Recommendation using Collaborative Filtering

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What is a Recommendation System?

- Predicts/Recommends the products or services that users would buy or consume
- Used in e-commerce, entertainment content, social media posts, advertisements, music, etc
- Types of recommendation
  - Collaborative-based Filtering
  - Content-based Filtering

What is Collaborative Filtering?

- Finds similar patterns among users
- Filters out items that users like based on the ratings or reactions of similar users

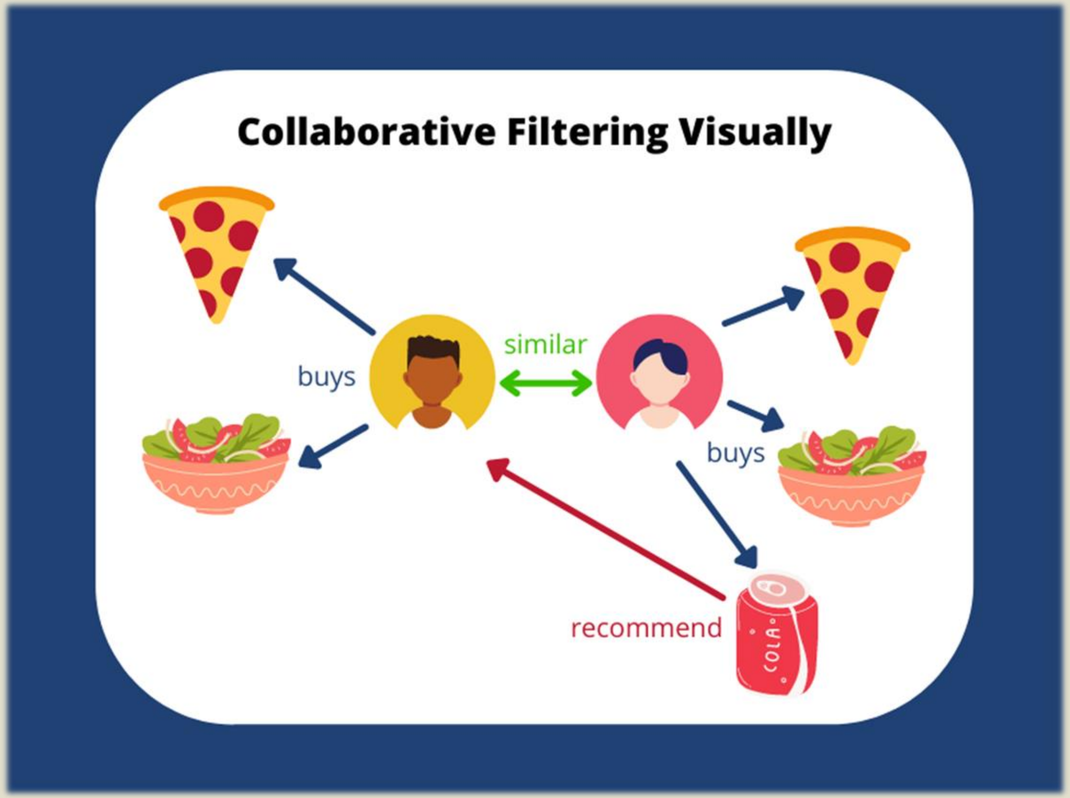


Image Credits

Types of Collaborative Filtering

Based on User similarity

- Find users sharing similar rating patterns with test user
- Ratings from these users used to calculate a prediction

Based on item similarity

- Relationships among items found using item-item matrix
- Match user's data with this matrix to get preferences

Similarity Check

Similarity can be computed as follows

$$r_{u,i} = \frac{1}{N} \sum_{u' \in U} r_{u',i}$$

$$r_{u,i} = k \sum_{u' \in U} \operatorname{simil}(u, u') r_{u',i}$$

where k is a normalizing factor defined as $k = 1/\sum_{u' \in U} |\operatorname{simil}(u, u')|$, and

$$r_{u,i} = \bar{r_u} + k \sum_{u' \in U} \operatorname{simil}(u, u')(r_{u',i} - \bar{r_{u'}})$$

