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Machine Learning Fortnight 2023

Introduction to Recommender Systems





Fully Connected Graph





Machine Learning Fortnight

Introduction to Recommender Systems

Who are we?

ML Month

GAPC









Our Wonderful Team



Fully Connected Graph



Last year... Predicting housing prices in the Netherlands



Overview

Start

Nov 14, 2022



1

Prizes & Awards

Kudos Does not award Points or Medals



Close

Dec 8, 2022

Participation

13 Competitors 8 Teams 133 Entries



This year... video games are amazing! But which one should you play?



Fortnight overview



Introduction to Recommender Systems



20 Nov

24 Nov



Finale & Award Ceremony

Weaviate Vector Databases



27 Nov

1 Dec

Contents

- What Are Recommender Systems?
- Types of Recommender Systems
 - Content filtering
 - Collaborative filtering
 - Hybrid filtering
- Recommendation Algorithms
- Practical Session

stems? tems

Prerequisites

Familiar with

- Machine Learning
- Linear Algebra (inner product, matrix vector product)
- Some experience with Tensorflow and pandas

, matrix vector product) rflow and pandas

The world generates 2.5 quintillion bytes per day. That's 1,000 petabytes!



Recommender Systems are methods to suggest relevant content to users based on their preferences and behavior.



They *filter* the information







Results



ZOTAC Gaming GeForce RTX 3060 Twin Edge OC 12GB GDDR6 192-bit 15 GDps PCIE 4.0 Graph IceStorm 2.0 Cooling, Active Fan Control, Freeze Fan Stop ZT-A30600H-10M

uses data to help predi

^{\$}289⁹⁹ List: \$339.99

Delivery **Fri, Nov 17** Ships to Netherlands More Buying Choices \$266.79 (34 used & new offers)

Overall Pick 🚺



PNY GeForce RTX™ 4060 8GB XLR8 Gaming Verto RGB Triple Fan Graphics Card DLSS 3

\$**329**99

Delivery Fri, Nov 17 Ships to Netherlands

Recommender systems are everywhere...

systems	×	<u>@</u>	۹	
News Books Flights Finance				
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ecommender_system 🚦				
ndations using only information about rating profiles g peer users/items with a rating	s for			
n in simple terms?			~	
mender system?			~	
ns and why are they important?			~	
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glossary > recomme				
LIBRARY COMMUNITY				
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SOULCALIBUR

boodschappen in huis



Content Based Filtering

Content-based filtering recommends items similar to those the user has shown interest in based on item features.



Content-based Filtering

watched by user





Content Based Filtering



Writing Essays

 $\langle x, y \rangle =$ $x_i y_i$

•••

import numpy as np

courses = np.array([
 [0, 1, 0, 1, 0],
 [1, 0, 1, 0, 1],
 [1, 1, 1, 1, 0]
])

student = np.array([
 [1, 1, 0, 1, 0]
])

print(np.dot(student, courses.T))

Output: [[2, 1, 2]]

Output: [[2 1 3]]

Content Based Filtering

Advantages:

- No need for data about other users; recommendations are user-specific.
- Scalable to a large number of users.
- Can recommend niche items tailored to 0 individual preferences.

Disadvantages:

- Requires domain knowledge for handightarrowengineering item features.
- Limited ability to expand on users' existing \bullet interests; recommendations are based on current preferences.

Collaborative Filtering

Collaborative filtering uses past similar decisions to predict future selections based on shared preferences.



