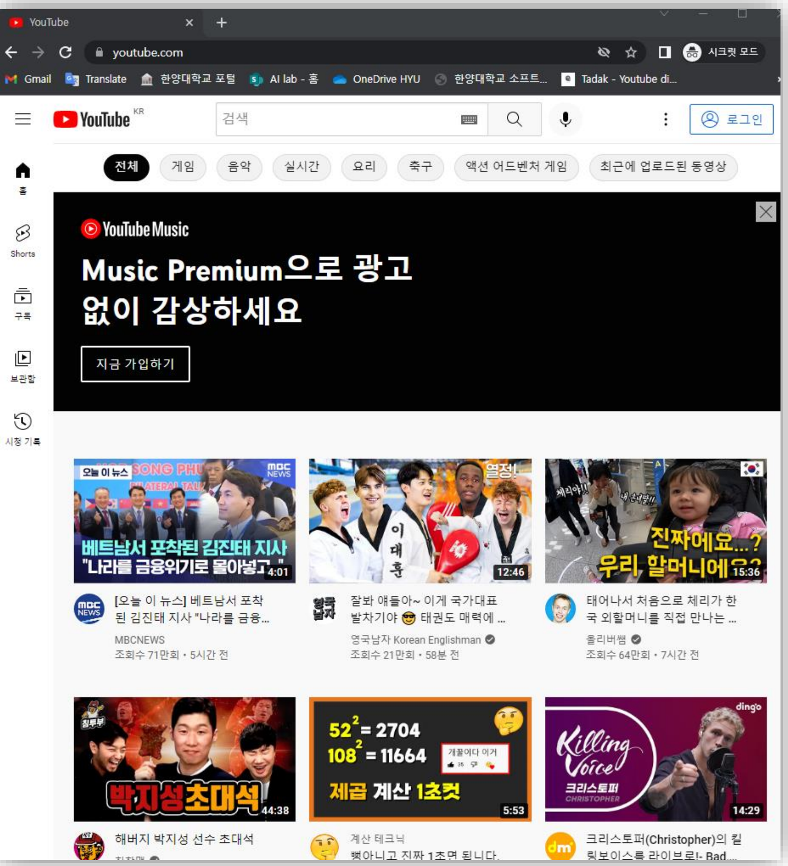
Hybrid Recommender System



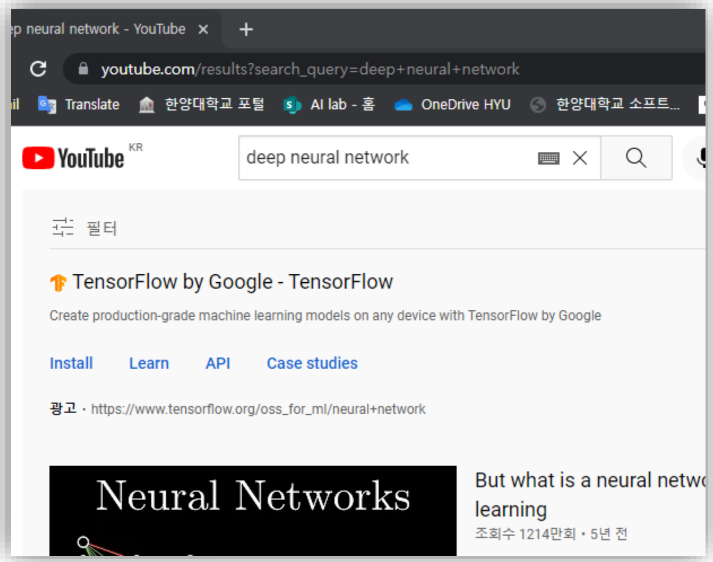
Technologies