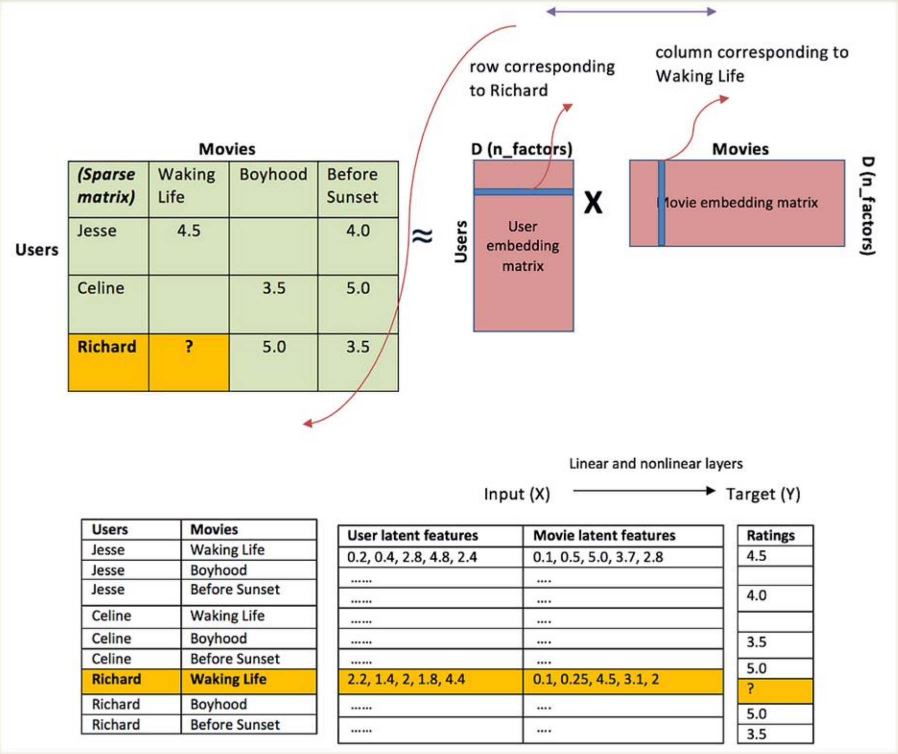
Source

$$\text{cosine similarity} = S_C(A, B) := \cos(\theta) = \frac{\mathbf{A} \cdot \mathbf{B}}{\|\mathbf{A}\| \|\mathbf{B}\|} = \frac{\sum_{i=1}^{n} A_i B_i}{\sqrt{\sum_{i=1}^{n} A_i^2} \sqrt{\sum_{i=1}^{n} B_i^2}}$$

Source

PyTorch

- Based on an open-source machine learning library called Torch
- Python frontend combined with Torch's powerful GPU-accelerated backend libraries to create a flexible and efficient system
- Framework for building Deep Learning models



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Embeddings

The users and movies are converted into embeddings

The multiplication of these matrices gives a prediction

This prediction is then scaled to the range of the ratings

PyTorch Deep Neural Network Implementation

```
RecommendationDataset(
  (u): Embedding(943, 50)
  (m): Embedding(1682, 50)
  (ub): Embedding(943, 1)
  (mb): Embedding(1682, 1)
  (lin1): Linear(in_features=50, out_features=2, bias=True)
  (lin2): Linear(in_features=2, out_features=1, bias=True)
  (drop1): Dropout(p=0.2, inplace=False)
  (drop2): Dropout(p=0.2, inplace=False)
)
```

Model Summary

```
The prediction for the users tensor([1, 1, 2, 2, 3, 3, 4, 4])  and movies  tensor([ 242,    1,  242, 1674,  242, 1674,  242, 16
74])  are  tensor([[3.1216],
        [3.1214],
        [3.0915],
        [3.1183],
        [3.1178],
        [3.1167],
        [3.1192],
        [3.0901],
        [3.1181],
        [3.1193],
        [3.1188],
        [3.0905],
        [3.1075],
        [3.1175],
        [3.0816],
        [3.1176]], grad_fn=<AddBackward0>)
```

