



Building Recommendation Systems in Python

PyData Geneva

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Outline

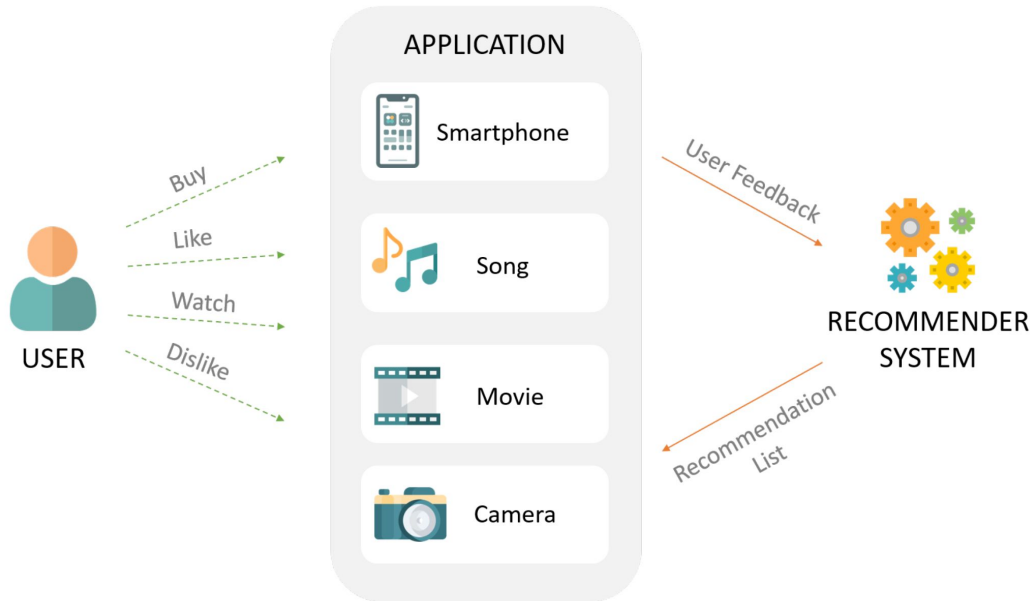
- RecSys Examples
- Intro to RecSys
- Collaborative Filtering
- Demo using RecBole

Intro to RecSys

Recommendations Everywhere



Recommendations Everywhere



Recommend Item **I** to the user **U**

The item could be anything:

- News
- Movies
- Videos
- Tweets
- Books
- ...

Let's see some examples

Recommendations Everywhere

Some Examples

In E-commerce



A

+



B

+



C

Total price: **\$208.9**

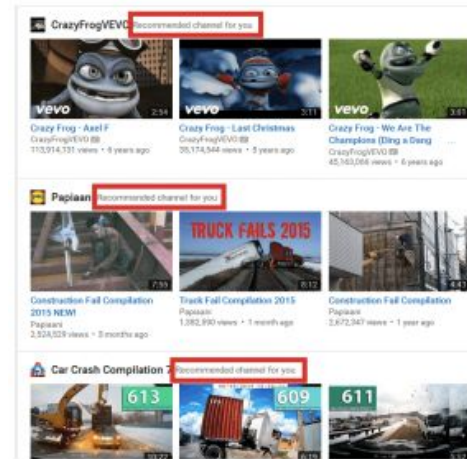
Add all three to Cart


Add all three to List

Recommendations Everywhere

Some Examples

Content Sharing





Recommendations Everywhere

Some Examples

Social Media





What is a Recommendation System?