Session-based recommender systems

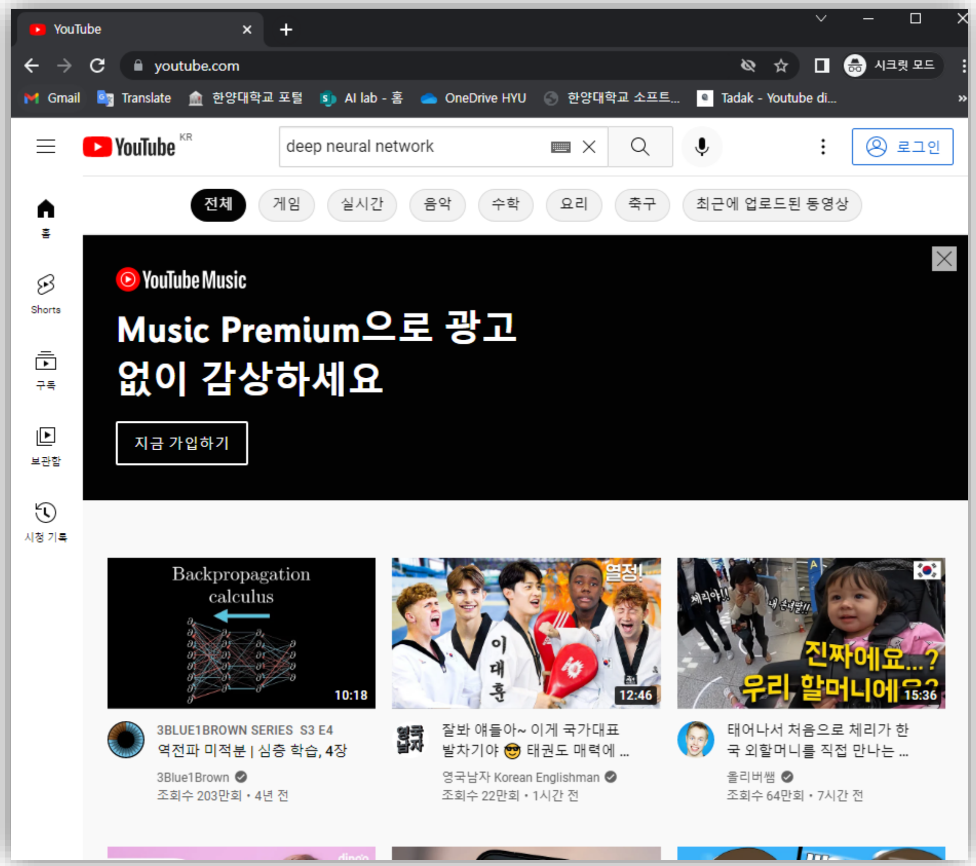
- 로그인 없이 (학습된 사용자 벡터 $\boldsymbol{u}_i$) 없이 추천