Predictions

	0	1	2	3	4
196	Ed Wood (1994)	Under Siege (1992)	Brother Minister: The Assassination of Malcolm X (1994)	Long Kiss Goodnight, The (1996)	Rumble in the Bronx (1995)
63	Under Siege (1992)	Ed Wood (1994)	Long Kiss Goodnight, The (1996)	Brother Minister: The Assassination of Malcolm X (1994)	Rumble in the Bronx (1995)
226	Ed Wood (1994)	Under Siege (1992)	Brother Minister: The Assassination of Malcolm X (1994)	Long Kiss Goodnight, The (1996)	Rumble in the Bronx (1995)
154	Ed Wood (1994)	Brother Minister: The Assassination of Malcolm X (1994)	Under Siege (1992)	Long Kiss Goodnight, The (1996)	0
306	Ed Wood (1994)	Brother Minister: The Assassination of Malcolm X (1994)	Under Siege (1992)	Long Kiss Goodnight, The (1996)	Rumble in the Bronx (1995)
...	...	...	...	...	...
799	Ed Wood (1994)	Brother Minister: The Assassination of Malcolm X (1994)	Under Siege (1992)	Long Kiss Goodnight, The (1996)	0
358	Ed Wood (1994)	Brother Minister: The Assassination of Malcolm X (1994)	Under Siege (1992)	Long Kiss Goodnight, The (1996)	Rumble in the Bronx (1995)
410	Under Siege (1992)	Ed Wood (1994)	Long Kiss Goodnight, The (1996)	Rumble in the Bronx (1995)	Brother Minister: The Assassination of Malcolm X (1994)
598	Ed Wood (1994)	Brother Minister: The Assassination of Malcolm X (1994)	Under Siege (1992)	Long Kiss Goodnight, The (1996)	0
873	Ed Wood (1994)	Long Kiss Goodnight, The (1996)	Under Siege (1992)	Rumble in the Bronx (1995)	Brother Minister: The Assassination of Malcolm X (1994)

Recommendation

Fastai Implementation

Collaborative filtering using fastai

What is fast ai? Library built on PyTorch

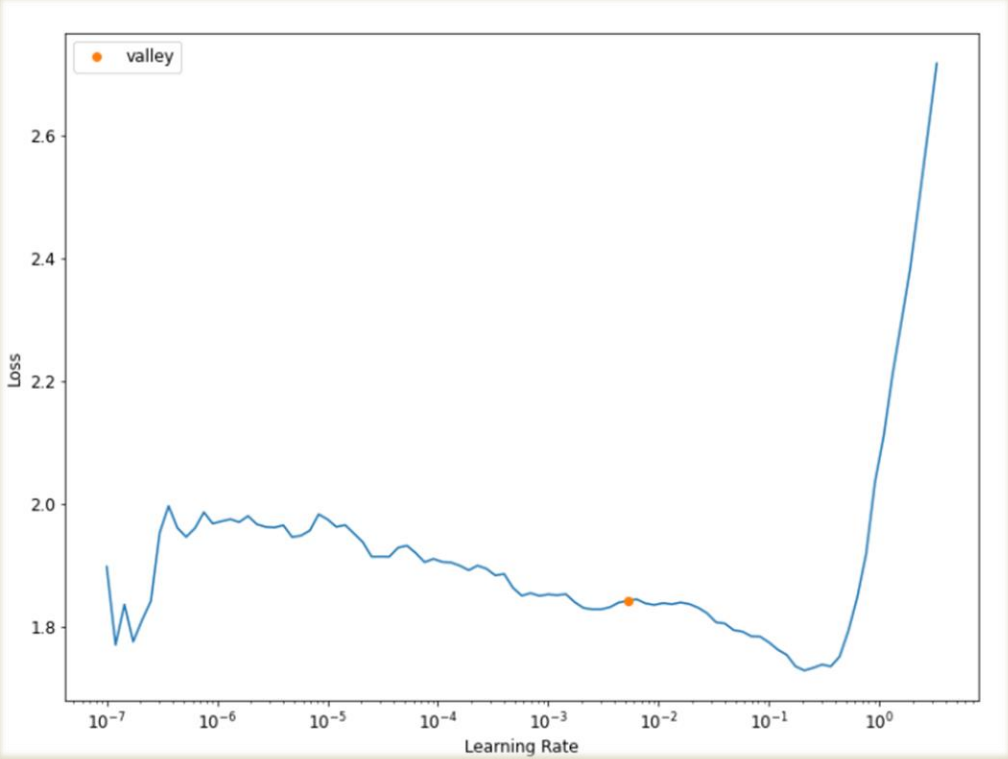
Elements used to build a collaborative filter from fast ai