- Recommend the best possible set of **items** to a given **user**
- Based on the history of **interactions** of the users with the items
- We have 3 main sets:
 - **U**: set of all **users** uniquely identified with and ID
 - **I**: set of all **items** uniquely identified with and ID
 - $R = U \times I$: matrix of user-item interactions



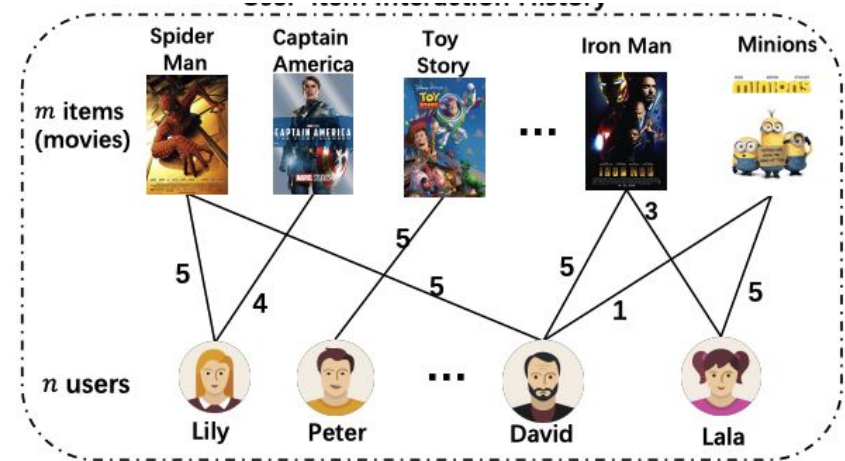
Type of Recommendation Systems

In general there are 3 types:

- **Content-based:** based upon the user and item descriptions or features
- **Collaborative filtering:** based upon the interaction of the users with the items
- **Hybrid:** combination of both

Collaborative Filtering












Learn from users preferences



Interaction Matrix

- Users in rows
- Items in columns
- Matrix elements as interaction records
- e.g. users rating movies

Items

						
	10	-1	8	10	9	4
	8	9	10	-1	-1	8
	10	5	4	9	-1	-1
	9	10	-1	-1	-1	3
	6	-1	-1	-1	8	10

Users

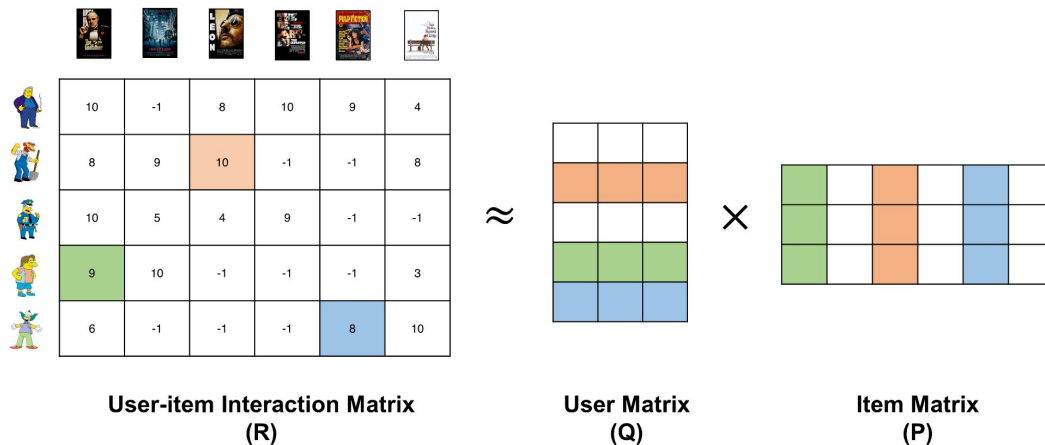
→ User-item Interaction matrix

**How can we learn to make
recommendations?**

Matrix Factorization

- Decomposing the interaction matrix as a product of:
 - User embeddings
 - Item embedding
- We have to find i.e. to learn those embeddings
- The estimated ranking is then:


















$$\hat{r}_{ij} = q_i p_j$$



How to learn the embeddings?

- Predicting the “missing” values
- We are intentionally hiding some values from the interaction matrix
- Then the model should learn to predict those values

Diagram illustrating the User-item Interaction matrix. The matrix is a 5x6 grid where rows represent Users and columns represent Items. Some values are missing (represented by gray squares).

	Items						
							
Users			-1	8	10		4
		8	9		-1	-1	8
		10	5	4	9	-1	-1
			10	-1	-1		3
		6	-1		-1	8	10

→ User-item Interaction matrix



How to learn the embeddings?

