NOVOMATIC

Recommender Systems

An Introduction



Outline

- What are Recommender Systems
- Problem Formulation
- Algorithms
 - Collaborative Filtering
- Where to go next

What are Recommender Systems











Ihre besuchten Seiten Ihre Empfehlungen Verbessern Sie Ihre Empfehlungen Gutscheine Mein öffentliches Profil Mehr dazu Mein Amazon



MEINE BESTELLUNGEN 7 kürzliche Bestellungen

Bestellungen anzeigen

In Ihrer Dez-Lieferung

3 hinzufügen, um zusätzlich zu sparen

PRIME-VORTEILE Unbegrenzter Fotospeicherplatz

AUDIBLE HÖRBÜCHER 90 Tage kostenlos testen

Mehr erfahren

Prime -

Listen -

KUNDE SEIT 2006

Für Sie empfohlen

Details anzeigen









Lesen Sie Mehr in Business & Karriere 32 ARTIKEL

88 ARTIKEL



Dokumentation in Video 91 ARTIKEL



94 ARTIKEL





Startseite Serien Filme Originale Kürzlich hinzugefügt

Meine Liste







Derzeit beliebt











Beliebt auf Netflix











Weil Ihnen "Indiana Jones Jäger des verlorenen Schatzes" gefallen hat











Why do we need recommenders?

- Offerings from "The Long Tail¹" must be presented to the right customers
- This should improve
 - User engagement
 - Retention rate
 - Conversion rate
 - Revenue
- Business value²
 - Netflix: 2/3 of the movies watched are recommended
 - Google News: recommendations generate 38% more click-through
 - Amazon: 35% sales from recommendations

¹ C.Anderson, "The Long Tail", 2008

² X.Amatriain lectures from 2014

Problem Formulation

Traditional Definition

Estimate an utility function that predicts how a user will like an item, based on:

- Past behavior
- Relations to other users
- Item similarity
- Context
- ...

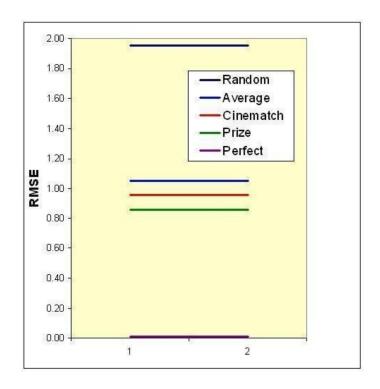
Target Variable

- User preferences
 - Explicit ratings
 - 1-5 stars ratings
- Purchase behavior
 - Implicit ratings
 - Yes / No
- Media consumption behavior
 - E.g. movies, songs or games
 - Implicit ratings
 - How many times played

Algorithms

The Netflix Prize

- 2006 2009
 - 1 million USD for 10% improvement of RMSE
 - ~ 100 million ratings
 - ~ 500 000 users
 - ~ 18 000 movies
- First conclusion¹:
 - it is really extremely simple to produce "reasonable" recommendations and extremely difficult to improve them



¹ X.Amatriain lectures from 2014

Algorithm Types

- Non-personalized Recommendations
 - Popularity based
- Content-Based Filtering
 - Item features necessary
 - Each user is predicted independently
- Collaborative Filtering
 - Features are learned
 - All user ratings help improve the prediction
- ...

Collaborative Filtering

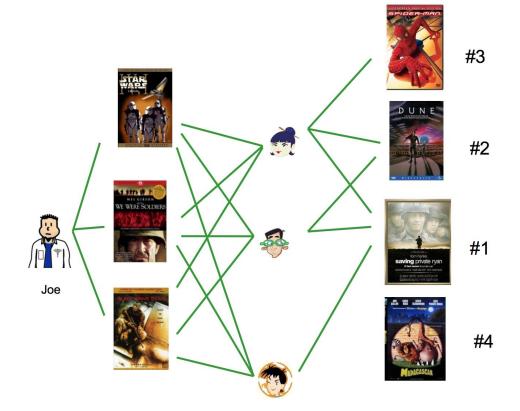
Ratings Matrix



CF Algorithms

- Neighborhood methods
 - User Similarity
 - Item Similarity
- Matrix Factorization

User Similarity - Concept



User Similarity - Implementation



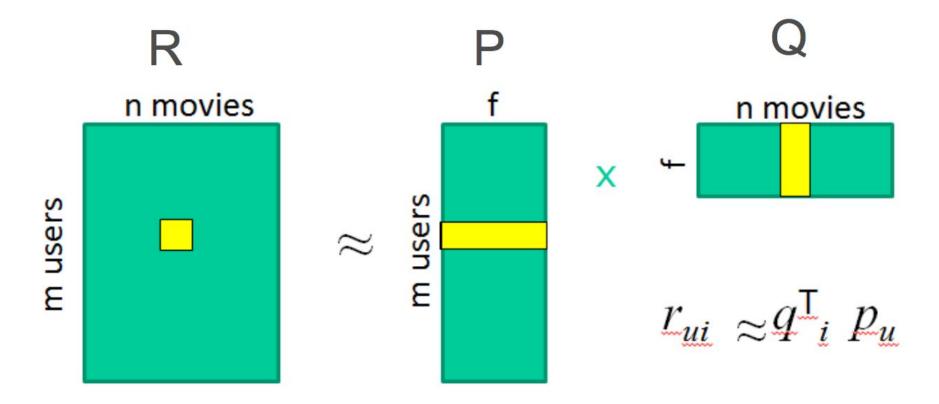
Item Similarity - Implementation



Matrix Factorization



Matrix Factorization



Problems of CF Methods

- Cold start
 - Changing user base
 - Changing inventory
- Matrix Factorization
 - Assumption about missing ratings
 - Retrain model when new ratings appear
- Neighborhood Methods
 - Similarity computation
 - Similarity matrix storage

Where to go next

Links

- Xavier Amatriain Lecture
 - http://technocalifornia.blogspot.co.at/
 - http://technocalifornia.blogspot.co.at/2014/08/introduction-to-recommender-systems-4.html
- Alex Smola Lecture
 - http://alex.smola.org/teaching/berkeley2012/recommender.html
- ACM RecSys Conference
 - https://recsys.acm.org/

Public Datasets

- MovieLens
 - https://grouplens.org/datasets/movielens/
- Netflix Prize
 - https://www.kaggle.com/netflix-inc/netflix-prize-data
- ACM RecSys Challenges
 - https://recsys.acm.org/

Libraries

- MyMediaLite
 - o .NET, command line
- Surprise
 - Python
- Spark MLlib
 - o Python, Scala, Java, R
- GraphLab Create
 - Python
- Lenskit
 - Java

Thank you!

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