Data loader

Learner

loss function(MSE)

Choosing a Learning rate



Model training

epoch	train_loss	valid_loss	time
0	0.950376	0.945305	00:13
1	0.842313	0.869440	00:13
2	0.744235	0.828205	00:13
3	0.580948	0.813320	00:13
4	0.471395	0.812804	00:13

	user	movie	rating	title
0	1	6	5	Shanghai Triad (Yao a yao yao dao waipo qiao) (1995)
1	9	6	5	Shanghai Triad (Yao a yao yao dao waipo qiao) (1995)
2	63	6	3	Shanghai Triad (Yao a yao yao dao waipo qiao) (1995)
3	79	6	4	Shanghai Triad (Yao a yao yao dao waipo qiao) (1995)
4	90	6	4	Shanghai Triad (Yao a yao yao dao waipo qiao) (1995)
5	409	6	4	Shanghai Triad (Yao a yao yao dao waipo qiao) (1995)
6	1	10	3	Richard III (1995)
7	7	10	4	Richard III (1995)
8	49	10	3	Richard III (1995)
9	59	10	4	Richard III (1995)

	Prediction
0	4.172879
1	4.326862
2	3.140697
3	4.168423
4	4.267342
5	3.732576
6	3.729470
7	4.075462
8	4.010137
9	3.723830