1) 로그인없이 접속시 홈화면

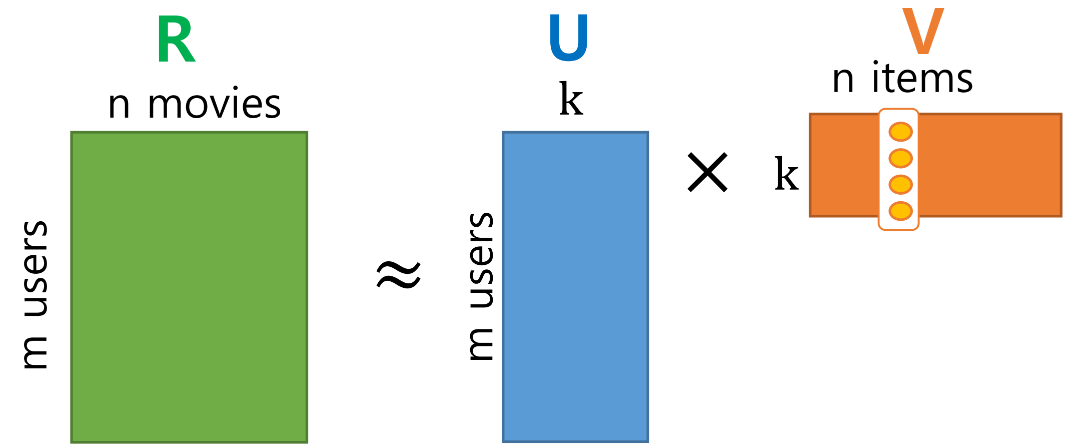


2) Deep neural network검색



3) 검색후 홈화면

Session-based recommender systems



기존 MF

$$r_{ij} \approx u_i^T v_j$$

$$r_j \approx f(\text{세션데이터})^{\mathrm{T}} v_j$$

Session based MF

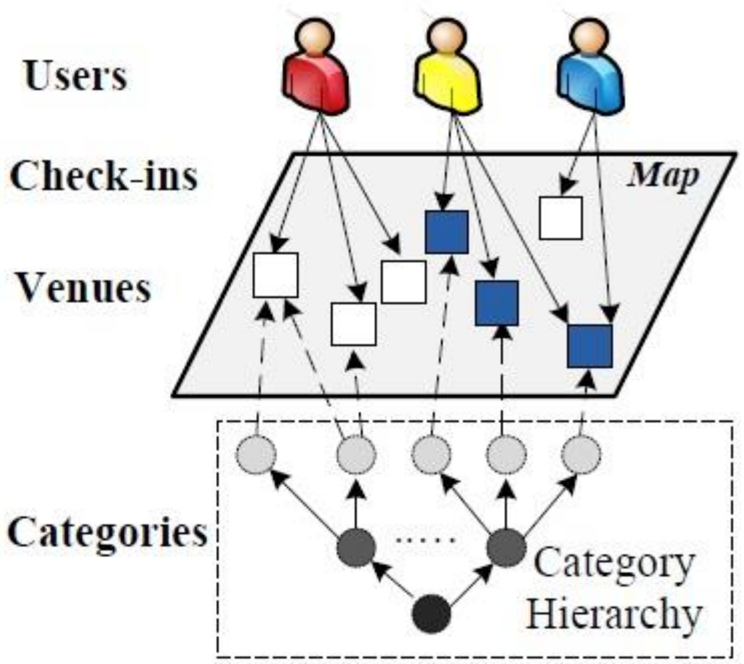
f: Sequence data 처리가 가능한 DNN (e.g., RNN)

세션데이터
- 검색기록
- 시청기록
- ...

Diversified Recommendation

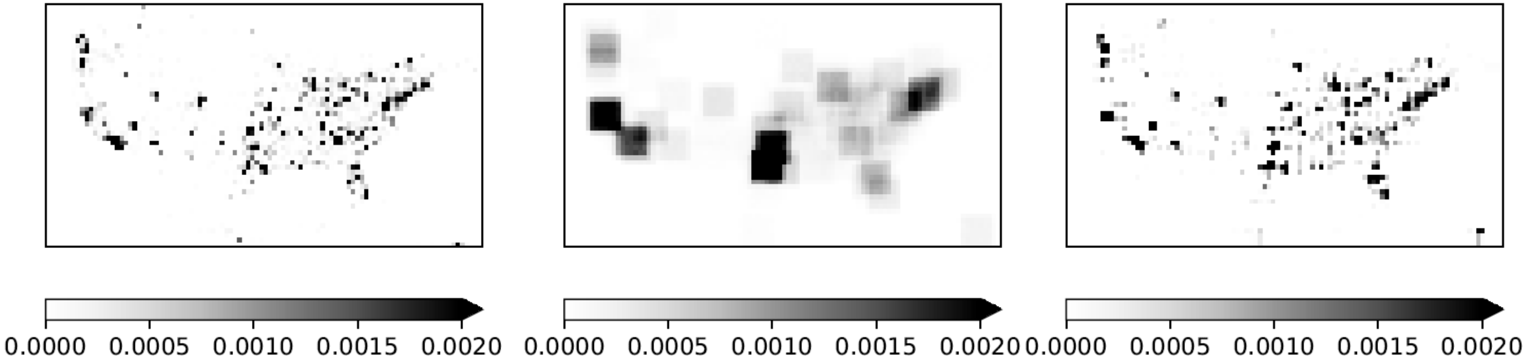
Netflix Recommendations: Beyond the 5 stars (Part 1) | by Netflix Technology Blog | Netflix TechBlog

Location based Recommender Systems



Location-based and Preference-Aware Recommendation Using Sparse Geo-Social Networking Data - Microsoft Research

Location based Recommender Systems :Privacy



(a) Original dist. (b) Perturbed dist. (c) Estimated dist.

Fig. 1: Spatial frequency distributions

Hong et al. IEEE TKDE 2022