Collaborative Filtering

watched by both users





Collaborative Filtering 1D embedding





Collaborative Filtering 1D embedding





Collaborative Filtering 2D embeddings



Children





Harry Potter



The Triplets of Belleville



Collaborative Filtering 2D embeddings





-.8 -.9 -.8 .9 -1 STA RIPLETTES OF BELLEVILL The Triplets of The Dark Shrek Memento Knight Rises Belleville \checkmark \checkmark \checkmark 1 1 \checkmark 1 \checkmark ? preference for arthouse <-> blockbuster preference for children's <-> adult's

Collaborative Filtering Matrix Factorization

Matrix Factorization

Matrix factorization is a simple embedding model. Given the feedback matrix A $\in R^{m imes n}$, where m is the number of users (or queries) and n is the number of items, the model learns:

- A user embedding matrix $U \in \mathbb{R}^{m imes d}$, where row i is the embedding for user i.
- An item embedding matrix $V \in \mathbb{R}^{n imes d}$, where row j is the embedding for item j.

	Harry Potter	THIPLETTES " BELLEVILLE The Triplets of Belleville	Shrek	The Dark Knight Rises	Memento				.9 2	-1 8	1 -1	1 .9	9 1
	1		4	1			1	.1	.88	-1.08	0.9	1.09	-0.8
		4			-	≈	-1	0	-0.9	1.0	-1.0	-1.0	0.9
	*	4	*				.2	-1	0.38	0.6	1.2	-0.7	-1.18
2				4	4		.1	1	-0.11	-0.9	-0.9	1.0	0.91



Collaborative Filtering Matrix Factorization

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- An item embedding matrix $V \in \mathbb{R}^{n \times d}$, where row j is the embedding for item j.

$$\min_{U\in \mathbb{R}^{m imes d}, \; V\in \mathbb{R}^{n imes d}} \sum_{(i,j)\in \mathrm{obs}} (A_{ij} - \langle U_i, V_j
angle)^2.$$

The task is similar to

However, it is not efficient enough :(





SVD

1	0	1	1	0		
0	1	0	0	1		
1	1	1	0	0		
0	0	0	1	1		
$ A - U V^{T} _{F}^{2}$ = $\Sigma_{(i, j)} (A_{ij} - U_{i} V_{j})^{2}$						

Collaborative Filtering Matrix Factorization

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$$\min_{U\in \mathbb{R}^{m imes d}, \; V\in \mathbb{R}^{n imes d}} \sum_{(i,j)\in \mathrm{obs}} (A_{ij} - \langle U_i, V_j
angle)^2.$$

Weighted Matrix Factorization:

$$\min_{U\in \mathbb{R}^{m imes d}, \; V\in \mathbb{R}^{n imes d}} \sum_{(i,j)\in ext{obs}} (A_{ij} - \langle U_i, V_j
angle)^2 + w_0 \sum_{(i,j)
otin ext{obs}} (\langle U_i, V_j
angle)^2.$$



Collaborative Filtering Matrix Factorization (Optimization)

Stochastic Gradient Descent (SGD)

generic algorithm to minimize loss functions.

Optimize U and V matrices together

Alternating Least Squares (ALS)

specialized to this particular objective.

- Fix U, optimize V
- Fix V, optimize U

Collaborative Filtering Matrix Factorization (SGD vs ALS)

SGD

- Very flexible—can use other loss functions.
- Can be parallelized.
- Slower-does not converge as quickly.

ALS

- Reliant on Loss Squares only.
- I Can be parallelized.
- Converges faster than SGD.



Harder to handle the unobserved entries (need to use negative sampling or gravity).



https://developers.google.com/machine-learning/recommendation

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n 🛛 -		Send feedback				
i me: 4 hours						
ndation Systems! We've designed this course to expand your knowledge of ms and explain different models used in recommendation, including matrix neural networks.						
ourpose of recommenda	ation systems.					
e components of a reco	ommendation system including ca	ndidate generation, scoring,				



Practical Session :D

Break till ...



ML Fortnight 2023

- Register yourself
- Read the Kaggle page
- Build a recommender system
- Evaluate your model
- Submit your results
- Iterate and improve!

Machine Learning Fortnight

Nov 20 - Dec 1

Learn, code, win!

- 3 lectures
- 1 competition
- cool prizes
- lots of fun!

Develop a game recommendation system and gain valuable experience in process!



Or just look up: mlfortnight.svcover.nl