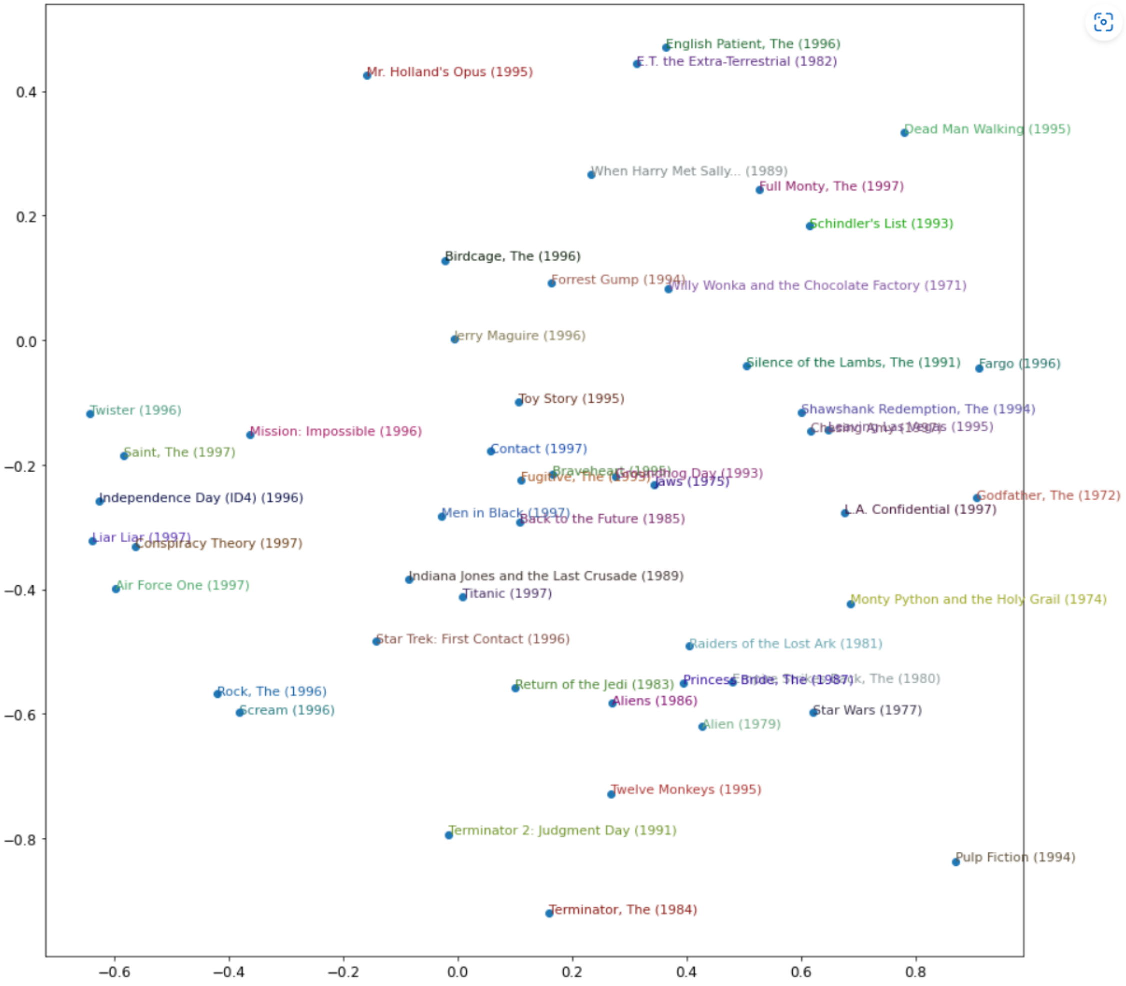
Test predicted and actual value

Dimension Reduction Methods

1. t-Distributed Stochastic Neighbor Embedding (TSNE)
2. Principal component analysis-PCA
3. Uniform Manifold Approximation and Projection, UMAP

Source

2D Embedding



	0	1	2	3	4
196	Amadeus (1984)	Lone Star (1996)	Crash (1996)	Platoon (1986)	Hotel de Love (1996)
63	Two Much (1996)	Three Lives and Only One Death (1996)	Colonel Chabert, Le (1994)	Telling Lies in America (1997)	Young Guns (1988)
226	Brothers in Trouble (1995)	What Happened Was... (1994)	Jupiter's Wife (1994)	Colonel Chabert, Le (1994)	Senseless (1998)
154	Full Speed (1996)	Mallrats (1995)	Lone Star (1996)	Serial Mom (1994)	Thin Man, The (1934)
306	Heathers (1989)	Young Poisoner's Handbook, The (1995)	Spice World (1997)	Telling Lies in America (1997)	Manny & Lo (1996)
...	...	...	...	...	...
799	Full Speed (1996)	My Favorite Year (1982)	U.S. Marshalls (1998)	Sleeper (1973)	Colonel Chabert, Le (1994)
358	Basquiat (1996)	Kalifornia (1993)	Mark of Zorro, The (1940)	When We Were Kings (1996)	Super Mario Bros. (1993)
410	Full Speed (1996)	Colonel Chabert, Le (1994)	Senseless (1998)	Heathers (1989)	What Happened Was... (1994)
598	Mallrats (1995)	Blue in the Face (1995)	Turbulence (1997)	Seven Years in Tibet (1997)	Philadelphia Story, The (1940)
873	Madonna: Truth or Dare (1991)	Big Bang Theory, The (1994)	Late Bloomers (1996)	Nightwatch (1997)	Ulee's Gold (1997)

Recommendation

Future scope

- Incorporate into real world applications
- Test for a larger data set
- Use a content-based recommendation for initial recommendation in addition to collaborative filtering

Sources

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