The simplest way is to minimize the squared difference between the true ratings and the estimated tanking:

$$\textit{minimize} \sum_{i,j} (r_{ij} - q_i p_j)^2$$

a.k.a. the Funk algorithm



Many other models

Based on the same principle

- [Singular Value Decomposition](#)
- Alternating Least Squares
- [Bayesian Personalized Ranking \(BPR\)](#)
- [Neural Collaborative Filtering \(NCF\)](#)
- [Restricted Boltzmann Machines \(RBMs\)](#)
- [GRU4Rec](#)
- [Wide and Deep](#)
- And many more ...

How to evaluate the recommendations?



Metrics

Scoring Metrics

- Root Mean Squared Error (RMSE)
- Mean Absolute Error (MAE)
- Area under the ROC curve (AUC)

Ranking Metrics

- Hit Rate
- Recall@K, Precision@k
- Mean Reciprocal Rank (MRR)
- Mean Average Precision (MAE)
- Discounted Cumulative Gain (DCG)



RecSys in Python

Numerous Open Source Libraries



- [TorchRec](#)
- [RecPack](#)
- [RecBole](#)
- [Implicit](#)
- [Microsoft Recommenders](#)
- [Vowpal Wabbit Recommenders](#)
- [Cornac](#)
- [Surprise](#)
- And many more ...



RecBole

Building Movie Recommender

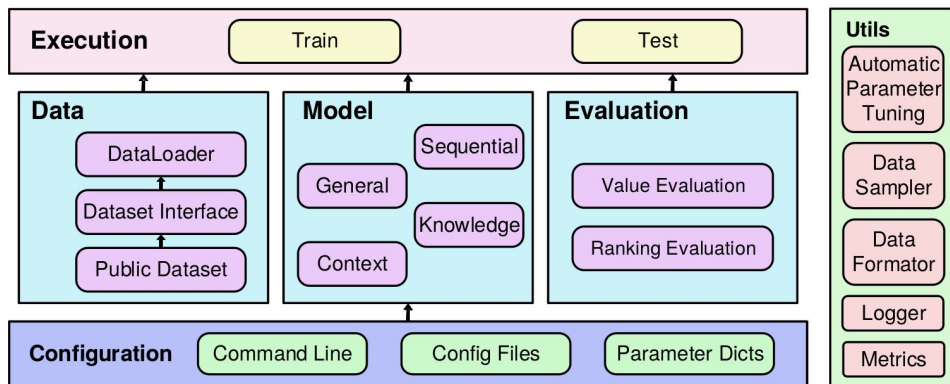


- It implements around [100 recommendation out-of-the-box models](#)
- Divided in 4 categories:
 - General recommendation
 - Sequential recommendation
 - Context-aware recommendation
 - Knowledge-base recommendation
- It is very easy to use

Movie Recommender using RecBole

- Everything via the YAML configuration:
 - Select model
 - Select data
 - Select evaluation metrics and strategy

RecBole Architecture



```
You, 52 minutes ago | 1 author (You)
## General
nproc: 1

## Model config
embedding_size: 64

## Dataset config : General Recommendation
USER_ID_FIELD: user_id
ITEM_ID_FIELD: item_id
load_col:
  inter: [user_id, item_id]


## Training
epochs: 500
train_batch_size: 512
eval_batch_size: 512

## Evaluation
metrics: ['Recall', 'MRR', 'NDCG', 'Hit', 'Precision']
topk: 10
eval_step: 2
valid_metric: MRR@10
```



Movie Recommender using RecBole

- Train a simple RecSys using the [NeuMF](#) model
- Using the [MovieLens](#) 100K toy dataset
 - Useful list of [RecSys Datasets](#)
- Data format: three [Atomic Files](#) with the following extensions
 - *.user: data about the users*
 - *.item: data about the item*
 - *.inter: interaction between users and items*



[Link](#) to the
GitHub repo

Movie Recommender using RecBole

Integrated TensorBoard logs:



Thank You for your attention!

Contact

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